A PRACTICAL PERSPECTIVE ON CONTRARIAN AND MOMENTUM INVESTMENT STRATEGIES' PROFITABILITY: EVIDENCE FROM THE US, UK AND EU12 STOCK MARKETS

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ABSTRACT

The stock return reversal effect (also known as the contrarian anomaly) and the stock return continuation effect (also known as the momentum anomaly) have been under close academic and professional scrutiny for over 20 years now. This is unsurprising given the potentially profound implications therefrom for the worlds of both theory and practice. In the former domain, support for the two past-return-based phenomena would represent strong and direct evidence against the cornerstone of modern financial theory, *i.e.* the efficient market hypothesis. In the latter domain, abnormal returns to contrarian and momentum investment strategies would mean that investors can outperform the market even by following a simple trading approach.

This study focuses on the practical implications of the contrarian and momentum anomalies by considering issues of greatest importance to investors, including: a practicable methodology; realistic stock market conditions; the wider investment context; the economic significance of returns; taxation policies; or risk and market microstructure characteristics.

Under consideration is a 12-year time period beginning in January 2000 and the following 13 stock markets: US (NYSE-AMEX), US (NASDAQ), UK (LSE), Bulgaria (BSE-Sofia), Cyprus (CSE), Czech Republic (PSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania (BVB), Slovakia (BSSE), Slovenia (LJSE) and the EU12.

The main results of the present research indicate that the contrarian and momentum effects are non-existent in the analysed populations, at least by the adopted specifications and standards. This finding is, therefore, strongly supportive of weak-form efficiency.

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PREFACE

It is the author's view that this thesis, as originally submitted to the University of York for examination, has been modified upon the request of the examination panel approved by the University of York in ways which not only significantly depreciated its value, but also introduced misleading and erroneous information. This view has been communicated to the examination panel, the supervisory panel and the administrative body of the University of York to no effect.

Most importantly, in line with the literature on the contrarian and momentum effects (see *e.g.*, De Bondt and Thaler, 1985; 1987; Jegadeesh and Titman, 1993), the original thesis considered a selection of 64 timeframes to investigate the persistence of the two studied effects. This has been limited to only one timeframe (*i.e.*, the six-month/six-month timeframe).

In the author's view, not only has the above-described modification deprived the reader of the information on the viability of contrarian and momentum investing for the vast majority of the timeframes that are relevant to this area of research, but it also introduced misleading information into the thesis. Namely, the contrarian effect, as presented in this thesis and in the cited literature (see pp. 34-65), is a long-term phenomenon[1], which means that it would be expected to manifest itself on timeframes with formation and test periods of beyond a year. Since this study has been limited to the six-month/six-month timeframe exclusively, no reliable conclusions can be drawn about the existence of the contrarian effect and the effectiveness of contrarian investing in the studied stock markets.

The thesis as originally submitted also provided the results for three methods of weighting returns (*i.e.*, equal weighting, market-value-of-equity weighting and price weighting), which enabled both institutional and retail investors to assess risk

[1] Here, 'long-term' is taken to mean beyond one year and 'short-term' is taken to mean under one month. While a short-term contrarian effect has also been documented by a number of scholars (see *e.g.*, Jegadeesh and Titman, 1995; Lehmann, 1990), it is not investigated in this thesis. This is, among others, on account of the fact that, as compared to the long-term effect, the associated tests have different data requirements (*N.B.*, this study only uses monthly data) and the associated strategies are considerably more transaction-cost intensive, thereby being inherently less practicable.

exposure more effectively. This has been limited to only one weighting method (*i.e.*, equal weighting). Similarly, the individual reports for the stock markets of Estonia (TSE), Latvia (RSE) and Malta (MSE) have been removed from the thesis.

Furthermore, it is the author's view that the results of the requested multifactor risk adjustments (see Appendix H) present misleading and erroneous information. As stated explicitly on page 174, there is insufficient data to calculate the Fama and French's (1996) factors for the EU12 stock markets, which represent over 81% of the studied stock markets. It should also be emphasised at this point that it is the EU12 stock markets and not the US or the UK stock markets that are of primary interest in this thesis. Instead of using the EU12 factors in the calculations for the EU12 stock markets, the requested multifactor risk adjustments are performed on the basis of the UK factors. Those factors are unlikely to be of any value in the EU12 context, especially considering the difference in the stages of development across the two investment environments.

What is more, the requested risk adjustment for the momentum effect, *vis-à-vis* the Carhart's (1997) four-factor model, is erroneous given that the momentum effect, alongside the contrarian effect, is one of the two effects that is investigated in the thesis. In consequence, the dependent variable and one of the independent variables in the four-factor model is essentially the same. The only reason why the regression results do not show this is the definitional difference between the two variables.

Other problems that have emerged as a result of the requested modifications to the original thesis include, **but are not limited to**, the inconsistent use of zero percentage return and the market return as the benchmark against which portfolio returns are evaluated; the suggestion that the evidence from the EU12 stock markets has any power *per se* to address the issue of data mining in the context of the US or the UK stock markets; or the inclusion of references to irrelevant academic publications in the 'Literature review' chapter and Appendix B.

Therefore, this version of the thesis only represents what the author has been required to produce in order to meet the requirements of examination. It does

not represent his own views about how this research should have been conducted nor what should be concluded.

ACKNOWLEDGEMENTS

I would like to thank my parents for their support, understanding and motivation.

AUTHOR'S DECLARATION

Except where stated otherwise, all material presented in this thesis is the work of the author, which has not been previously published and is not currently under consideration for publication in any form.

1. INTRODUCTION

1.1. ARE STOCK MARKETS EFFICIENT?

The efficient market hypothesis (EMH) has been the central proposition in economics and finance for nearly half a century now. It states that capital markets are informationally efficient, which means that security prices at any time fully reflect all available information (Fama, 1970), at least up to the point that the marginal benefits and costs associated with acquiring as well as acting on that information are equal (Fama, 1991; Jensen, 1978; Grossman and Stiglitz, 1980).

To more accurately pinpoint the level of capital markets' informational efficiency, the EMH studies have investigated if prices fully reflect three particular subsets of available information, which in descending order of accessibility are the following: (1) historical information, especially past price or past return information, (signifying weak-form efficiency); (2) publically available information, especially newly released information, (signifying semi-strong-form efficiency); and (3) insider information (signifying strong-form efficiency). While the extreme model of strong-form efficiency is perhaps best viewed as a reference point to judge the severity of deviations from market efficiency, rather than as an exact description of the world, the two remaining models have received widespread support in the academic community. If the weak-form and the semi-strong-form efficiency are assumed to hold, then this has a number of significant and far-reaching implications for all capital markets' participants. In particular, in its least restrictive form, the EMH entails that it is not be possible to devise an investment strategy based on historical information that will consistently earn net profits in excess of a fair return for the riskiness associated with the owned portfolio of securities.

The above premise has been challenged by, most notably, behavioural finance economists, who argue that investors do not always take rational economic decisions, on account of the fact that, as all people, investors are subject to cognitive biases. The consequent suboptimal investment choices are said to be systematic in nature and cause stock prices to deviate from fundamental value for extended periods of time, resulting in long-lasting and recurring market inefficiency. Among the proponents of this relatively new school of thought one might count De Bondt and Thaler (1985; 1987) as well as Jegadeesh and Titman (1993), who provided empirical evidence to show that past stock return information might be successfully used in practice to predict and profit from future stock return movements. The significance of this finding, if verified, has two dimensions, one theoretical and one practical. For finance and economics theorists this means that the EMH does not hold at the most basic of the three efficiency levels, which calls into question the validity of key financial models. For finance practitioners, this means that it is possible to outperform the market even by following relatively simple trading rules and, therefore, active portfolio management needs not to be a 'loser's game' after all. The emphasis of this thesis is on the latter, practical dimension of the past-return-based phenomena.

Specifically, the ensuing scientific enquiry is concerned with contrarian and momentum investment strategies, which are trading methods designed to exploit the return reversal and the return continuation stock market 'anomalies', respectively. What reflects the practical orientation of this research is the explicit focus on issues that might be considered to be of foremost importance to investors, which embrace but are not limited to the following elements: an intelligible and practicable methodology; realistic stock market conditions; the wider investment context; the economic, rather than merely the statistical, significance of returns; taxation policies; risk; and market microstructure, including transaction costs.

The investment environments that constitute the context for studying the two specific past-return-based phenomena are the stock markets of the US (including the NYSE-AMEX stock universe and The NASDAQ Stock Market), the UK and the EU12[2] (including the collective EU12 stock universe). Under consideration is the time period extending from the beginning of January 2000 up to the end of December 2011.

[2] The EU12 countries are those members of the European Union (EU) that gained full accession between the 1st of May 2004 and the 31st of June 2013 inclusive. Consequently, the EU12 comprises the following 12 sovereign states: Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia. However, two issues should be carefully noted. First, upon the request of the examination panel appointed by the University of York, **the main results for Estonia (TSE), Latvia (RSE) and Malta (MSE) are not reported in the thesis** (see the 'Preface' to the thesis). Second, Croatia, which joined the EU on the 1st of July 2013, as well as any potential future EU members are not studied in the thesis.

It is, therefore, the primary objective of this research to determine if, in recent years, it has been possible to systematically earn abnormal returns in any of the inspected stock markets by following either a contrarian or a momentum strategy. By implication, this enquiry also represents a test of weak-form efficiency for all of the 13 stock markets.

1.2. MOTIVATION FOR THIS WORK

Although research devoted to analysing departures from market efficiency, *i.e.* the so-called stock market anomalies and the corresponding investment strategies, has been extensively published over the past few decades for developed markets, there seems to be a notable gap in the literature. Namely, very little is known on the degree of predictability of the less-developed[3] EU stock markets in general and whether they are converging on the more mature and efficient markets (Cajueiro and Tabak, 2005). In particular, there is no prior research, academic or non-academic, testing either the contrarian or the momentum hypothesis for those countries, which can be argued to be one of the most very basic practical tests of weak-form stock market efficiency.

As well as addressing the issue of data mining associated with the aforementioned concentration on developed stock markets, a study of the less-developed EU economies should also be considered important due to the fact that the constantly increasing degree of integration with global financial markets potentially makes them a valuable source of diversification and investment opportunities.

The benefits of international portfolio diversification have been broadly discussed in a number of influential academic papers. Solnik (1974), being among the first academic scholars exploring this field of knowledge, concluded that based on the U.S. and European data between 1966 and 1971, "an internationally well-diversified portfolio would be one-tenth as risky as a typical security and half as risky as a well-diversified portfolio of U.S. stocks (with the same number of holdings)" (p. 51). More recent studies by Goetzmann, Li and Rouwenhorst (2005) as well as Gupta and Jithendranathan (2008) found that although the ability to effectively spread risk across countries is reduced due to high average correlations between developed markets, especially when the market conditions are worst (*i.e.*, in 'bear markets'), the extra risk reduction could be gained from less-developed nations, such as the EU12. Principal Components Analysis (PCA), used in this study as a supporting test to

[3] The terms 'less-developed', 'underdeveloped', 'developing' and 'emerging' are used interchangeably in this thesis to describe those stock markets, economies or countries that have not satisfied a given set of criteria to qualify as developed stock markets, economies or countries. As explained in, among others, the 'Methodology' chapter, this study adopts the Dow Jones Indexes Country Classification System (S&P Dow Jones Indexes, 2011) as the basis for determining stock market maturity.

evaluate portfolio diversification prospects (see Appendix A), confirms that the aggregate EU12 stock market, and most of the examined individual EU12 stock markets, can, indeed, provide diversification benefits.

Another important aspect of investing in the EU12 is that, unlike other developing economies, the EU12 members have met a broad set of rigorous political, economic and institutional requirements, as summarized in the EU Copenhagen criteria, which include the existence of a fully functioning market economy as well as stability of institutions guaranteeing democracy, the rule of law, human rights and respect for and protection of minorities. These measures should efficaciously mitigate many of the difficulties commonly associated with foreign investment (both direct and indirect) in the developing regions of the world by, among others, decreasing information asymmetries resulting from obscure accounting standards, laws and systems.

However, the trading conditions in the EU12 are still more favourable for the Western EU investors. The provisions of the European Community law, specifically Article 56 (ex Article 73b), stipulate that all restrictions on the movement of capital and all restrictions on payments between Member States and between Member States and third countries are prohibited (European Commission, 1997). The Court of Justice of the European Communities has interpreted the meaning of the concept of 'capital movements' in a long line of cases and, in order to clarify the provisions of Article 56, there is a list of operations that may constitute capital movements. One type of operation is of interest here, *i.e.* operations falling under the heading of 'acquisition of domestic securities'. The Commission is of the opinion that the acquisition by nationals of another Member State of shares and bonds issued by a domestic company may be considered a capital movement (*ibid.*). Furthermore, nationals of other Member States should be free to acquire controlling stakes and to exercise the resulting voting rights under the same conditions as are laid down by the Member State for its own nationals (non-discrimination on grounds of nationality) (*ibid.*). In consequence, these and other regulations further alleviate, if not eliminate, potential problems pertaining to foreign investment, such as foreign shareholding restrictions, sovereign risk, substantial transaction costs or double taxation, while providing those who invest in the less-developed EU economies with valuable diversification.

Furthermore, considering the characteristics of developing stock markets, it is expected that a higher degree of predictability in price movements may be found there, which would suggest inefficiency and imply interesting investment opportunities (Cajueiro and Tabak, 2005). The vast majority of efficient market research to date has focused on the more mature US and Western European securities markets. Far fewer have investigated developing markets, possibly due to the absence of sufficient data in a convenient form, structural profile, inconsistencies in accounting regulations or "lack of supervision and administrative loose in the implication of existing rules" (Mobarek and Keasey, 2000, p. 2). In the case of the EU12, another possible reason for their exclusion from the literature is the relatively short operational period of the national stock markets. It is important to note that even though most of the EU12 stock exchanges were re-established in the early 1990s (following the collapse of the Soviet Union), the transition process to the market-based economy itself was not officially completed until those countries joined the EU in the 2000s (EBRD, 2006).

It is not unlikely, however, that the market participants in those countries are deficiently informed and, thus, behave irrationally as compared to well organised financial markets. The causes of inefficiency might stem from certain market imperfections, such as redundant transaction costs, thin trading, illiquidity, lack of timely information, cost of acquiring new information and possibly greater uncertainty about the future (Goldsmith, 1971; Mason, 1972; Taylor, 1956; Wai and Patrick, 1973). Harvey (1995), *inter alios*, reports that stock returns of emerging countries are highly predictable and have low correlations with stock returns of developed countries, thereby concluding that emerging markets are less efficient than developed markets and that higher returns and lower risk can be obtained by incorporating emerging market stocks in investors' portfolios. Similarly, Claessens, Dasgupta and Glen (1995) conduct tests of market efficiency and seasonality for emerging countries using stock indices as well as portfolios of different sizes and find significant serial correlation in equity returns in 19 out of 20 emerging markets studied, which suggests that stock prices in those markets violate the weak-form of the efficient market hypothesis.

Therefore, studying the less-developed EU stock markets in depth should bring attention to those regions and lessen the home bias phenomenon (observed, for example, by French and Poterba, 1991; Karlsson and Norden, 2007) to the benefit of investors, local economies and the EU at large. It is for this reason that the EU12 stock markets are of central importance to this research.

1.3. HOW DOES THIS THESIS CONTRIBUTE?

The original contributions of this thesis to knowledge can be classified into four main categories. Three of these categories are directly related to the research on the contrarian and momentum effects as well as their practical application, whilst one category is of general significance to the professional economics and finance communities. Each category will now be briefly discussed in turn.

First, the existing contrarian and momentum literature shows a few important gaps in coverage. Most notably, alike most other areas of research on stock market anomalies and stock market efficiency, very little attention has been paid to the developing regions of the world. In particular, there are no publications examining either contrarian or momentum profitability in the EU12 stock markets, which are of growing economic importance internationally as a result of increasingly integrated Europe and significant for reasons outlined in the previous section. In the case of the US stock markets, on the other hand, there is scarce coverage of The NASDAQ Stock Market, which is the world's second largest stock market by market capitalisation. In addition, virtually no US-stock-market-based studies on contrarian investing have covered sample periods beyond the late 1980s and, therefore, it is not clear whether these strategies are still profitable. Out of all 11 publications that have focused on the contrarian effect in the US stock market to date, only Chen and Sauer (1997) examined a sample that ended after 1989 (*i.e.*, in 1992). More importantly still, the use of almost identical sample periods also raises concerns about the possibility of data mining. These and other less-prominent contributions related to the literature coverage are discussed in more detail in the 'Literature review' chapter, especially in the 'Conclusion' section.

Second, this study represents a unique investigation into the past-return-based stock market phenomena in terms of its comprehensiveness, which fact is not only reflected by the synergism of the contrarian and momentum effects, but also by the examination of, among others, multiple stock markets, risk proxies, market microstructure proxies, statistical significance tests and economic significance tests. The current wide-ranging application allows bridging the methodological discrepancies in the existing literature, which often generate incompatible evidence, leaving many debates inconclusive and many issues unresolved. This problem is particularly, but by no means exclusively, pertinent to the few publications concerned with developing stock markets. A more concrete discussion of the methodological issues to be found in the contrarian and momentum literature is available in the 'Literature review' chapter, with the overviews and summaries presented in the 'conclusions' to the two main sections and the chapter.

Third, in addition to the wide range of aspects of the two past-return-based effects already deliberated upon across publications on the subject, this research also covers a number of hitherto unexplored elements in the present context. To begin with, complementary to the tests of statistical significance are herein the tests of economic significance, which provide information regarding the economic (or practical), rather than merely statistical, importance of the observed phenomena. This practice is line with, among others, the American Psychology Association guidelines, which represent editorial standards for more than 1000 journals in the social and behavioural sciences (Fidler, Cumming, Burgman and Thomason, 2004). Furthermore, alongside a comprehensive range of standard measures, the current study employs two practical, and arguably more useful to investors as compared to conventional, risk proxies. These are downside standard deviation and downside beta. The greater usefulness thereof has to do with the important distinction between downside risk and upside potential, which the conventional measures simply fuse together, thereby equating a strategy's capacity to generate lower profits than expected with its capacity to generate higher profits than expected. Among other original reapplications, the above-mentioned elements are elaborated upon in the 'Methodology' chapter and highlighted on a number of occasions in the 'Empirical results and analysis' chapter.

Fourth, as an unexpected consequence of the data screening and analysis process, the present research helped to improve the quality and reliability of two major data sources used by thousands of professionals worldwide (*i.e.*, the Thomson Reuters Datastream database and the Center for Research in Security Prices database). The details of this high-impact input are presented in the respective subsections devoted to the two data sources in the 'Methodology' chapter.

1.4. STRUCTURE OF THE THESIS

This thesis has been organised into five chapters. Following this introduction is the 'Literature review' chapter, which surveys the existing studies on the contrarian effect and the momentum effect. It is important to note that the literatures on the two past-return-based phenomena have developed almost entirely independently of each other, which fact justifies the separation of the material into two main sections as well as partly explains the relative size of that chapter. Once all the pertinent studies have been reviewed, the thesis progresses to the 'Methodology' chapter, which familiarises the reader with the specifics of the present research. This entails the delineation of the two research questions, the data sources and the data processing techniques. Next is the 'Empirical results and analysis' chapter, which begins with a section devoted to the analysis of the relevant investment environments and proceeds to formally addressing each of the two proposed hypotheses. A concluding chapter closes this study with a re-evaluation of the conceptual framework, a summary and discussion of the results as well as a number of recommendations for future work.

2. LITERATURE REVIEW

2.1. INTRODUCTION

This literature review aims to provide the reader with an analysis of academic publications on the practical aspects[4] of contrarian and momentum investment strategies. The practical aspects principally encompass the magnitude and statistical significance of the documented contrarian and momentum profits as well as the risk and market microstructure considerations associated with generating those profits.

The reminder of this chapter has been organised into two main parts: (1) 'Contrarian investment strategies'; and (2) 'Momentum investment strategies'. The reason for such an arrangement is that the literatures in the areas of contrarian and momentum investing have developed largely independently of each other, despite the fact that the methodological disambiguation between the two approaches is essentially arbitrary on account of their conceptual and logical homogeneity. Therefore, this literature review, effectively, combines two separate strands of literature, each evidenced by a substantial body of research, which fact justifies the relative size of the chapter.

Each one of the two constituent parts of this review has been further divided into sections based on the geographical location of the stock market studied and, subsequently, on the core themes pertinent to the current research. The first criterion is motivated by the need to reconcile the fact that, in terms of both quantity and importance, most academic publications in the area of contrarian and momentum investment strategies examine the US stock market with the practical consideration to maintain each section of the chapter in proportion. Therefore, the two main parts of this chapter are partitioned into a section on the 'Evidence from the US stock market' and a section on the 'Evidence from international stock markets'. The second criterion ensures that the literature review continuously maintains a sharp focus on those aspects of the two studied investment methods that are of primary relevance to this research.

[4] For a discussion of the theoretical aspects see Appendix B.

2.2. CONTRARIAN INVESTMENT STRATEGIES

2.2.1. INTRODUCTION

Contrarian investment strategies represent a group of trading methods that aim to exploit the stock market effect first identified by De Bondt and Thaler (1985), hereafter DBT (1985), whereby stocks that have performed extremely well in the past ('winners') underperform the market and stock that have performed extremely poorly in the past ('losers') outperform the market over the next three to five years.

The scholars interpreted these findings as being consistent with the overreaction hypothesis, a well-known observation from the field of applied psychology, where people in violation of Bayes' rule overreact to unexpected sensationalized news events, regardless of whether the events are positive or negative in nature. This overreaction results in stock prices deviating from the actual values as implied by the new information initially, but once investors have considered the news in more detail, prices move back to their equilibrium level.

The apparent implication is that past returns may be highly useful in creating a contrarian strategy, suggesting that investors should simultaneously long (buy) past losers and short (sell) past winners, yielding arbitrage profits. Alternatively, investors may focus only on one aspect of the contrarian effect[5] and, consequently, either long past losers or short past winners. The decision should mainly depend on whether the winner-loser effect is observed for both winners and losers, or only for one of the two groups, as well as on portfolio-characteristics considerations, especially transaction costs associated with short-selling winners.

Most importantly, however, unless this investment opportunity is explained by risk or market microstructure effects, such as transaction costs, short-sale constraints or

[5] Henceforth, the terms: the contrarian effect, the contrarian hypothesis and the winner-loser effect, will be used interchangeably to refer to the anomaly described by DBT (1985; 1987). The main reason for using such a wide variety of terms to describe this one anomaly is to be faithful to the terminology used in the discussed literature, which unfortunately is not very consistent. Importantly, numerous papers refer to the phenomenon documented by DBT (1985) as the overreaction hypothesis, while investor overreaction itself is only one of many possible explanations for the observed winner-loser effect.

illiquidity, which would render contrarian strategies impracticable, the findings of DBT (1985) present direct evidence against the efficient market hypothesis, the cornerstone of modern financial theory, which states that it should not be possible to earn systematic abnormal profits by following a trading rule based on publicly available information, such as past returns.

Therefore, the main objective of this section is to investigate the pertinent literature and determine whether the contrarian effect documented by DBT (1985) is likely to persists after controlling for risk and microstructure effects or not. If it does, then it should be possible to devise a successful trading strategy, *i.e.* a contrarian strategy, in order to exploit this anomaly. An indication of abnormal profitability is also usually required to justify further research into an investment method (but see *e.g.*, footnote 6).

The reminder of this section is organised into two parts: (1) 'Evidence from the US stock market' and (2) 'Evidence from international stock markets'. The reason for the aforesaid arrangement is that the US research in this area of knowledge leads research in other countries. As it will become apparent in the second part of this review, academic papers investigating the winner-loser effect from an international perspective build on the methodologies and findings of the US-stock-market-based studies.

2.2.2. EVIDENCE FROM THE US STOCK MARKET

2.2.2.1. FIRM-LEVEL RISK FACTORS

DBT (1985) were the first[6] academics to notice that stock prices in the US marketplace systematically overshoot and that their reversal is predictable from past return data alone.

Specifically, since the authors focused on stocks that go through more (or less) extreme return experience (during the formation period), two hypotheses were tested: (1) Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction; (2) The more extreme the initial price movement, the greater will be the subsequent adjustment.

Based on the Center for Research in Security Prices (CRSP) monthly returns file database, DBT (1985) found that for the period between January 1926 and December 1982 the difference in cumulative average residuals between extreme portfolios of stocks, designated as 'losers' (35 worst performing stocks) and 'winners' (35 best performing stocks), equals 24.6% three years after portfolio formation. Not only is this effect still observable as late as two years posterior, but by lengthening (or shortening) the portfolio formation period, more (or less) extreme observations are showed to be generated. Thus, as cumulative average residuals (during the formation period) for both winners and losers grow larger, so do the subsequent price reversals.

In a follow-up paper to DBT (1985), DBT (1987) extended their earlier tests to address a number of unresolved issues regarding the winner-loser effect. Three findings therefrom are of particular relevance to this subsection.

To begin with, following the supporting evidence from DBT (1985) on a tendency for the most extreme initial winners and losers to exhibit the most extreme subsequent price reversals (a phenomenon also known as the magnitude effect), it was found that

[6] Although DBT (1985) are commonly recognised in the academic community as the pioneers of the contrarian investment method, Beaver and Landsman (1981) examined stock return behaviour by employing a strikingly similar design four years before DBT (1985), albeit in a slightly different context. Interestingly, there was no indication of a stock market inefficiency reported in the earlier work.

this effect, in fact, only holds for losers, with the average Spearman rank correlations of -0.14, -0.28, -0.22, -0.29 and -0.30 for the five years of the test period, respectively.

Furthermore, DBT (1985) was showed that regardless of the length of the formation period, the beta for the loser portfolio is always lower than the beta for the winner portfolio. However, Chan (1988), studying CRSP data, as well as Vermaelen and Verstringe (1986), who replicated the winner-loser anomaly for the Belgian stock market, argued that "the usual procedure of estimating betas over a period is inappropriate if betas vary with changes in market value" (DBT, 1985, p. 564) and, thus, they suggested that the winner-loser effect may disappear if the risk estimates are obtained during the test period, rather than the formation period. DBT (1987) tested this hypothesis by constructing 'arbitrage' portfolios that finance the purchase of losers by short-selling winners and found that although the test period loser-beta is indeed greater than the winner-beta, this difference in risk is insufficient to explain the 5.9% positive return of the arbitrage portfolio. Thus, as the authors concluded, this test of the risk change hypothesis fails to explain the winner-loser effect.

Another important issue addressed by DBT (1987) was that pertaining to the difference between the winner-loser effect and the small firm (or size) effect. In particular, the authors inquired if the loser firms are particularly small and if small firms are for the most part losers.

Using the Compustat tape, it was found that while firms in the loser extreme cumulative average excess return (also referred to as CAR[7] by DBT, 1985) portfolio are, indeed, smaller than those in the middle portfolios, the average market value for the loser quintile is still about 30 times the average market value for the smallest quintile ranked by the market value of equity at the end of year. Hence, DBT (1987) concluded that: "the winner-loser anomaly cannot be accurately described as primarily a small firm phenomenon" (p. 571).

[7] Dissanaike (1994) noted that DBT (1985; 1987) as well as Chan (1988) refer to the arithmetic method as the CAR method, implying monthly returns summation instead of multiplication, which effectively makes it unrealistic. This is discussed in greater depth in the 'Evidence from overseas stock markets' subsection of the 'Contrarian investment strategies' section.

Nonetheless, similarly to Chan (1988), Ball and Kothari (1989) hypothesised that the observed significant negative serial correlation in both relative (*i.e.*, market-adjusted) and constant-beta-adjusted returns (*i.e.*, abnormal returns, assuming relative risk to be constant in time) is induced by time-varying expected returns in an efficient market, rather than stock market mispricing or investor overreaction to information. The authors argued that at both the aggregate and individual security level, negative serial correlation in stock returns can be attributed to variation in expected returns on the market portfolio, variation in relative risks of firms' investments, and variation in leverage, which is: "a decreasing function of past equity returns, provided firms do not maintain dynamically constant market-valued capital structures" (*ibid.*, p. 53).

Ball and Kothari (1989) examined serial correlation in returns and abnormal returns on all stocks from the CRSP monthly tapes and form 20 portfolios on the basis of either ranked ex post returns or size, with a minimum of ten years of data centred on any of the 52 years from 1930 to 1981. Then, annual buy-and-hold returns on each security for each of the five years in the ranking and post-ranking periods were calculated.

Although the negative serial correlation remains after controlling for aggregate returns, there appear to be large beta changes as a function of past returns, especially for extreme portfolios. Portfolio 1's beta increases by 78% (from 0.91 to 1.62), while portfolio 20's beta decreases by 57% (from 1.51 to 0.86). The authors asserted that these changes in relative risk from the ranking to the post-ranking period are consistent with changing expected returns and, therefore, "could explain the negative serial correlation in relative returns" (p. 59). However, due to the fact that risk changes are consistent with, but not predicted by, the mispricing hypothesis, the authors examined abnormal returns in the ranking and post-ranking period as a discriminating test. Whereas the ranking-period abnormal returns are monotonically increasing in the portfolio ranks (ranging from -24.0% to 32.1% for portfolio 1 and 20, respectively), the post-ranking period abnormal returns are, by contrast, distributed over a narrow range: from a high of 1.7% for portfolio 4 to a low of -2.7% for portfolio 20. In addition, the post-ranking-period abnormal returns are small both in absolute and relative terms. Overall, these findings were interpreted as being consistent with the efficient market hypothesis (EMH) as the relative risk adjustment eliminates most of the negative serial correlation in returns. Although Ball and Kothari (1989) could not definitively discriminate between the hypothesis of a small degree of mispricing and two other possible explanations consistent with the EMH (*i.e.*, the 'sample size' and 'imperfect CAPM' hypotheses), it was suggested that the pattern of abnormal returns is most likely due to a small amount of the size effect (also known as the small-firm effect).

These findings are substantiated by Zarowin (1990) who, after performing two sets of tests to examine the role of firm size in the contrarian phenomenon specifically, showed that the tendency for losers to outperform winners is not due to investor overreaction, but results from losers being smaller-sized firms than winners. Losers, the author argued, "(…) are likely to be smaller-sized firms than winners since losers, by definition, have lost market value relative to winners" (*ibid.*, p. 118). Yet, in spite of the fact that in this study the size phenomenon appears to subsume the three-year return reversals as documented by DBT (1987), Zarowin (1990) reported that the short-term (*i.e.*, one-day through one-month) contrarian anomaly remains. More surprisingly still, the author indicated that whereas losers seem to be considerably riskier than winners, the differences in risk cannot account for the return discrepancy and, even after controlling for risk (using the Sharpe-Lintner CAPM), losers outperform winners.

By contrast, Chopra, Lakonishok and Ritter (1992) applying Ball and Kothari's (1989) concept of allowing time variation in betas, the empirically-determined price of beta risk, comprehensive adjustment for size in the calculation of abnormal returns, and examining intermediate-term abnormal returns, found that there is an economically-significant contrarian effect present in the US stock market.

Using CRSP monthly tape of New York Stock Exchange (NYSE) issues from 1926 to 1986 and overlapping observations, whereby one year is skipped before the subsequent calculation, the authors preformed 52 groupings of all stocks into 20 portfolios on the basis of their prior five-year buy-and-hold returns.

The prior-period losers (portfolio 1) were reported to have a post-ranking-period average annual return of 27.3%, while for the prior-period winners (portfolio 20) the return is 13.3%, which effectively yields an annual difference of 14% and a cumulative difference over the five-year post-ranking period of 70% before compounding. Although Chopra *et al.* (1992) used 'slightly' different sample selection criteria from Ball and Kothari's (1989), in order to avoid a survivorship bias, there seems to be an overall agreement that much of the difference between the two portfolios can be explained by CAPM. However, Chopra *et al.* (1992) argued that numerous empirical studies have invariably found a much flatter slope than that implied by the Sharpe-Lintner model.

Having estimated the empirical relation between risk and return, the authors discovered that differences in betas do not generate differences in returns as great as predicted by CAPM (*i.e.*, 14%-15% difference in annual abnormal returns when CAPM is used *vs*. 6.5% for the estimated market compensation per unit of beta risk). Therefore, using the Sharpe-Lintner model for the calculation of theoretical risk premium leads to an underestimation of the contrarian effect. This is confirmed by the returns observed for the short windows surrounding quarterly earnings announcements, which are consistent with the overreaction hypothesis even after adjusting for the size effect and the higher risk present at earnings announcements.

In addition to the above, Chopra *et al.* (1992) found that greater return reversals can be seen for portfolios formed on the basis of five-year returns rather than one-year returns. The latter type of portfolios also display an interesting pattern of return momentum, which is similar to momentum patterns reported by, among others, DBT (1985) as well as Ball and Kothari (1989).

In terms of the correlation between size and prior returns, it was showed that the smallest size quintile contains 40% of extreme losers and 10% of extreme winners, which suggests that a simple size adjustment may cause the contrarian effect to be underestimated. The authors confirmed this initial conjecture by controlling for the correlation between size and prior returns, and concluded that the contrarian effect is not a manifestation of the size effect.

Similar results were reported by Albert and Henderson (1995) who focused on Zarowin's (1990) size-matching methodology and found a bias in the manner firms are ranked, thus providing further evidence that: "the return reversal is not subsumed by the firm-size effect" (Albert and Henderson, 1995, p. 60). More specifically, in relation to the Zarowin (1990) paper, the authors showed that splitting extreme winners and losers into quintiles ranked by size, as Zarowin (1990) did, does not ensure that winners and losers in these quintiles will be size- and performance-matched. In fact, while the quartile[8] of smallest firms contains more losers than winners and more winners than losers can be found in the quartile of the largest firms, the difference in terms of quantity between winners and losers in any of the size quartiles is insignificant. Hence, "Chopra *et al.* results are not unique to their methodology" (Albert and Henderson, 1995, p. 60) and seem more consistent with the magnitude effect, as predicted by the overreaction hypothesis, than the size effect.

In summary, the findings presented in this subsection strongly indicate that the winner-loser effect is unlikely to be exclusively driven by small companies, and, therefore, explained by risk as proxied by the market value of equity. It seems more likely that beta could account for much of contrarian profitability in the US stock market, despite some evidence implying the contrary (see *e.g.*, DBT, 1985; 1987; Chopra *et al*., 1992).

2.2.2.2. ECONOMY-LEVEL RISK FACTORS

The economy-level risk factors associated with the contrarian effect have been explored by Chan (1988), DBT (1987) as well as Chen and Sauer (1997).

Chan (1988), using alternative methods allowing for time-varying betas, found that the combined observations of a small alpha, a small beta, and a large return may be explained by positive correlation between the time-varying betas and the expected market risk premium responding to common state variables. To investigate this issue, DBT (1987) recalculated the regressions in a way that permits two betas to be

[8] Albert and Henderson (1995) split extreme upper and lower quintiles, derived from DBT (1987) replication, into quartiles based on the average size of DBT (1987) winners and losers at the end of each formation period (ENDSIZE).

estimated - one for periods of 'bull markets' and another for 'bear markets'. The authors reported that the arbitrage portfolio does well in both markets: for the winner portfolio the up-beta is 0.993, while the down-beta is 1.198; and for the loser portfolio, the betas are 1.388 and 0.875, respectively. In rising markets, losers tend to gain more than winners, while in falling markets winners tend to lose more than losers. This questions the adequacy of 'time-varying split betas' as a measure of risk, since it would seem odd to conclude that: "a portfolio with a beta of 1.602 in up markets and .591 in down markets is riskier than one with up and down betas of .854 and 1.439" (*ibid.*, p. 569).

However, adopting a methodology largely in accordance with Chopra *et al.* (1992), Chen and Sauer (1997) showed that the contrarian effect may not be persistent over time which, in conjunction with the evidence of cyclicality in profits, suggests that following a contrarian strategy could be associated with excess exposure to common macroeconomic risk factors.

While the authors departed from the methodology of the preceding paper in two aspects, *i.e.* (1) firms are removed from the studied sample as they are delisted from the exchange and (2) the analysis includes six more years of data[9], the reported results are only slightly lower than those observed by Chopra *et al.* (1992). Namely, the average annual return on the loser portfolio (rank 1) is 23.74%, while the corresponding figure for the winner portfolio is 12.43% (rank 20). All *t*-statistics are significant at $\propto = 1\%$.

However, in order to investigate whether the contrarian anomaly is persistent over time, Chen and Sauer (1997) performed a sub-period analysis of the post-ranking period, which exposed the fact that the 58 time-series arbitrage portfolio returns (with an approximate 11% annual average over the entire 66-year period) are quite volatile over time. In particular, contrarian profitability appears to vary procyclically with the state of the economy, which points towards macroeconomic risk factors as the source of the documented profits.

[9] The study spans from 1926 through 1992.

Therefore, it would seem that contrarian investment strategies are not time-stationary and during some periods earn a tremendous profit (*e.g.*, during the recovering years of the Great Depression), while during other periods make losses (*e.g.*, the years of the Great Depression and the early 1980's) or no abnormal profit at all (*e.g.*, from mid-1940s to mid-1950s). Nonetheless, under closer scrutiny it transpires that, for instance, the *t*-statistics corresponding to the presented evidence of contrarian losses are all statistically insignificant in 19 out of 20 cases and, in fact, in the period to which those relate (*i.e.*, the post energy crisis regime) there are four times more observations of statistically significant positive contrarian profits. Similarly, during the period of relative stability (*i.e.*, from mid-1940s to mid-1950s), the loser portfolio outperforms all other portfolios and this outperformance is statistically significant in 20% of cases. Furthermore, the authors claim that the U-shaped pattern of the time-series of portfolio standard deviations suggests that extreme past-performance portfolios are less likely to maintain their relative position over successive time periods as compared to, for instance, mid-rank portfolios, which underscores the volatility of the contrarian effect. However, this suggestion does not seem to be supported by the, indeed, remarkably consistent, but not always statistically significant, outperformance of losers and underperformance of winners over all individual sub-periods studied.

To conclude, the evidence put forward by DBT (1987) clearly shows that the returns to contrarian strategies cannot be persuasively explained by the correlation between the time-varying betas and the expected market risk premium responding to common state variables, as suggested by Chan (1988). In a later publication on the theme, Chen and Sauer (1997) examined the time-series properties of the winner and loser portfolios, and showed that contrarian profits vary with the business cycle, which suggests that contrarian strategies may earn a positive macroeconomic risk premium. However, while the presented findings indicate that this may, indeed, be the case to some extent, it would appear that some of the statistics are misrepresented and the consistent, but not always statistically significant, outperformance of the winner-loser arbitrage portfolio is understated.

2.2.2.3. MARKET MICROSTRUCTURAL EFFECTS

There are three publications that focus on the issue of market microstructural effects in the context of contrarian strategies, these have been authored by: Conrad and Kaul (1993); Ball, Kothari and Shanken (1995); and Loughran and Ritter (1996).

To begin with, Conrad and Kaul (1993) suggested that previous studies, implementing the long-term contrarian strategy as described by DBT (1985), are upwardly biased as a consequence of their single-period (monthly) method of calculation cumulative returns over long intervals.

Using a sample of NYSE firms over the 1926 to 1988 period, the authors replicated DBT's (1985) empirical procedures and, following Blume and Stambaugh's (1983) reasoning, assumed that the bid-ask spread is the only source of measurement errors in observed prices[10].

Having delineated methods employed in previous studies for the purpose of estimating the average cumulative abnormal returns (ACARs), Conrad and Kaul (1993) showed that if losers are low-priced and winners are high-priced relative to the average NYSE firm, there may be an upward bias in the ACAR of loser firms and a downward bias in the ACAR of winner firms, which could also explain the return reversal asymmetry. Furthermore, the biases in ACARs were reported to increase linearly with the measurement interval and, thus, the difference between the average cumulative abnormal returns (DACAR) should exhibit exactly the same upward 'drift' as hypothesised by proponents of long-term overreaction. More importantly, though, the authors argued that "the absolute magnitude of the upward bias in *single-period* returns is invariant with respect to the length of the period over which the return is measured" (*ibid.*, pp. 45-46) and that this nonlinearity can also be observed in the relation between the bias and the price. What follows is that the upward bias will be more prevalent in daily as compared to monthly returns and that the cumulative

[10] Conrad and Kaul (1993) do acknowledge the importance of price discreteness and nonsynchronous trading as a source of measurement errors, but argue that bid-ask errors may have a more serious impact on the properties of asset returns.

returns of low-priced stock will be substantially more biased than the high-priced stocks (*e.g.*, a $1 stock has a bias of 56.25%, and the bias in a $3 stock is only 6.25%).

Furthermore, the authors showed that conditional on past prices, there is no relation between cumulative returns to losers or winners and their market values, which result seems to substantiate the bid-ask bias hypothesis and, in addition, refute the size effect as a partial explanation of the winner-loser effect. However, it would appear that a simple price-based buy-and-hold investment strategy underlain by the arbitrage portfolio of low- and high-price firms has two to four times larger cumulative abnormal returns than an equivalent strategy underlain by the loser-winner arbitrage portfolio. On that account, Conrad and Kaul (1993) suggested that the returns to long-term contrarian strategies are unrelated to the concept of overreaction, or even prior performance, but are in fact a result of a low-price phenomenon.

Analogous research was carried out by Ball *et al.* (1995), yet with two important differences: one related to the research time frame and the other one to the research scope. The former is reflected by the fact that the authors concentrated on problems in measuring raw and abnormal five-year buy-and-hold contrarian portfolio returns, rather than three-year returns as discussed by Conrad and Kaul (1993). For the latter aspect, Ball *et al.* (1995) did not restrict their analysis to the bid-ask bias alone, but considered microstructure effects[11] (or microstructure-induced biases) in general as well as other performance measurement problems, in the context of DBT's (1985, 1987) contrarian research design.

To test the contrarian hypothesis (or the winner-loser effect), the authors ranked all New York and American Stock Exchange (NYSE-AMEX) stocks on the CRSP monthly tape from 1931 to 1984 on the basis of their buy-and-hold returns over the preceding five years (*i.e.*, the ranking period) and sorted these into loser (bottom 50 stocks) and winner (top 50 stocks) groups, whose performance was then monitored for the proceeding five-year period (*i.e.*, post-ranking period).

[11] That is, effects pertaining to, *inter alia*, spreads, liquidity, and brokerage costs.

To begin with, Ball *et al.* (1995) argued that, taken uncritically, the difference in mean raw returns, as opposed to *e.g.* median raw returns, between losers and winners may appear to show support for the contrarian hypothesis. Nonetheless, while the December-end five-year post-ranking-period mean returns for the winner and loser portfolios differ by 91%, the difference in median returns over the same period is only 14%. In consequence, an upward returns adjustment of $0.125, which may reflect either a small dollar amount of mispricing or a conservative estimate of microstructure factors that might be considered part of the costs of trading in stocks, results in a 25% reduction in the average return on the loser portfolio (from 163% to 138%) and only a 2% fall (from 72% to 70%) in the case of the winner portfolio. By contrast, the median return on losers declines only from 49% to 44%.

Furthermore, having conducted price-quartile and regression analyses, the authors emphasised three observations. First, it can be observed that losers tend to have low prices and small market capitalisation, which may lead to problems with implementing DBT's (1985, 1987) research design as it assumes that positions can be established at CRSP closing prices and, thus, ignores microstructure-induced biases. Ball *et al.* (1995) showed that the bid-ask spreads and transaction costs may, indeed, be large for this type of stocks. Second, the authors suggested that the price difference between winners and losers is not controlled for in simulated contrarian portfolios. By short-selling comparatively high-priced winner stocks and going long in comparatively low-priced loser stocks, these portfolios are unhedged with respect to price-related microstructure effects. Third, it was speculated that the low market capitalisation of the loser stocks renders prior research on contrarian strategies essentially useless for the investment community.

As far as systematic risk estimates are concerned, these were found to correspond to the ones reported in previous studies. Therefore, the observed higher portfolio beta for losers, as compared to the winner portfolio's beta, seems consistent with the changes in leverage caused by their ranking-period performance, as presented by Chan (1988), and Ball and Kothari (1989). However, in contrast to Chopra *et al.* (1992), Ball *et al.* (1995) predicted that a CAPM-based benchmark will, in fact, overstate contrarian abnormal returns, since an equal-weighted market index, adopted for the purposes of this study, has an alpha of zero and, thus, no improvement in terms of efficiency is possible.

Overall, the above-discussed problems with both raw and abnormal five-year buy-and-hold contrarian portfolio returns are, Ball *et al.* (1995) argued, unusually severe for contrarian portfolios specifically, due to the fact that they invest in extremely low-priced 'loser' stocks.

However, Loughran and Ritter (1996) demonstrated that Conrad and Kaul's (1993) conclusions, and by implication those by Ball *et al.* (1995), had been driven by survivor bias and long-term mean reversion in the aggregate stock market, rather than cross-sectional patterns on individual stocks. Although the authors did not disagree with the important part of the two articles, *i.e.* regarding the fact that price can be used to predict future returns, and that bid-ask spreads lead to an upward bias in monthly CARs on low-priced stocks, several consequential problems with the evidence and interpretation thereof were highlighted.

On the basis of monthly returns, price, and market value data obtained from the CRSP 1992 tapes of AMEX-NYSE stocks, the authors reported results for 58 overlapping three-year periods, starting in 1929 for NYSE firms (1965 for AMEX firms) and ending in 1988.

The analysis started by examining the sensitivity of average returns to the choice of either buy-and-hold returns or CARs for the purpose of sorting individual securities into the loser (defined as the 35 firms with the lowest raw returns) and winner (defined as the 35 firms with the highest raw returns) portfolios. It was found that using buy-and-hold returns, rather than CARs, to determine portfolio cut-offs results in greater price ($22.54 *vs.* $33.39), market capitalisation ($68.4m *vs.* $14.96m), prior return (486.8% *vs.* 526.9%), and test-period return (*e.g.*, 42.8% *vs*. 55.1% for three-year holding-period returns) dispersions. Additionally, unlike other procedures, the CARs method sometimes classifies firms as extreme winners or losers, due to extreme monthly returns.

These findings provide one possible explanation as to why studies using buy-and-hold returns to form portfolios (*e.g.*, Ball and Kothari, 1989; Chopra *et al.*, 1992) document greater differences in test-period returns than studies using CARs (*e.g.*, DBT, 1985). Nevertheless, Loughran and Ritter (1996) argued that while the buy-and-hold method provides a sharper distinction between portfolios when classifying firms (*i.e.*, during portfolio formation), once the portfolios are formed, "CARs and buy-and-hold returns give rise to similar empirical conclusions" (p. 1963).

Furthermore, the authors noted that Conrad and Kaul (1993) had departed from DBT methodology in three ways. First, a different sample period was used. Second, the authors included AMEX as well as NYSE firms in the last 35% of their sample period, which has a substantial impact on the results, "since the vast majority of the low-priced losers (and 54% of all of our losers) in recent decades are on the AMEX" (Loughran and Ritter, 1996, p. 1961). Third, Conrad and Kaul (1993) introduced a survivor bias. Taken together, these three elements explain the difference in the 36-month arbitrage portfolio results between DBT (1985) and Conrad and Kaul (1993).

In addition, the empirical results obtained by Conrad and Kaul (1993) from pooled cross-section time series (CS-TS) regressions, showing that the logarithm of price is the most important determinant of subsequent returns among extreme winners and losers, suffer from three problems which, combined, substantially increase the influence of log price. First, the sample was restricted to firms that survive for 36 months after the portfolio formation date, which introduced a survivor bias. Second, Conrad and Kaul (1993) used pooled CS-TS regressions to measure cross-sectional patterns, which when compared with the Fama-MacBeth regressions show, *ceteris paribus*, a 15-fold increase in the difference between the three-year return on a stock with the mean price of losers and a stock with the mean price of winners. Third, *t*-statistics appear to be misstated in the pooled CS-TS regressions, because each of the 35 observations in each cohort had been assumed to be independent, whereas there is arguably a substantial contemporaneous correlation in the residuals among the firms in a given cohort.

Lastly, in response to Conrad and Kaul's (1993) assertion that "conditional on beginning of the period prices, there is *no* relation between long-term returns and past performance." (p. 59), Loughran and Ritter (1996) demonstrated that, even if this is not true for some arbitrary interval, such as three years, essentially all low-priced stocks on the AMEX and NYSE are extreme losers relative to some price in their past. Therefore, segmenting by price has no power to reject the overreaction hypothesis.

To summarise, there seems to be some academic support for the notion that contrarian investing is heavily affected by factors relating to market microstructure. Although Loughran and Ritter (1996) suggested that this finding might be underpinned by the biased methodology of Conrad and Kaul (1993), and by implication Ball *et al.* (1995), in reality the presented evidence mostly relates to the former paper. However, it is clear that more research needs to be conducted to allow any definite conclusions to be drawn, especially considering that essentially only three studies have looked into this issue to date.

2.2.3. EVIDENCE FROM INTERNATIONAL STOCK MARKETS

For a prolonged period of time after the pioneering work of DBT (1985), the debate on the viability of contrarian investment strategies largely focused on the US marketplace. However, a considerable number of more recent papers, usually drawing strongly on the findings discussed earlier in this chapter, attempted to verify the transferability of this strategy to other stock markets in the world.

To begin with multi-country papers, in a comprehensive time-series cross-sectional study, Baytas and Cakici (1999) analysed data from seven industrialised countries[12] and, using Conrad and Kaul's (1993) methodology to evaluate the performance of arbitrage portfolios based on past performance, price, and size, tested for the contrarian hypothesis.

Based on data obtained from the Worldscope Disclosure Database for a sample of stocks in each country between 1982 and 1991, the authors calculated holding period returns (HPRs) both to sort stocks into the winner and loser portfolios as well as to measure their test-period performance. Importantly, although Loughran and Ritter's (1996) criticism of cross-section time series (CS-TS) regressions was addressed to some extent, Baytas and Cakici (1999) primarily focused on Conrad and Kaul's (1993) pooled CS-TS approach to assess the impact of price and size on HPRs.

Consistent with the contrarian hypothesis, it was reported that in all countries, with the notable exception of the US, a significant positive return to the three-year period arbitrage portfolio based on past performance can be observed. For example, the average return to the arbitrage portfolio of losers and winners is 94.5% in Japan, 62.9% in France, 58.5% in UK, 50.5% in Germany, 21.6% in Italy, and 12.4% in Canada.

Somewhat different results to those of Baytas and Cakici (1999) were reported by Mun, Vasconcellos and Kish (2000) who, using a non-parametric methodology with a multi-factor asset pricing model, analysed monthly data for both the US and the

[12] Those seven industrialised countries are: US, Canada, UK, Japan, Germany, France, and Italy.

Canadian stock markets. The dataset was for the period from 1986 to 1996. It contained both time series and cross-sectional observations as well as covered the US Standard and Poor's, hereafter S&P's, 500 index returns and the Morgan Stanley Canadian market index returns.

The use of non-parametric parametric techniques was justified by the evidence of non-normality and non-stationarity within stock markets (see *e.g.*, Aburachis and Kish, 1999; Chen and Sauer, 1997). Notably, since it is not unlikely that both individual stock prices as well as stock market indices may follow a random walk, "(any) attempt to regress a non-stationary random walk on another non-stationary random walk results in a spurious regression model with both low predictive power and low explanatory power." (*ibid.*, p. 54). This shortcoming, the author argued, can be rectified with, among others, a non-parametric analysis. In addition, a non-parametric bootstrap simulation was also conducted to recover the underlying distribution of the estimates.

The summary statistics of bootstrapped average excess returns for the US reveal that all one-, two-, and three-year portfolios for winners and losers are significant (*i.e.*, exhibit significant differences in excess returns) using parametric estimates, which contrasts with the earlier-discussed findings of Baytas and Cakici (1999). However, a non-parametric estimator, which is arguably more conservative and provides better estimates, showed significance only in the one- and two-year portfolios and, what is more, it seems that the further out in time, the lower the possible arbitrage profits are. For example, the one-year portfolio yields 5.03% and 5.07% in excess returns for the formation losers and winners, measured non-parametrically, reduces to 2.06% and 2.27% for the two-year portfolios and down to 0.01% and 0.00% for the three-year portfolios. Interestingly, in contrast to some prior evidence, the distributions of returns are symmetrical for winners and losers.

As far as differences in risk are concerned, all the results show insignificance in risk coefficients and, when the multi-factor model is used, these coefficients do not significantly change over time. More importantly still, the analysis demonstrated that: "increases in excess returns are not always accompanied by higher risk and, therefore, can be potentially attributed to investor overreaction, among other things" (*ibid.*, p. 66).

In contrast to the US stock market, where all the shorter- (one-year) and intermediate- (two-year) term portfolios show significant contrarian returns but insignificant contrarian returns for all the longer-term (three-year) portfolios, the Canadian results are less definitive in absolute values of the returns and indicate that only the shorter-term winners, intermediate-term winners, and intermediate-term losers tend to exhibit a pronounced contrarian effect. For instance, based on non-parametric rank-based regressions, the average return to an intermediate-term arbitrage portfolio ranges from 0.76% (for the formation losers) to 1.13% (for the formation winners). Additionally, none of the three groups showing a strong contrarian effect can be characterised by meaningfully changing risk coefficients.

While less pronounced for Canada than for the US, the observed shorter-term contrarian effect, at first, seems to be inconsistent with the earlier studies by, among others, Foerster, Prihar and Schmitz (1995) as well as Cleary and Inglism (1998), who had documented statistically significant return continuation behaviour for that timeframe on the Toronto Stock Exchange (TSE) from the mid- to late-20th century. Nonetheless, unlike Mun *et al.* (2000), the two studies focused on large capitalisation stocks only and adopted a parametric research approach, which might be considered to be much less reliable with a small portfolio size, such as that used in the two studies, *i.e.* of less than 15 stocks, on average. Furthermore, the aforementioned absence of contrarian profits in the long-term is in line with the main results of Kryzanowski and Hao (1992), who used a different database to Mun *et al.* (2000) (that is, the TSE/Western database) and, hence, it might be concluded that this finding is robust to the choice of data source.

Finally, the econometric tests of Mun *et al.* (2000) showed that, for both the US and Canadian stock markets, there is no significant January effect or temporal dependence, no serial correlation in the errors, and the errors have homogeneous variances.

Therefore, it would appear that, overall, in both markets shorter-term contrarian portfolios tend to do better than intermediate-term contrarian portfolios, which in turn tend to do better than longer-term contrarian portfolios. Moreover, "significant contrarian returns are never associated with an increase in risk coefficients from the formation to the test periods" (*ibid.*, p. 69).

In a follow-up paper to Mun *et al*. (2000), Mun, Kish and Vasconcellos (2001), having employed a revised non-parametric estimator of excess returns and risk coefficients, specified in a time-varying risk multi-factor CAPM model[13], documented only weak support for the contrarian effect.

It is crucial to stress, however, that in this paper the authors predominantly focused on comparing the parametric *versus* non-parametric approach in estimating the parameters of both the single-factor and multi-factor CAPM models in the context of contrarian investing, concluding that, *ceteris paribus*, the non-parametric approach yields significantly better estimates than do parametric approaches.

Nevertheless, Mun *et al.* (2001) explicitly stated that: "insignificant Contrarian/Overreaction excess returns (documented in this study) should not simply be dismissed as a strategy that does not work. Instead, it actually may work but the excess return effects are dampened, by construction, by the multifactor model." (p. 69). Thus, "after taking into consideration (for example) the absorption effects of the multifactor model, excess returns from the Contrarian/Overreaction portfolios are indeed higher and perhaps more significant than indicated initially" (*ibid.*).

Therefore, it might be concluded from the evidence for the developed international stock markets analysed thus far that the contrarian effect is not only present outside the US, but, with the exception of Canada, it also appears to be greater in magnitude. Moreover, consistent with the US studies of DBT (1985; 1987), a risk premium does not appear to underpin the winner-loser effect in the markets under consideration.

[13] The authors presented the Fama and French's (1996) three-factor model as a variation of the single-factor CAPM model and refer to it by a 'multi-factor CAPM model'.

2.2.3.1. EUROPE

2.2.3.1.1. UK

Similarly to Mun *et al.* (2001), based on the UK stock market empirical evidence, Dissanaike (1994) pointed out that: "estimates of portfolio performance can be sensitive both to the method used to compute test-period returns and the method used to calculate rank-period returns" (*ibid.*, p. 1093).

In particular, the author argued that the arithmetic method (often referred to as the CAR method) of calculating cumulative returns (presented in, *inter alia*, DBT, 1985; 1987; Chan, 1988) is an unsatisfactory method of computing multi-period returns from single-period returns, because monthly returns are summed instead of being multiplied. The combined impact of the resultant biases could, in some instances, even alter conclusions about the contrarian effect and portray an unrealistic investment experience. Thus, Dissanaike (1994) recommended using either the realistic counterpart to the CAR method, known as the rebalancing (RB) method[14] or the buy-and-hold (BH) method, being more suitable performance metrics.

This observation is in accordance with the findings reported by Conrad and Kaul (1993), who were among the first academics to call attention to the weaknesses of cumulative performance measures in the context of contrarian investing. However, it is important to note that, contrary to Conrad and Kaul's (1993) suggestion, the procedure of cumulating monthly returns may not necessarily benefit from compounding (see Loughran and Ritter, 1996).

Not surprisingly, Dissanaike (1994), after analysing monthly returns obtained from London Share Price Database (LSPD) for all constituents of the FT 500 Index from 1981 to 1990, reported that when the rank period arithmetic returns are used for a 36-month formation period, the results are largely inconclusive for both the CAR and RB methods, that is inconsistent with the contrarian hypothesis in test period one, but exhibiting the contrarian effect in test period two. However, when RB and BH

[14] For details, see Dissanaike (1994).

portfolios are formed using a multiplicative ranking scheme (*i.e.*, RB-based), the overall evidence seems consistent with the contrarian hypothesis.

These findings are strongly substantiated by a subsequent paper by Dissanaike (1997) where, using principally the same data and methodology, the BH loser portfolio outperforms the BH winner portfolio by nearly 100% on average, four years after portfolio formation. The results for the RB method are even more striking, with the average return differential between the two portfolios of 137%, for the same period. While the above-mentioned BH portfolio returns were computed for each of the four event years, in each of the 48-month test periods, the annually rebalanced BH arbitrage portfolio still yield a respectable 11.58% return, on average, per year.

In terms of explanations alternative to overreaction which have emerged in the literature, bid-ask biases and infrequent trading were found to be unlikely explanations because this study was: (1) restricted to larger and better-known firms; (2) used monthly data; and (3) focused on a buy-and-hold method of computing returns. Furthermore, the magnitude of the return differentials as well as the fact that the buy-and-hold method was used, rules out transaction costs as a possible explanation.

This may be contrasted with the findings of Clare and Thomas (1995) who, using monthly data, focused on all the stocks quoted on LSPD tapes from 1955 to 1990, rather than the FT 500 firms only. While it was found that losers outperform winners by a statistically significant 1.7% per annum, after controlling for size using Zarowin's (1990) methodology this return difference can be explained by the small firm (or size) effect. In particular, the authors noted that there is: "no significant difference between the post portfolio performance of small and large firms" (Clare and Thomas, 1995, p. 968). This observation, consistent with Zarowin (1990), presents evidence against overreaction as the primary source of the winner-loser anomaly. However, the authors pointed out that: "Ball and Kothari (1989) find that when annual return rather than monthly return data is used, support for the Overreaction Hypothesis becomes weaker; hence our results for the UK using monthly return data should be viewed with some caution." (*ibid.*, p. 972).

Furthermore, as far as risk is concerned in the study by Dissanaike (1997), if risk is adjusted for by adopting a methodology that takes account of Chan's (1988) criticism, then contrary to evidence presented in Chan (1988) the loser portfolio actually appears to be less risky than the winner portfolio. This suggests that the use of market-adjusted returns actually underestimates the evidence in favour of the contrarian hypothesis. In a supplementary test, when risk is measured by adopting an approach similar to that used by Ball and Kothari (1989), then the extreme portfolios still do not appear to be more risky than, for example, the market portfolio.

In addition to the above, Dissanaike (1997) described three important features pertaining to the overall results that are relevant to this debate. First, while the test-period positive return on the loser portfolio exceeds the negative return on the winner portfolio (in absolute terms), the authors argued that this may be due to losers reversing from a lower base. Second, a slightly higher rate of attrition can generally be found in the loser portfolio, as compared to other portfolios. Conditional on the validity of the earlier-discussed CAPM-based risk-related results, it would seem dubious that losers face a higher likelihood of liquidation and bankruptcy, since this would imply being inherently more risky. Therefore, the author suggested that, alternatively, losers may be more likely to be taken over. Third, in the case of a 24-month rank period, there was some evidence of momentum for up to the 24-month mark, which bears resemblance to the momentum patterns for the medium-length rank periods reported in the US marketplace by, among others, DBT (1985), Ball and Kothari (1989), and Chopra *et al.* (1992).

Further evidence supportive of the winner-loser effect in the UK stock market was presented later by Mazouz and Li (2007), who employed both the CAR and BH methods on monthly and annual data extracted from Datastream for FTSE All Shares Index in the LSE from 1972 to 2002. The authors aimed to avoid a possible large firms bias in Dissanaike's (1994; 1997) studies, where the dataset was restricted to only large companies listed on FT 500 Index, and, unlike Clare and Thomas (1995), to control for the time-varying nature of risk. It was found that, on average, after three years of the portfolio formation for the 25 overlapping test periods, both methods suggest that the loser portfolio outperforms the winner portfolio (by 16.4% and

18.3%, using average CAR and BH returns respectively). Similar to Power, Lonie and Lonie (1991), when using the BH method, the winner-loser strategy yields better results than with the CAR method. As in Antoniou, Galariotis and Spyrou (2006), no seasonal pattern, such as January or April effect, was detected within the sample. While Mazouz and Li (2007) identified a size effect in the sample, the contrarian effect cannot be fully explained by the size effect not only because the loser (winner) portfolio is much larger (smaller) than the corresponding small (large) firm portfolio, but also because portfolios based on market values do not seem to reverse fully.

Furthermore, having accounted for time-varying risk following Chan's (1988) methodology, the test period abnormal returns for both the winner and loser portfolios were, on average, statistically insignificant at 0.72%. In addition, since the average beta of the loser portfolio is slightly bigger than that of the winner portfolio in the rank periods, losers may be considered to be a little riskier. Nonetheless, Mazouz and Li (2007) observed that when abnormal return are increasing (decreasing) the loser (winner) portfolios become less (more) risky. This result, the authors argued, presents strong evidence against CAPM, and corresponds with the findings of Loughran and Ritter (1996).

In conclusion, the UK evidence provides further support to the original argument of Conrad and Kaul (1993) that cumulating returns, rather than compounding, not only portrays an unrealistic investment experience, but it may also lead to different conclusions. Therefore, Dissanaike (1994; 1997) recommended using either the rebalancing method or the buy-and-hold method, whereby the latter might be obviously expected to be associated with lower transaction costs. Furthermore, contrarian strategies appear to be profitable in the UK, even after accounting for risk using CAPM. This result also appears to be robust to the market microstructural effects, considering, for instance, that Dissanaike (1994; 1997) focused only on large-capitalisation stocks, albeit no formal analysis of the market microstructure was performed. The only evidence to suggest that the UK contrarian strategies do not generate excess returns comes from Clare and Thomas (1995), whose findings, nonetheless, need to be considered in the light of the fact that the authors adopted the earlier-discussed biased methodology of Zarowin (1990).

2.2.3.1.2. OTHER EU COUNTRIES

Evidence on the viability of contrarian investing from European stock markets other than UK, discussed above, has been provided by, *inter alios*, Mun, Vasconcellos and Kish (1999) for the French and German stock markets, and Alonso and Rubio (1990) for the Spanish stock market, all of whom documented a statistically significant (risk adjusted) winner-loser effect.

To begin with, Mun *et al.* (1999), applying a methodology identical to Mun *et al.* (2000) for the US and Canadian stock markets, analysed monthly returns from the Compustat and Global Vantage data tapes for the French and German stock markets[15] from 1991 to 1996.

In the French stock market, it was found that all winner and intermediate-term (one-year) loser portfolios show significant contrarian returns. At the same time, no significant January effect or temporal dependence was observed. However, the authors noticed that in the vast majority of cases returns increase (or decrease) over time for losers (or winners), resulting in losers becoming winners and *vice versa*. Finally, Mun *et al.* (1999) concluded that there is little or no association between the portfolio returns and risk structure, thus "The returns seen are purely contrarian returns and indicative of overreaction because all the monthly excess returns are greatest in the short run and lowest in the long run without regard to the risk changes." (p. 225).

The econometric analysis of the German stock market reveals very similar characteristics to the French stock market. Overall, the only appreciable difference between the two markets is that German returns are larger than French returns on average. For example, for one-year loser portfolios, the average return in Germany amounts to 2.07%, which is greater than 1.54% in the French market.

The general trend in both markets presented in Mun *et al.* (1999) is identical to that in Mun *et al.* (2000), that is: (1) contrarian returns are never associated with an

[15] All data obtained from the Global Vantage data tapes is dominated by firms listed on the Paris and Frankfurt Stock Exchanges.

increase in risk coefficients from the formation period to the test period; and (2) there is a pervasive tendency for contrarian returns to decrease over time.

Overall, the results of Mun *et al.* (1999) are particularly interesting considering the support for, methodologically opposite, momentum investment strategies for the same markets over the same time horizon.

Alonso and Rubio (1990), on the other hand, examining the Spanish stock market from 1965 to 1984, documented evidence clearly accepting the contrarian hypothesis, even after correcting for size. Using monthly data for all non-overlapping three-year periods, it was found that over the last 20 years arbitrage portfolios of five stocks outperformed the return implied by the empirically implemented zero-beta CAPM by, on average, 24.5% twelve months after portfolio formation. More impressively still, the difference between the extreme portfolios increases to 35% and 36.9% 24 and 36 months after portfolio formation, respectively. While these findings are not supported by the statistical tests of Forner and Marhuenda (2003), who studied the Spanish stock market during the period from 1963 to 1997, the latter authors documented both statistically and economically significant contrarian and momentum profits for other time horizons, which suggests that the discrepancy between the two studies might be a result of different methodological approaches.

Furthermore, Alonso and Rubio (1990) reported that whereas the average size of winners is consistently smaller than that of losers, none of the two groups belong to either the ten smallest or the ten largest firms. This implies that the size effect could explain part of the excess profit, but at the same time, it is a distinct phenomenon from the winner-loser effect. In addition, no evidence of seasonality was recorded.

2.2.3.2. ASIA-PACIFIC AND BRAZIL

As far as stock markets from the Asia-Pacific region are concerned, the winner-loser effect has been studied by Gunaratne and Yonesawa (1997) in Japan, Fung (1999) in Hong Kong, Gaunt (2000) in Australia as well as da Costa (1994) in Brazil[16]. All of the

[16] In addition to the studies listed here, the contrarian effect has been examined in the context of Chinese stock market(-s) by, among others, Chen, Jiang and Li (2012); Kang, Liu and Ni (2002); Li, Qiu

discussed papers presented evidence in favour of contrarian investing after factoring in risk, with the exception of Gaunt (2000).

Importantly, considering that the evidence from the developed countries of the Asia-Pacific is not of immediate relevance to this research and Japan, Hong Kong as well as Australia are classified as developed by the Dow Jones Indexes Country Classification System (S&P Dow Jones Indexes, 2011), which is used for the purposes of this research as the basis for establishing stock market maturity, only a brief overview of the corresponding studies shall be provided.

To begin with, Gunaratne and Yonesawa (1997), using Hitachi Information Systems' monthly return data for the period from 1955 to 1990, adopted a methodology broadly consistent with the work of Ball and Kothari (1989) to analyse the performance of the winner-loser portfolios on the Tokyo Stock Exchange.

It was found that an arbitrage portfolio of losers and winners formed at the beginning of the post-ranking period would produce approximately 11%, on average, per annum and, for the longest post-ranking period under analysis in this study (*i.e.*, four years), the accumulated figure would be 44.27%. Furthermore, in contrast to the change of returns, the change of relative risks in the Japanese market is marginal from the ranking to the post-ranking period and, thus, it could only explain a very small portion of the variation of returns between the two periods. This clearly contrasts with the findings of some of the earlier-discussed studies based on US data (*e.g.*, Chan, 1988; Ball and Kothari, 1989).

As far as the Hong Kong Stock Exchange is concerned, Fung (1999) tested the contrarian hypothesis for the period from 1980 to 1993, by using monthly returns on stocks in the Hong Kong Hang Sang Index (HSI)[17] for the formation of portfolios of three losers and three winners over two or three years. The rationale behind using

and Wu (2010); and Wu (2011). It is critical to stress, however, that the aforementioned publications exclusively focused on short-term (*i.e.*, below one month) and intermediate-term (*i.e.*, between one month and one year) contrarian strategies, which are fundamentally different from the long-term (*i.e.*, beyond one year) contrarian strategies discussed in this literature review.

[17] The data were taken from Datastream and PACAP.

only three stocks in each portfolio was to mitigate any potential problems pertaining to short-selling, market liquidity, regulations, transaction costs, and ease of executions.

Alike Dissanaike (1994), Fung (1999) employed the geometric mean instead of the arithmetic mean, in order to reduce the error caused by the bid-ask spread, as suggested by Conrad and Kaul (1993).

Importantly, whereas it was reported that the loser portfolio outperforms the winner portfolio by nearly 10% *p.a.* in the testing period of one year, one should note the significant variability of the return differential for the 12 testing periods, ranging from +24.8% to -9.9% per year. Furthermore, betas of the loser portfolios and the winner portfolios in the testing periods of 0.9877 and 0.9157, respectively, as well as the fact that beta itself accounts in this study for a difference in return of less than 2% a year, suggest that the varying risk premium hypothesis presented by Chan (1988) is not supported for the Hong Kong stock market.

Although the winner-loser effect, as documented by Fung (1999), is very powerful in HSI, it is crucial to emphasise that this paper concentrated exclusively on stocks of large market capitalisation and liquidity, which may affect the transferability as well as comparability of the results.

Gaunt (2000), on the other hand, found no reversal in performance by the loser portfolio and no significant difference in the test period performance between the winner and loser portfolio in the Australian stock market.

The author, using DBT's (1985) methodology, analysed data from the price relative files of the Centre for Research in Finance (CRIF) for the period from 1974 to 1997 and showed that while there is evidence of both the reversal for the three-year rank period losers and winners as well as positive abnormal returns for the arbitrage portfolio, this result largely disappears when a buy and hold strategy is employed. After adjusting for risk applying the Sharpe-Lintner CAPM and Chan's (1988) methodology, the performance reversal experienced by the loser portfolio using the multiplicative rebalancing approach is considerably reduced, but a significant positive abnormal return to the arbitrage portfolio is still present. Nonetheless, this again disappears when a multiplicative buy and hold method is used.

The last study to be discussed in this section is that by da Costa (1994) of the Brazilian stock market, or more specifically the Sao Paulo Stock Exchange. The author used monthly prices data of 121 stocks, which accounted for more than 70% of the traded volume in the period under analysis, *i.e.* from 1970 to 1989.

Following DBT's (1985) methodology, for every test period the author computed the cumulative average abnormal returns (CAR) of all stocks in each of the five portfolios during the two years of the test period. Both market-adjusted returns and the standard Sharpe-Lintner CAPM-adjusted returns were used.

Consistent with most of the evidence on long-term contrarian strategies, the results suggest that there is a significant contrarian effect in the Brazilian stock market. After one year of the test period the performance differential between the loser portfolio (portfolio 1) and the winner portfolio (portfolio 5) is 25.69% (t-statistic = 2.92) and after two years losers outperform the market by 17.63% (t-statistic = 2.62), while winners underperform the market by 20.25% (t-statistic = -2.98).

Furthermore, considering the fact that the average betas of the securities in the winner and loser portfolios are 1.060 and 1.062, respectively (t-statistic for the difference: 0.04), the Sharpe-Lintner CAPM was found to be unable to explain the differential performances of the two portfolios. These results are reported to be broadly consistent with those for market-adjusted returns.

Lastly, although in contrast to DBT (1985) the Brazilian contrarian effect appears to be symmetric at first, when the 'reversal coefficient' technique developed by Dissanaike (1992, as cited in da Costa, 1994, p. 641) was used, the price reversals relative to formation-period performance became asymmetric due to the values of the winner portfolios having reverted relative to the market.

2.2.4. SUMMARY AND CONCLUSION

In the mid-1980s, De Bondt and Thaler documented that stocks which experienced extreme long-term loses in the past tend to significantly outperform stocks which experienced extreme gains in the past over the next three to five years. The existence of this phenomenon, also known as the winner-loser or contrarian effect, was argued by the scholars to prove that investors in the US marketplace systematically overreact to stock market information, resulting in prices being too high or too low for prolonged periods of time. What follows is that it is possible to construct a profitable trading strategy based on past returns, *i.e.* a contrarian investment strategy, which outperforms the market in the long-term.

These findings explicitly contradict the efficient market hypothesis, the mainstream theory of financial markets, which asserts that investors are rational and, hence, value stocks rationally as it should not be attainable to systematically earn profits above the average market return by following a mechanical trading rule, unless those profits were to represent a fair compensation for bearing additional risk or vanish after considering microstructure effects. Therefore, a number of academics attempted to verify if abnormal returns to contrarian strategies are, indeed, eliminated after accounting for risk or microstructure factors.

Chan (1988) and Vermaelen and Verstringe (1986) suggested that the anomaly described by DBT (1985) might be explained by either time-varying betas or mean reverting factor risk premia. These doubts were, however, dispersed by DBT (1987), who showed that differences in risk between losers and winners cannot account for the recorded abnormal returns on contrarian portfolios. Having improved on Chan's (1988) methodology to demonstrate larger beta shifts for stocks selected under a contrarian strategy, Ball and Kothari (1989) argued that the observed winner-loser effect is induced by time-varying expected returns in an efficient market, rather than stock market mispricing or investor overreaction. Whereas this finding was later partly confirmed by Chopra *et al.* (1992), the authors showed that the model used by previous studies for the calculation of theoretical risk premium, the Sharpe-Lintner CAPM, underestimates the contrarian effect and when price of beta risk is determined empirically, then the theoretical risk premium is more than halved, leaving a considerable part of the contrarian return unaccounted for.

In addition to the above, a number of scholars investigated whether the contrarian effect can be explained by the small firm (or size) effect, being in finance a commonly used proxy for investment risk. Overall, there seems to be a broad agreement among academics that the size and the contrarian anomalies are largely separate phenomena. The only evidence to the contrary was presented by Zarowin (1990) and Ball and Kothari (1989), whose methodologies were, however, significantly called into question by Albert and Henderson (1995), and Chopra *et al.* (1992), respectively.

In terms of exposure to macroeconomic risk factors, Chen and Sauer (1997) documented that contrarian profitability varies procyclically with the states of the economy, which suggests that the discussed strategies may be affected to some extent by variables related to macroeconomic risk. Nonetheless, some problems have been noted as regards the representation of the reported statistics as well as the consistent, but not always statistically significant, outperformance of the winner-loser arbitrage portfolio.

Conrad and Kaul (1993), and Ball *et al.* (1995), on the other hand, argued that the winner-loser effect is subject to microstructure biases and once those are considered, no abnormal profitability can be observed. The former focused on the bid-ask bias exclusively and contended that if losers are low-priced and winners are high-priced relative to the average NYSE firm, there may be an upward bias in the average cumulative abnormal returns (ACARs) of loser firms and a downward bias in the ACAR of winner firms. This suggestion was supported by Ball *et al.* (1995), who considered all microstructure-induced biases. However, Loughran and Ritter (1996) argued that the conclusions of Conrad and Kaul (1993), and Ball *et al.* (1995) are driven by a survivor bias and long-term mean reversion in the aggregate stock market, rather than cross-sectional patterns on individual stocks.

To conclude, there is insufficient evidence to suggest that profits to contrarian investment strategies can be fully eliminated by accounting for risk or microstructure effects. However, it is important to stress that research in this area is still very limited. In particular, given that all of the discussed US-based studies considered almost identical sample periods, it is not clear whether the observed winner-loser effect is not a result of data snooping and, consequently, is not specific to the time period under analysis. Furthermore, the above papers did not consider portfolios of different sizes or different weighting methods (so as to give large-capitalisation stocks more importance), which would provide strong evidence in support or against the possibility that the contrarian effect can be explained either by size or microstructure effects.

The international evidence on contrarian investing is scarce and almost exclusively concerned with developed markets, with the only emerging market considered being Brazil (da Costa, 1994). Furthermore, whereas international papers often draw on the methodologies of the US studies, it is not uncommon for the former to adopt techniques later showed to be biased by US scholars (*e.g.*, Baytas and Cakici, 1999; Clare and Thomas, 1995; Gunaratne and Yonesawa, 1997).

These issues aside, contrarian investment strategies appear to be profitable in Europe and Asia, but not in Canada and Australia. The study by Clare and Thomas (1995) of the UK stock market seems to be an exception at first, but under closer inspection it transpires that the authors adopted the biased methodology of Zarowin (1990) and, therefore, that study cannot be viewed as meaningful deviation from the general pattern.

Taking the above into consideration, it seems clear that more research is needed to investigate the contrarian effect in emerging markets. At this point, there is virtually no evidence which would allow to draw any reliable conclusions as to whether contrarian investing is more profitable in less-developed economies, where the financial markets are likely to be less efficient and, thus, more susceptible to investor irrationality. The evidence from developed countries is also, overall, very controversial and, especially considering that academics have analysed similar sample periods, it is important to verify if the winner-loser effect has stood the test of time.

2.3. MOMENTUM INVESTMENT STRATEGIES

2.3.1. INTRODUCTION

The momentum anomaly[18], at least in its most popularised form[19], was first identified by Jegadeesh and Titman (1993), hereafter JT (1993), who documented abnormal returns to strategies which buy stocks that have performed well in the past ('winners') and sell stocks that have performed poorly in the past ('losers') over three- to 12-month holding periods. It is important to note that although seemingly conflicting, JT's (1993) tests are in principle based on the same assumption as those of DBT (1985), that is if stock prices are systematically influenced by investors' incorrect reaction to new information, then it should be possible to devise profitable stock selection strategies based on past return data alone.

Therefore, analogously to the case of contrarian investment strategies, the notion that stocks generating higher than average returns in one period will also generate higher than average returns in the following period over the intermediate term is explicitly against the efficient market hypothesis. According to this widely acclaimed theory of financial markets, it should not be possible to earn abnormal profits in the long-term by following a mechanical trading strategy, especially one which is based on information as elementary as past returns, unless this strategy selects stocks which are riskier than the average stock or is not viable after adjusting for microstructure effects.

The main objective of this section is, therefore, to verify if momentum investment strategies are still successful once risk and market microstructure factors are taken into consideration. If, having accounted for those factors, excess momentum profits

[18] The momentum anomaly is also referred to in the finance literature as the return momentum, price momentum, price persistence or price continuation effect. Although, clearly, the price and return of a stock are distinct variables, over time periods of up to 12 months the difference between the two might be argued to be negligible, since in this case net capital gains would normally constitute the main source of return on investment.

[19] As JT (1993) pointed out, there are a number of earlier papers studying the so-called relative-strength strategies (see *e.g.*, Copeland and Mayers, 1982; Grinblatt and Titman, 1989; Jensen and Bennington, 1970; Levy, 1967; Stickel, 1985). Although those strategies also exploit price continuation in stock returns, they do not follow the exact investment strategy as implemented by JT (1993).

were to be still detectable, then this would clearly be an indication of stock market inefficiency which could be easily exploited by a simple trading strategy based on past return data alone.

The reminder of this section is outlined as follows.

In the first part of this review, the evidence on the momentum effect from the US marketplace will be investigated as, similarly to the instance of the finance literature on contrarian investment strategies, the US research seems to lead research in other countries in this domain.

The second part of this review looks at the momentum effect from an international perspective. To begin with, comprehensive cross-sectional studies of several stock markets worldwide are covered, which is followed by the discussion of price persistence in Europe and the Asia-Pacific region specifically. Where applicable, the analysis in this part will be performed in a manner corresponding to that for the US evidence, *i.e.* starting with firm-level factors, through economy-level factors and finishing with market microstructural factors.

2.3.2. EVIDENCE FROM THE US STOCK MARKET

2.3.2.1. FIRM-LEVEL RISK FACTORS

JT (1993) are commonly recognised as the first academics to document that stocks with high (low) returns over periods of three to 12 months continue to have high (low) returns over subsequent three to 12 month periods.

In an attempt to exploit this temporary continuation of past performance, the authors constructed 32 strategies, 16 of which skip a week between the portfolio formation period and the holding period, in order to avoid some of the bid-ask spread, price pressure, and lagged reaction effects that underlie the evidence documented in earlier studies (see *e.g.*, Jegadeesh, 1990; JT, 1995; Lehmann, 1990; Lo and MacKinlay, 1990).

Based on the CRSP daily returns file database for NYSE and AMEX stocks over the 1965 to 1989, JT (1993) found that the returns of all zero-cost portfolios are positive, with the most successful strategy selecting stocks based on their returns over the previous 12 months and then holding the portfolio for three months (*i.e.*, a 12-month/3-month strategy), which effectively produces a significant 1.31% per month if there is no time lag between the portfolio formation and holding periods, and 1.49% per month if there is a one-week lag. The six-month/six-month strategy, being the most representative of all other strategies, still yields a respectable profit of approximately 1% per month. These findings were substantiated by a follow-up paper by JT (2001), showing remarkably similar profits for the 1990-1998 sample period, which provides reassurance that the momentum anomaly is not entirely owing to data snooping biases. The later publication by the authors also demonstrated that momentum profitability does not disappear after adjusting for the Fama-French factors, which is consistent with Fama and French (1996) as well as Wang and Wu (2011), despite the fact that the latter scholars constructed a procedure based on the linear Fama-French three-factor model that allows for the systematic dynamics of momentum portfolio factor loadings.

Nonetheless, what is important is that half of the abnormal returns generated in the year following the portfolio formation date dissipate within the ensuing two years. JT (2001) confirmed that both winners and losers experience negative abnormal returns in years two through five, although noted that positive momentum returns are only sometimes associated with post-holding period reversals, depending on the composition of the sample, the sample period, and, in some instances, risk adjustment. This evidence clearly supports a notion critical to this thesis that the contrarian and momentum effects may well exist in different timeframes, such that the latter effect is detectable in months one through 12, whereas the former effect in months 12 through 60.

Furthermore, additional evidence revealed that momentum profitability is not primarily due to systematic risk, size effect, seasonality, event time or lead-lag effects that result from delayed stock price reactions to common factors, as suggested by, among others, Lo and MacKinlay (1990) with respect to short-term contrarian strategies, but is more likely to stem from delayed price reactions, or more simply underreaction, to firm-specific information.

More specifically, in terms of investment risk, the authors considered the two most common indicators of systematic risk for extreme past-performance portfolios: (1) the post-ranking betas; and (2) the average market capitalisation of stocks. While the betas of the winner and loser portfolios are higher than the average beta for the market, past losers have higher betas than past winners, which results in the negative beta estimate for the arbitrage portfolio. Similarly, the average market capitalisation for the highest and the lowest past returns portfolios is lower than the market average, however, the loser portfolios consist of smaller companies than the winner portfolio, which again suggest that momentum profits are not due to the risk factor proxied by company size. It is clear, nonetheless, that the above conclusion only applies to the case of the arbitrage portfolio, which relies on the, not always applicable, concept of short-selling (see the 'Market microstructural effects' part of this section). Even in the presence of no short-sale constraints, trading in winners or losers alone would be associated with above market-average investment risk, as proxied by either beta or market capitalisation, and, thus, more research would be needed to evaluate whether that excess risk could explain momentum profits.

JT (1993) also suggested that since size and beta are usually considered to be related to both risk and expected returns, the cross-sectional dispersion in expected returns should be less within the winner and loser subsamples than in the full sample of all stocks.

However, Bulkley and Nawosah (2009) hypothesised that the momentum effect can, in fact, be rationally explained as a consequence of the cross-sectional variation of expected returns, which might be, for example, determined by the Sharpe-Lintner CAPM, when the average return over the full sample period is used as a measure of unconditional expected returns, rather than company size or beta.

The conventional tests for momentum applied to the series of demeaned returns, based on a sample inconsequentially different from that in JT (1993), showed no evidence of momentum, thereby suggesting that stocks with relatively high unconditional expected returns on average outperform in both the portfolio formation and test periods.

This suggestion is not new, which is hardly surprising considering the lack of consensus about the correct model for expected returns. Conrad and Kaul (1998) similarly argued that the cross-sectional variation can account for momentum profits (but not contrarian profits!), using a model that assumes expected returns to be rationally determined, different across stocks and time-invariant. However, as mentioned before, JT (2001) reported that beyond the 12-month time point past winners start to become losers, which indicates that expected returns are time-varying and, hence, the model of Conrad and Kaul (1998) can be rejected as an explanation of momentum. This conclusion is further supported by a more comprehensive study of Conrad and Kaul's (1998) methodology, in which JT (2002) showed that the results of bootstrap simulations presented in the discussed academic paper are contaminated by a small sample bias. An unbiased version of the bootstrap experiment suggests that the earlier findings can, in fact, be entirely attributed to a small sample bias, leading the authors to draw erroneous inferences.

With reference to the aforementioned discourse between JT (2001; 2002) and Conrad and Kaul (1998), Bulkley and Nawosah (2009) asserted that while the effect of the dispersion in unconditional expected returns might be overwhelmed at longer horizons by the return reversal, the presented evidence suggests that this is not the case at shorter horizons.

Nevertheless, Bhootra (2011) pointed out that the absence of momentum in demeaned returns observed by Bulkley and Nawosah (2009) is not robust to commonly employed adjustments that mitigate microstructure biases, such as skipping a month between the formation and test periods (*i.e*., 'skip-a-month' filter) or excluding 'penny stocks' from the sample (*i.e*., 'penny stock' filter). Once those microstructure screens are introduced the average monthly momentum profit in demeaned returns increases from -0.37% to 1.02% for the sample corresponding to that of the previous study.

In consequence, taking the above-presented evidence into consideration, there is insufficient evidence in support of the hypothesis that momentum profits are due to a firm-level risk factor, such as beta, company size or cross-sectional dispersion in expected returns (where the expected returns might be determined by, for instance, the Sharpe-Lintner CAPM or other asset pricing model). The only studies suggesting the contrary are those by Bulkley and Nawosah (2009) as well as Conrad and Kaul (1998), whose argumentation may, nonetheless, be dismissed on grounds of methodological shortcomings, as pointed out by JT (2001) and Bhootra (2011), respectively.

The return continuation effect has also been documented to be influenced by a range of other firm-specific variables, such as earnings (*e.g.*, Chan, Jegadeesh and Lakonishok, 1996; 1999; Chordia and Shivakumar, 2006), dividends (*e.g.*, Asem, 2009) or revenues, costs and growth options (*e.g.*, Sagi and Seasholes, 2007). Although an elaborate discussion of the aforementioned academic papers is beyond the scope of this review, whose emphasis is on the officially recognised risk and market microstructural factors[20], an important fact is that the presented evidence of momentum profitability is broadly consistent with the findings of JT (1993). In addition, whereas it would appear that the performance of momentum strategies could be improved by accounting for the three groups of factors, none of those variables can fully capture the momentum effect.

2.3.2.2. ECONOMY-LEVEL RISK FACTORS

At the economy level, inclusive of the industry level, the return continuation effect has been linked to risk factors associated with industries, the business cycle and growth rates. As the studies in the first and last areas depart from the main theme of this part of the review, only a brief summary of the findings thereof is provided.

As far as exposure to industry risk is concerned, Moskowitz and Grinblatt (1999) identified industry momentum as the primary source of momentum trading profits and argued that once industries are considered, momentum profits from individual equities are, for the most part, statistically insignificant. However, Ahn, Conrad and Dittmar (2003) clearly showed that the stochastic discount factor estimated from industry-sorted portfolios can explain only about half the level of individual momentum profits and virtually none of industry momentum profits, thereby suggesting that those profits are likely to be generated by distinct phenomena. This conclusion is strongly supported by Grundy and Martin (2001), who maintained that not only cannot momentum profitability be fully explained by industry effects, but also by cross-sectional variability in stocks' average returns or as a compensation for dynamic exposure to the three factors of Fama and French (1996).

Chordia and Shivakumar (2002), in accordance with Grundy and Martin (2001), showed that individual stock- and industry-based momentum returns are distinct

[20] Dividend maintenance, studied by Asem (2009), might be argued to proxy for risk, in a sense that dividend-maintaining companies may be considered to be less risky than non-dividend-maintaining companies on account of the fact that earlier cash flows from any investment are less risky than (potential) later cash flows. However, the author focuses on combining the information on past returns and dividend maintenance to create a superior investment strategy, which renders that study to be of secondary interest to this review.

phenomena and that industry momentum alone is insufficient to fully explain the profitability of momentum strategies, even for the shortest portfolio formation horizons. Instead, similarly to Chordia and Shivakumar (2006), the authors argued that momentum profits are attributable to intertemporal variations in the macroeconomic factors which are related to the business cycle (*i.e.,* dividend yield, default spread, short-term interest rates, and term structure spread).

To study the relative importance of common factors and firm-specific information, Chordia and Shivakumar (2002) followed JT (1993) methodology to form portfolios from the NYSE and AMEX universe of stocks recorded on the monthly CRSP files between 1926 and 1994.

While the average monthly post-formation return for the entire sample period is an insignificant +0.27%, excluding the pre-1959 period rises this percentage to +0.83% for the years 1951-1963 and to +0.73% for the years 1963-1994. Having further divided the sample into different business cycle periods, the authors suggested that momentum strategy payoffs are positive only during expansionary periods. The difference in returns between the two periods is a statistically and economically significant 1.25% per month. This conclusion may, however, be debatable given that six out of nine post-war recessionary periods studied have positive momentum payoffs and although only one of these is statistically significant, the shorter durations of recessionary periods as compared to expansionary periods could account for this lack of significance.

Still, Cooper, Gutierrez and Hameed (2004), studying all the NYSE and AMEX stocks listed on the CRSP monthly file from 1926 to 1995, confirmed that momentum profits may depend on the state of the market.

The authors defined two states of the past market performance: ‘up’ when the lagged three-year market return is non-negative, and ‘down’ when it is negative. Consistent with Chordia and Shivakumar (2002), the intermediate-term momentum profits seem to exclusively follow up markets, generating a subsequent average monthly raw profit of 0.93% (or 1.12% if CAPM-adjusted) for the six-month/six-month momentum strategy, which contrasts considerably with an insignificant -0.37% profit after three-year down markets. Furthermore, similar to the evidence in JT (2001), the up-market profit reverses in the long-run, becoming reliably negative (*i.e.*, -0.36% per month) over holding period months 13 to 60. What is more interesting, though, is that the authors found significant long-run reversals following down markets, despite the absence of the intermediate-run down-state momentum. While this phenomenon can hardly be explained by the overreaction theories of momentum, Cooper *et al.* (2004) conjectured that there might well be other factors driving long-run reversal in general.

The common macroeconomic variables recognised by Chordia and Shivakumar (2002) as the main sources of momentum profits were, however, unable to capture the asymmetry in momentum profits across up and down markets. Moreover, unlike the lagged return of the market, the macroeconomic multifactor model described in the preceding paper was neither found to be robust to microstructure-induced biases (*e.g.*, liquidity, transaction costs or bid-ask bounce), nor able to predict the time-series of momentum profits out-of-sample.

This observation appears to be in accordance with the results reported by Avramov and Chordia (2006) who, having developed a framework to test if asset pricing models can explain various financial market anomalies, confirmed that while it appears that payoffs to the momentum strategy based on NYSE, AMEX, and NASDAQ stocks traded over 1964-2001 do indeed vary with the business cycle, no rational asset pricing model, or a known risk factor, can fully explain firm-level momentum. Correspondingly, Karolyi and Kho (2004), proposing a slightly different set of macroeconomic and market-wide instrumental variables to Chordia and Shivakumar (2002), including lagged one-month Treasury bill yield, the CRSP value-weighted index's dividend yield, the US bond default as well as term premiums, and a January dummy, found on a sample of NYSE, AMEX and NASDAQ stocks for the 1963-2000 period that their estimation-based bootstrap simulation procedure of testing different returns-generating models produces simulated momentum returns that can explain only up to 75-80% of the actual winner-loser spreads.

Overall, Cooper *et al.* (2004) interpreted their findings as consistent with the overreaction, rather than rational risk-based, models. Whereas overreaction and subsequent correction cannot completely explain the intermediate-run momentum and long-run reversal phenomena, they seem to account for a large portion of the lagged-return anomalies.

In the light of the asymmetric momentum profits following up and down markets documented by the above paper, Asem and Tian (2010) examined the effect of market continuations and market transitions on momentum profitability.

On the basis of all stocks in the CRSP database observed monthly from 1927 to 2005, similarly to Cooper *et al.* (2004), the authors differentiated between up markets (when the past 12-month value-weighted return is non-negative) and down markets (when the past 12-month value-weighted return is negative). In addition, each of the two macroeconomic states was further subdivided into -two groups: (1) the return in the subsequent month is of the same sign (*i.e.*, the markets continue in the current state); or (2) the return in the subsequent month is of the opposite sign (*i.e.*, the markets transition to a different state).

The main results indicate that, following 'bull (bear) markets', the mean momentum profit decreases from 2.09% (3.53%) per month when the markets continue in up (down) states to -0.01% (-2.54%) when they transition to a down (up) states. This is in conflict with the findings of Chordia and Shivakumar (2002), and Cooper *et al.* (2004), who reported that momentum profits do not exist in 'bear markets', and points to the psychological biases of investor overconfidence and self-attribution as the potential sources that underpin the momentum effect, rather than to a business cycle-related risk factor.

Another study to suggest that the winner-loser portfolio may be viewed as a risk factor in the present context that earns a risk premium is that by Fuertes, Miffreb and Tanc (2009), who found that the risk associated with holding a winner (loser) portfolio is higher (lower) during economic expansions than recessions, indicating that momentum trading should involve dynamic asset allocation to be suitable for a rational risk-averse investor. It was hypothesised that non-normality in the return distribution of momentum strategies, reflected by the fact that winner returns are more negatively skewed and have higher positive kurtosis than loser returns, has a positive impact on profits which represents a compensation for risk.

The authors considered monthly stock prices of NYSE, AMEX and NASDAQ companies for the period 1973-2004 as obtained from Datastream. Employing the Fama and French's (1993) methodology, skewness- as well as kurtosis-mimicking portfolio returns were computed to subsequently serve as additional risk factors to augment the Single Index as well as Fama and French's (1993) models.

It was demonstrated that skewness risk explains some of the momentum returns at better than the 5% level in the case of most momentum strategies, which is over and above the market, size and book-to-market risks, while the kurtosis beta is always insignificant. Furthermore, all systematic risk exposures of the momentum portfolios considered evolve over the business cycle. In particular, momentum strategies appear to be riskier during up markets as they are long (short) stocks with relatively higher (lower) market beta and negative (positive) skewness than during down markets. However, while those findings seem to contradict the earlier-discussed evidence showing that the macroeconomic risk cannot explain return persistence, Fuertes *et al.* (2009) admitted that a large proportion of momentum profits still remains unexplained.

Lastly, in addition to the economy-level risk factors associated with industries and the business cycle, Liu and Zhang (2008) found that recent winners have temporarily higher loadings on the growth rate of industrial production than recent losers. Considering that the growth rate of industrial production is a priced risk factor in standard asset pricing tests, this means that macroeconomic risk may account for, at least, a part of momentum profits. A similar point was made by Johnson (2002), who suggested that the momentum effect need not to imply investor irrationality by using stochastic expected growth rates to explain the momentum anomaly. Nonetheless, the results of Liu and Zhang (2008) as well as Johnson (2002) only offer a partial rationalisation of the studied phenomenon, at best.

In conclusion, although there appears to be unanimity among academics that momentum profitability does vary with the business cycle, none of the business cycle-related predictive variables, which might be considered to proxy for a hitherto undefined macroeconomic risk factor, can fully explain return persistence. This is analogous to the case of firm-level risk factors analysed in the preceding part of the subsection as well as the industry-related or the growth-rate-related risk factors analysed in this part of the subsection. There is substantial evidence, however, to suggest that momentum strategies yield higher returns during economic expansions than recessions (*e.g.*, Avramov, Chordia, Jostova and Philipov, 2007; Chordia and Shivakumar, 2002; Cooper *et al.*, 2004; Fuertes *et al.*, 2009; but also see Asem and Tian, 2010).

Therefore, variously defined factors that may proxy for macroeconomic risk cannot capture the effect of return persistence. In virtually all cases, the proposed models can rationalise only a small proportion of the observed abnormal profits. In the absence of a persuasive firm-level or economy-level risk-based explanation of the momentum phenomenon, the only consideration that remains to be addressed before recognising momentum strategies as a legitimate investing approach based on an exploitable stock market inefficiency is the consideration of the market microstructural effects, which is discussed in the following part of the section.

2.3.2.3. MARKET MICROSTRUCTURAL EFFECTS

Regardless of whether the momentum anomaly can be explained by risk or not, most of the earlier-discussed studies concede that momentum investing is trading intensive and, therefore, high transaction costs, illiquidity, short-sale constraints or other microstructure effects may prevent profitable strategy execution.

Lesmond, Schill and Zhou (2004), examining the composition of the momentum portfolios described by JT (1993; 2001), showed that the return to momentum strategies does not exceed trading costs, which is primarily due to their reliance on heavy trading in disproportionately high cost stocks.

On the basis of a series of trading cost estimates, the authors argued that JT's (1993; 2001) assumption of one-way costs to be less than 0.5% is unrealistic for several reasons. To begin with, JT (1993) used the trade-weighted mean commission of 1985 NYSE trades, which might be considered inappropriate due to the fact that transaction costs exhibit significant cross-sectional variation and extreme performer stocks may attract larger-than-average costs. Furthermore, considering that this is a single period measure (solely based on the transaction data from January to March 1985), time-series variation in trading costs, again, is not accounted for.

Indeed, most studies on momentum investing assume that transaction costs are constant over time and investors are free to choose when to trade. However, similarly to Lesmond *et al.* (2004), Sadka (2003), studying intraday data for stocks traded on NYSE over the 1983-2001 period as recorded on the Trade and Quote (TAQ), and the Institute for the Study of Security Markets (ISSM) databases, found that liquidity varies over time causing a premium associated with liquidity risk to rise. In particular, the author showed that liquidity risk is priced and the related risk premium may explain half of the momentum anomaly, with the unexplained momentum profits being mainly due to firms whose level of liquidity is low.

Another problem with applying JT's (1993) benchmark, according to Lesmond *et al.* (2004), is that it underestimates full trading costs by excluding *e.g.* bid-ask spread, holding-period risk, taxes and short-sale costs. This is particularly concerning given the strategies' high trading frequency of poorly performing stocks (*i.e.*, holding short positions on losers).

The main results indicate that for the standard momentum strategy presented in JT (1993), requiring four trades (opening and closing the position in two sets of stocks), the average one-way trading cost, as estimated by limited dependant variable (LDV) procedures, is 2.3%, which contrasts greatly with 0.5% considered by JT (1993). Although slightly less for the strategies described in JT (2001), *i.e.* of 1.9%, the costs were still considerably underestimated.

Thus, the authors concluded that the profitability of momentum strategies is overstated in the literature to the point that it creates an illusion of profit opportunity when, in fact, none exists.

However, Korajczyk and Sadka (2004), who analysed the effect of trading costs on the profits from maintaining long positions in the winner-based momentum strategies, showed that neither spreads nor price impacts of trades can fully rationalise the return continuation exhibited by past winners. Specifically, the authors attempted to determine the maximum momentum-based fund size that can be achieved before excess returns are either driven to zero or become statistically insignificant.

Using all NYSE, AMEX and NASDAQ stocks on the CRSP monthly data files from 1967 to 1999 as well as transaction data from the TAQ database, Korajczyk and Sadka (2004) followed JT (1993) methodology to form the winner and loser portfolios. Despite the evidence from, among others, JT (2001) and Lesmond *et al.* (2004) that the greater part of momentum profits is generated by past losers rather than past winners, the authors limited the ensuing analysis to winners alone due to the inability of the employed measures of price impact to capture additional costs related to short-selling large positions.

The results from four alternative measures of trading costs demonstrate that abnormal returns to some momentum strategies disappear only after $4.5bn-$5bn is invested in such strategies. Furthermore, in general, equally-weighted portfolios (studied in *e.g.*, Fama and French, 1996; Moskowitz and Grinblatt, 1999; Grundy and Martin, 2001; Lesmond *et al.*, 2004) have higher price impact related costs than value-weighted portfolios, since their performance decreases dramatically even in the case of relatively small investments. Thus, as in Lesmond *et al.* (2004), transaction costs seem to eliminate most profits to equal-weighted strategies, although the estimates of proportionate spread costs are notably higher (*i.e.*, from 18% higher to 455% higher) in the preceding paper. Nevertheless, Korajczyk and Sadka (2004) showed that value-weighted and liquidity-weighted strategies provide considerably greater post-price impact profits, despite the imposed short-sale constraints in the form of considering only strategies consisting of long positions.

In reality, restricting analysis to long positions might not be completely unjustified as, among others, Ali and Trombley (2006) observed that short-sale constraints are an important factor in preventing arbitrage of momentum in stock returns.

As a proxy for loan fees, which are the direct cost of short-selling, the authors combined stock characteristics that capture the short sellers' borrowing demand and the lenders' supply of stocks into an aggregate measure called 'Prob'. The relationship of this measure with momentum returns was showed to be stronger and incremental compared to the model used in Lesmond *et al.* (2004) as far as short-selling costs are concerned. More importantly, though, since short positions in the momentum-related arbitrage are held over several months, Ali and Trombley (2006) argued that short-selling costs tend to be greater than direct transaction costs, such as bid-ask spread or commissions discussed by Lesmond *et al.* (2004).

The authors used both the CRSP and Compustat data for NYSE, AMEX and NASDAQ securities for the sample period from 1984 to 2001.

Having confirmed that 'Prob' is a satisfactory proxy for short-sale constraints and momentum returns over the period 1984-2001 are related to each of the factor's components (which include: firm size, book-to-market ratio, share turnover, cash flow and IPO status), Ali and Trombley (2006) found that 'Prob', while being positively related to momentum returns, is negatively related to future returns. In consequence, momentum strategies are nominally profitable, at least, in part on account of short-sale constraints.

In the light of the aforementioned evidence of transaction cost-related difficulties in implementing momentum strategies profitably, Ammann, Moellenbeck and Schmid (2011) suggested a number of cost-saving adjustments. To begin with, the sample was restricted to large-capitalised, blue-chip stocks from the S&P 100 index, which is alike the earlier-discussed approaches of Chan *et al.* (1999) and George and Hwang (2004). Furthermore, short positions, which as Ali and Trombley (2006) showed constitute the most expensive aspect of arbitrage, are only held in the stock index, while individual stocks are held in long positions. Lastly, the authors did not invest in decile portfolios, but exclusively in the single best and worst performing stocks.

All data were obtained directly from the S&P Corporation as well as Datastream for the period from 1982 to 2009.

It was reported that buying the best performing stock and short-selling the S&P 100 index generates monthly mean abnormal returns of between 1.16% and 2.05%. If instead of only one, three, five or ten best stocks are selected, the excess returns decline but remain positive and in most cases statistically significant, which is argued by the authors to suggest that the momentum effect is strongest for the very best performing stocks. Shorting loser stocks rather than the S&P 100 index, not surprisingly, produces lower and always statistically insignificant returns. Finally, adjusting for risk using a conditional risk model, whereby the Fama and French's (1993) three-factor returns and the strategies' alphas are conditioned on the set of macroeconomic variables used in Chordia and Shivakumar (2002), reduces the returns only slightly.

Therefore, the results of Ammann *et al.* (2011) suggest that it is still possible to execute momentum investment strategies profitably, having considered risk, transaction costs and short-sale constraints, which were reported by Ali and Trombley (2006) to be the most costly aspect of arbitrage.

Another factor that has been regarded in the literature as a potential limit of arbitrage is volatility, especially idiosyncratic volatility (also referred to as simply 'IVol'), as documented by Shleifer and Vishny (1997) or, in the context of the momentum effect, by Ang, Hodrick, Xing and Zhang (2006) as well as Arena, Haggard and Yan (2008).

Similarly to other proponents of the efficient market hypothesis and the risk-based explanations of the return continuation, Arena *et al.* (2008) speculated that since momentum profits persist many years after the revelation of the effect and, in an efficient market, any profitable anomaly is eliminated by rational arbitrageurs, then it must be the case that investors are limited in their ability to arbitrage the momentum phenomenon for profit. The role of idiosyncratic risk in the aforementioned process, as explained by Shleifer and Vishny (1997), would be that arbitrageurs, assumed to manage investors' funds, often need to close trading positions over a short period of time if the portfolio performance is insatisfactory. Considering the investment size needed to make meaningful profits through arbitrage, arbitrageurs tend to be poorly diversified, which creates an excess exposure to firm-specific risk and, consequently, discourages investing in stocks with high IVol. Therefore, under this theory, one would expect stocks with higher IVol to display greater return momentum, which is precisely what Arena *et al.* (2008) set out to investigate.

Specifically, the authors studied common stocks traded on NYSE, AMEX and NASDAQ between 1965 and 2002 with a share code of 10 or 11 in the CRSP database (*i.e.*, no foreign stocks, real estate investment trusts, funds, *etc*. were considered).

In substantiation of the Shleifer and Vishny's (1997) model, it was reported that momentum returns, as well as their statistical significance, increase across portfolios based on idiosyncratic volatility from 0.55% (for the lowest IVol portfolio) to 1.43% (for the highest IVol portfolio) per month, which amounts to a difference of 0.88% per month, or 10.56% per year. This result is mainly driven by stocks with high IVol and low past returns (losers), and cannot be explained by the Fama-French (1993) factors, price delay, transactions costs, distress risk, turnover, different sample periods, different formation and holding periods or alternative specifications of IVol.

The above-referred findings are, therefore, consistent with the hypothesis that IVol represents an important limit of arbitrage, which may offer a partial explanation of the momentum phenomenon. This conclusion is corroborated by Ang *et al.* (2006), despite different model specifications, who reported that high IVol is associated with 'abysmally low returns', yet the observed effect remains significant after controlling for momentum.

Notwithstanding the above-presented evidence, Hogan, Jarrow, Teo and Warachka (2004) showed that momentum strategies modelled after the momentum strategies tested in JT (1993) may, in fact, present a riskless arbitrage opportunity in their original form, despite adjusting for liquidity buffers for the marking-to-market of short-sales, transaction costs, size effect, margin requirements, and higher borrowing rates.

Using the CRSP monthly data for ordinary common stocks traded on NYSE, AMEX and NASDAQ over the 1965-2000 period, the authors devised and carried out tests for determining whether a trading strategy generates statistical arbitrage.

It was found that, consistent with JT (1993), the examined arbitrage portfolios' expected profits are almost always statistically greater than zero. The presence of market inefficiency is evident in 14 out of 16 portfolios, six of which produce riskless arbitrages with decreasing time-averaged variances at the 5% significance level and three at the 10% significance level. Moreover, for instance, the probability of incurring a loss for the 6-month/12-month momentum strategy that longs the highest return decile and shorts the lowest return decile is below 1% after just 89 months of trading. Thus, roughly half of the momentum strategies evaluated by Hogan *et al.* (2004) test positively for statistical arbitrage, which is difficult to reconcile with market efficiency.

Overall, taking all of the evidence analysed in this section into consideration, it would seem that direct transaction costs, liquidity, short-sale constraints as well as idiosyncratic volatility are all factors which can considerably affect the profitability of momentum investment strategies. Nonetheless, as the papers by Korajczyk and Sadka (2004), Ammann *et al.* (2011), and Hogan *et al.* (2004) showed, those practical considerations alone are unlikely to render momentum investing ineffective. In particular, while Ali and Trombley (2006) demonstrated that the proxy for loan fees used in their study is both stronger and incremental compared to the transaction cost measure employed by Lesmond *et al.* (2004), Korajczyk and Sadka (2004), Ammann *et al.* (2011), and Hogan *et al.* (2004) proved that momentum strategies remain highly profitable even after accounting for short-sale constraints discussed by Ali and Trombley (2006). Similarly, momentum profits remain both statistically and economically significant once idiosyncratic volatility is considered (see *e.g.*, Arena *et al*., 2008; Ang *et al*., 2006).

2.3.3. EVIDENCE FROM INTERNATIONAL STOCK MARKETS

As in the case of contrarian investment strategies, the considerable profits to momentum strategies documented in the US stock market have motivated numerous researchers to investigate the effectiveness of this type of investing from an international perspective.

This section scrutinises the international evidence on the momentum effect and is organised as follows. In the beginning the analysis is concerned with comprehensive cross-sectional studies covering several stock markets and then it narrows to more specific European as well as Asian-Pacific studies. Where applicable, publications are examined in a manner corresponding to the US evidence, *i.e.* moving from firm-level-orientated papers through economy-level-orientated papers to market-microstructure-orientated papers.

To begin with, one of the earliest studies on international momentum was conducted by Rouwenhorst (1999), who studied data from 20 emerging markets over the 1982-1997 period as obtained from the Emerging Markets Database (EMDB) of the International Finance Corporation (IFC).

The author reported that the return continuation effect is present in 17 out of 20 countries examined, with the average excess return on an arbitrage portfolio implemented simultaneously across all 20 markets of 0.39% per month when stocks are equally-weighted (and 0.58% per month if countries are equally-weighted), which is lower than the 1% per month, on average, for the US stock market as documented by JT (1993). However, the aforementioned cross-country return is associated with substantial country-to-country variation from -0.79% to 2.09% per month. In particular, six out of 20 stock markets demonstrate momentum returns above 1%.

Furthermore, it seems that the cross-sectional differences between expected returns cannot be attributed to global or even regional risk exposures, but seem to be primarily driven by local factors. There is no evidence, nevertheless, to suggest that local beta risk, estimated by regressing a local currency return on the local currency

IFC Global index return of the analysed country, is compensated in average returns. Contrary to Sadka (2003), the return premium for momentum strategies also does not reflect a compensation for illiquidity, although there is a positive cross-sectional correlation between the two factors. Instead, Rouwenhorst (1999) argued that unless investors have strong sceptical prior beliefs, the evidence seems to favour the hypothesis that momentum is compensated for in average returns around the world.

It is important to point out, however, that to form the winner and loser portfolios, Rouwenhorst (1999) considered stocks from the top and bottom 30% of the prior return distribution, while JT (1993) only used stocks from the top and bottom 10%. Thus, a coarser sort might, attenuate the strength of the momentum effect in emerging markets.

Evidence supportive of the momentum anomaly in emerging markets was also published by De Groot, Pang and Swinkels (2012), who studied the value and momentum effects on S&P and Interactive Data Exshare data for 24 frontier markets, including Bulgaria, Lithuania, Romania, Slovakia and Slovenia, over a 12-year period from 1997 to 2008. Importantly, while this recent study covers, to some extent, a comparable spectrum of countries and firm characteristics to that presented in this research, it will be argued that, despite making a meaningful contribution to knowledge, the analysis thereof suffers from some consequential shortcomings.

To begin with, the scholars found that the 6-month/12-month arbitrage portfolio yields 1.19% per month, with a statistically significant *t*-value of 2.80. Not only is this result approximately 40% greater than the corresponding figure from JT (1993), but more importantly Rouwenhorst (1999) documented momentum profits to be three times smaller in emerging markets. The discrepancy between the findings of Rouwenhorst (1999) and De Groot *et al.* (2012) might be partially explained by the fact that although both studies departed from the methodology of JT (1993; 2001) in a similar way, *i.e.* by not using decile portfolios, this problem affects the more recent study to a lesser extent. This is because the study by De Groot *et al.* (2012) was based on quintile portfolios and not tercile portfolios, or more accurately 30% cut-off limits, as it was designed by Rouwenhorst (1999). Still, it is impossible to determine the source of the observed difference in the magnitude of momentum returns between the three studies with any accuracy, due to the fundamental incompatibility between the employed methodologies.

Furthermore, De Groot *et al.* (2012) did not consider individual stock markets, but the collective universe of S&P Frontier BMI stocks for which data is available. Therefore, it is impossible to discern if the investigated momentum strategies are profitable in any specific stock market, including any of the European stock markets of interest to this research. Potentially making matters even worse is the fact that, unlike the case of the EU12, the stock markets' underlying the S&P Frontier BMI are very dispersed geographically, spanning four continents of America, Europe, Asia and Africa. Whereas following a strategy based on such a portfolio of stocks might be of interest to some investors, who desire extreme international diversification, the practical difficulties and total transaction cost associated with this undertaking are likely to outweigh its potential benefits to most investors.

Lastly, the authors only examined a limited number of momentum strategies, with three-, six- and 12-month formation periods and only one, *i.e.* 12-month, test period, which presents some considerable challenges in terms of comparability with other studies. For instance, JT (1993) reported that the most successful strategy is the 12-month/3-month strategy, whereas the most representative strategy is the six-month/six-month strategy, both of which are not considered by De Groot *et al.* (2012).

Nevertheless, despite the aforementioned limitations, De Groot *et al.* (2012) provided important evidence of a statistically significant momentum effect in emerging markets, which can neither be explained by an exposure to global, frontier market, country or regional risk nor by conservative estimates of transaction costs of 2.5% per single-trip transaction.

This result appears to be in accordance with Muga and Santamaria (2007a) who, studying Latin American emerging markets between 1994 and 2005 based on monthly return data as supplied by Bloomberg and stock market indexes, found that the momentum anomaly is unlikely to result from omitted risk factors.

The authors adopted JT's (1993) methodology as well as the stochastic dominance approach, not requiring asset pricing benchmarks or assumptions about the distribution of asset returns to test whether general, rational asset pricing models can explain momentum.

Consistent with Groot *et al.* (2012), the mean return on the arbitrage portfolio across all holding periods is above the corresponding figure from JT (1993) and amounts to roughly 1.17% per month. This result is particularly impressive given that, as the authors pointed out, Latin American markets suffered severe economic crises and financial turbulence during the period covered by the study. In line with, among others, Chordia and Shivakumar (2002) as well as Cooper *et al.* (2004), Muga and Santamaria (2007a) documented considerably higher momentum payoffs during periods of relative stability in the region, with a mean monthly return of 1.67%. The reported profits, however, are entirely due to winners, which is unlike the results of, among others, JT (2001) and Lesmond *et al.* (2004) who found larger contribution on the part of losers. Stochastic dominance tests strongly confirm that winners dominate losers at second and third order, indicating that risk-averse investors actually would have preferred to buy winners and sell losers over the entire sample period. Therefore, any standard asset pricing model assuming investor risk aversion fails to capture the anomaly. While factors such as liquidity or transaction costs, incorporating a 1% price-impact cost following Lesmond *et al.* (2004), cannot explain momentum, the stock type as well as, consistent with Rouwenhorst (1999), country factors have explanatory power. Overall, the authors argued that the evidence points towards an explanation based on investor behaviour.

In terms of industry-level risk factors in international markets, a notable study was conducted by Scowcroft and Sefton (2005) who, in line with Moskowitz and Grinblatt (1999), showed that as much as 48-70% of momentum profits can be produced by an implicit sector rotation strategy, while only 8%, on average, can be attributed to firm-specific momentum. Neither cross-sectional dispersion in industry mean returns nor varying systematic risk exposure appear to drive this phenomenon. It is important to note, nevertheless, that at the small-capitalisation-level industry momentum can explain only 20% of the total momentum returns, whereas stock-specific effects capture, on average, 66%, thereby assuming much greater importance. Thus, a conclusion that return persistence is mainly driven by an industry-related risk factor might be considered premature and subject to a potential sample bias.

Differently, Griffin, Ji and Martin (2003), following the work of Chordia and Shivakumar (2002), investigated the relation between momentum returns and macroeconomic risk variables in an international context by adopting an unconditional model based on the Chen *et al.* (1986) factors as well as a conditional forecasting model based on lagged instruments.

The authors studied monthly stock return data for 40 countries derived from CRSP and Datastream International for the full sample period beginning in 1995 and ending in 2000, with an explicit focus on the six-month/six-month strategy.

It was found that momentum profits are both statistically and economically significant in all of the analysed regions except Asia, which seems to substantiate the findings of Swinkels (2002) for Japan. However, with the exception of Africa (with an average monthly return of 1.63%), the reported momentum payoffs are below 1% per month, which is consistent with Rouwenhorst (1999), showing a weaker momentum effect outside the US. Furthermore, Griffin *et al.* (2003) demonstrated that momentum profits are only weakly correlated within regions and across continents, thereby suggesting that a global risk factor is unlikely to drive the phenomenon. Both unconditional tests and a conditional application adopted from Chordia and Shivakumar (2002) confirm that country-specific macroeconomic risk factors also do not capture the variation in payoffs. In fact, in line with Cooper *et al.* (2004), the model put forward by Chordia and Shivakumar (2002) is shown to generate forecasts unrelated to the documented momentum profits, which remain positive in both good and bad business cycle states. This clearly supports the evidence from Rouwenhorst (1999) as well as Muga and Santamaria (2007a) for international markets. In addition, similarly to most of the earlier-discussed studies, Griffin *et al.* (2003) observed return reversal over one- to five-year horizons, which effect also seems inconsistent with the proposed risk-based explanations of momentum.

In summary, while the academic evidence does not clearly indicate whether momentum returns are higher, or lower outside the US stock market in general, all of the above-discussed studies documented statistically and economically significant profits to strategies based on return continuation. The only exception seems to be the case of Japan, where presumably as a result of country-specific cultural factors (see *e.g.*, Brush, 2007) the returns are almost always negative. Furthermore, similarly to the US evidence, risk factors related to individual firms or the economy are able to capture the momentum anomaly in the analysed international markets.

2.3.3.1. EUROPE

Contemporaneously with research investigating the viability of momentum investing across continents, several papers focused on the developed European countries exclusively.

Rouwenhorst (1998) was the first to study monthly returns to momentum strategies for 12 European stock markets over the sample period from 1978 to 1995. Having employed the arbitrage winner-loser portfolios as in JT (1993), the author found price continuation lasting for about one year of approximately 1% per month in all 12 countries, which corresponds with the US results of JT (1993). Furthermore, consistent with Grundy and Martin (2001), adjusting for market risk or exposure to a size factor, in fact, increases the mean abnormal performance of momentum strategies. It is interesting to note, however, that the return persistence documented in Europe is not independent of the US experience, suggesting that momentum returns may have common components across markets. This observation seems to contradict the conclusion of JT (1993), who argued that the profitability of momentum strategies is not driven by the lead-lag effects related to delayed stock price responses to common factors, but is consistent with underreaction to firm-specific information.

As far as industry-level risk considerations are concerned, Nijman, Swinkels and Verbeek (2004) found that the individual component of the momentum effect explains roughly 60% of the total effect, whereas industries and countries can account for only about 30% and 10%, respectively. This is in sharp contrast with the results of, among others, Scowcroft and Sefton (2005) who, studying exactly the same database of international stocks, found that industry momentum can contribute up to 70% to momentum returns, while the firm-specific effects merely 8%. According to this paper, therefore, industry momentum, characterised by excess industry-level risk exposure, does not drive individual stock momentum, as in *e.g.* Moskowitz and Grinblatt (1999), but consistent with Grundy and Martin (2001) those seem to largely separate phenomena. Furthermore, similarly to Rouwenhorst (1998), the country-neutral momentum strategies in Europe perform only marginally worse than the unrestricted momentum strategies. In terms of economic magnitude, nonetheless, both Scowcroft and Sefton (2005) and Nijman *et al*. (2004) reported abnormal returns of approximately 12% per year without transaction costs, which is in line with JT (1993). Finally, in corroboration of Van Dijk and Huibers (2002), the above results are robust to the inclusion of the value and size effects, which are only statistically and economically significant in few cases.

Differently, Antoniou, Lam and Paudyal (2007), following the works of Chordia and Shivakumar (2002) for the US as well as Griffin *et al.* (2003) for international markets, examined whether business cycle (or behavioural variables) affect the profitability of momentum investing in France, Germany and UK as based on monthly data derived from the Datastream and I/B/E/S[21] records between 1977 and 2002.

The authors applied the conditional asset pricing model of Avramov and Chordia (2006) extended by behavioural characteristics as well as business cycle variables from Chordia and Shivakumar (2002). As in all preceding papers, momentum portfolios were constructed in accordance with JT (1993).

It was documented that the six-month/six-month momentum strategy generates monthly payoffs of 2.10%, 1.82% and 1.44% for the UK, Germany and France,

[21] Institutional Brokers Estimate System.

respectively, which is considerably more than reported by the earlier-discussed US or European studies. In line with Cooper *et al.* (2004) and Griffin *et al.* (2003), among others, the predictive regression framework developed by Chordia and Shivakumar (2002) is incapable of explaining momentum profits, except in the UK. The Avramov and Chordia's (2006) model, on the other hand, confirms the existence of business cycle patterns within momentum profits, thereby suggesting that an unidentified, business-cycle-related risk factor may contribute to the return momentum in Europe. This is substantiated by the fact that the incorporation of behavioural variables into the model has no significant impact on the overall results, which seems to contradict the behavioural explanations of the momentum anomaly.

In summary, the European evidence analysed thus far strongly suggests that while return persistence is not an effect which can be captured by the firm-specific or industrial risk factors, hitherto unidentified excess macroeconomic risk exposure on the intra-country (*e.g.*, Antoniou *et al.*, 2007) as well as international (Nijman *et al.*, 2004; Rouwenhorst, 1998) level may play an important role in the momentum anomaly. In terms of magnitude, the returns to the momentum strategies in Europe seem to match and exceed the US results.

2.3.3.1.1. UK

In the UK context, Weimin, Strong and Xinzhong (1999) confirmed the profitability of momentum strategies on weekly Datastream figures for LSPD stocks over the 20-year period from 1977 to 1996. The authors employed the approaches of both JT (1993) and Lehmann (1990).

The main results of the paper are as follows. All arbitrage portfolios generate significantly positive profits, using both Lehmann's (1990) portfolio weights as well as regular decile portfolios. The strategy based on 12-month ranking period and three-month holding period is the most profitable with an annual return of 23.3%, which matches the findings of JT (1993), who documented the highest return of 16.9% for the same strategy. Similarly, Rouwenhorst (1998), studying 12 European stock markets, reported a return of 17.5% to the 12-month/3-month strategy. Importantly, unlike JT (1993), Weimin *et al.* (1999) analysed only non-overlapping momentum strategies, which are notably less trading intensive and, thus, assuming transactions costs of 0.5% does not affect the overall results. Whereas, contrary to Van Dijk and Huibers (2002), the authors confirmed the presence of value effects in UK stock returns, these phenomena cannot explain momentum profits. Further analysis reveals that, in contrast to Rouwenhorst (1998), momentum profits are not captured by serial correlation in the realisations of a single common factor or delayed price reaction to common factor realisations, but seem to stem from a delayed response to either industry- or firm-specific information. The reported findings are additionally robust across two sub-samples as well as to systematic risk, seasonal effects and skewness bias, discussed by Fuertes *et al.* (2009) in the US context.

Ellis and Thomas (2003), studying monthly returns for the constituent companies of the FTSE 350 as derived from Datastream for the period 1989-2003, also found that zero-cost portfolios exhibit return continuation in the UK and there is no evidence to suggest that holding excess systematic risk drives this result.

Implementing the JT (1993) methodology as most of the above-discussed papers do, the authors found that the average monthly return for all arbitrage portfolios considered in this study is around 1.4% per month, which is more than reported by JT (1993) or Rouwenhorst (1998). The 12-month/3-month strategy, however, produces a payoff of 20.4% per year, which is below the corresponding low-volume portfolios in the UK and generate nearly 40% higher returns than the simple momentum strategies. In addition, transaction costs, including bid-ask spread, commission, impact cost, short-selling cost and stamp duty, are estimated to be about three times higher than assumed in the existing literature and amount to 5.8% per year.

The overall results presented by Ellis and Thomas (2003) are consistent with Chordia and Shivakumar (2002) and Cooper *et al.* (2004), since as many as 27 out of the 30 zero-cost momentum portfolios have negative annual returns in stressed markets. Excluding those extreme periods from the sample raises the annual average return from 16.93% to 27%, which seems to bring into question the validity of the sub-sample analysis in Weimin *et al.* (1999) and, in line with the earlier-reported findings of European studies, points towards excess macroeconomic risk exposure.

A similar point was made by Hon and Tonks (2003) who argued that momentum investing in the UK is only profitable over certain time periods. As in Weimin *et al.* (1999), all tests in this paper were based on the non-overlapping application of JT's (1993) methodology and the LSPD tape of returns from 1955 to 1996.

To begin with, it was found that most of the 64 trading strategies analysed yield positive and statistically significant average returns, with the 12-month/6-month strategy being the most profitable and earning an annualised return of 16.2%. This result is consistent with JT (1993), and Ellis and Thomas (2003). However, splitting the sample into two sub-periods from 1955 to 1976 and 1977 to 1996 revealed that momentum investing is only viable over the latter period, which may suggest that, contrary to Weimin *et al.* (1999), momentum is not a general feature of the UK equity market, but is confined to sub-samples.

Nevertheless, it is important to point out that the main findings of Hon and Tonks (2003) are not supported by a more recent paper by Galariotis, Holmes and Ma (2007) who, investigating the profitability of 64 strategies based on past returns, both contrarian and momentum, on the London Stock Exchange between 1964-2005 and 1975-2005, found that momentum profitability is approximately four times lower in the former period, which suggests exactly the opposite conclusion to that in the preceding paper.

Still, in line with Weimin *et al.* (1999), Ellis and Thomas (2003) as well as Hon and Tonks (2003), Galariotis *et al.* (2007) reported that, unlike the case of contrarian strategies, profits to strategies exploiting return continuation cannot be explained by the Fama and French's (1996) risk factors.

More specifically, though, on the subject of time-dependency and macroeconomic risk behind the momentum anomaly, Chelley-Steeley and Siganos (2004) found that momentum profits in the UK are influenced by a range of macroeconomic and market wide variables in a study of LSPD listed companies between 1975 and 2001.

The authors substantiated the findings of Weimin *et al.* (1999) and Hon and Tonks (2001), showing that buying prior winners and selling prior losers generates a monthly market adjusted return of about 1.3%. This return was shown to be positively correlated with real GDP, risk free returns and the value of indirect taxes, while at the same time being negatively related to the amount of portfolio funds flowing out of the UK to investments abroad. Whereas no market sentiment variables seem to affect losers, market volatility is negatively related to winner profits. Thus, it is in times of economic expansion that momentum strategies in the UK tend to perform exceptionally well, which is consistent with the hypothesis of excess macroeconomic risk exposure and the findings of Ellis and Thomas (2003). Lastly, Chelley-Steeley and Siganos (2004) observed that when the market closes below its opening level over the previous six months, momentum profits increase, possibly reflecting mean reversion in the market.

In a follow up paper, Siganos and Chelley-Steeley (2006) further investigated the earlier-implied relation between market state and momentum returns, studying the same sample of companies during economic expansionary and recessionary sub-periods. Market conditions were identified based on the market return of the FTSE-All Share index over time horizons ranging from one to 12 months.

The main findings of this study indicate that the documented monthly continuation profits of approximately 1.3% for the whole sample period are produced by the winner portfolio during up markets and by the loser portfolio during down markets. More importantly, though, there seems to be a negative correlation between momentum profits and past market performance. In particular, the longer the period used to define the recessionary state, the stronger the price continuation effect. Analogously, returns to momentum investing strategies are negative after strong market gains. However, rather than interpreting these results as consistent with a rational risk-based explanation, the authors favoured a behavioural model, whereby investors who realised losses (gains) over the past tend to be more pessimistic (optimistic) for the future and, as a result, underreact (overreact) to present share information, generating high (low) momentum profits. The model also predicts a reversal effect following strong past market returns.

A different approach was adopted by Li, Miffre, Brooks and O'Sullivan (2008) who applied a GJR-GARCH(1,1)-M framework that does not require pre-specified conditional variables, either macroeconomic or firm-specific, on monthly data obtained from LSPD over the period 1975 to 2001.

It was found that momentum portfolios earn an average return of 1.51% a month, which corresponds with the earlier-discussed results for the UK. However, interestingly, here it is the six-month/six-month strategy that yields the highest return, estimated at 1.93% per month. Whereas consistent with rational expectations the momentum portfolios generating higher payoffs are also more risky, the traditional model of Fama and French (1996) fails to explain momentum profits, which was corroborated by, *inter alios*, Galariotis *et al.* (2007) as well as Karolyi and Kho (2004) for the UK and US stock markets, respectively. However, results obtained from the more pertinent to that study GJR-GARCH(1,1)-M models seem to suggest that momentum profits are a compensation for the time-varying unsystematic risks, which although common to both winner and loser stocks, affect the former more than the latter. This result is surprising, given the very strong evidence, both for Europe as whole as well as the UK in specific, pointing towards a macroeconomic, rather than firm-specific, risk factor, yet it is consistent with the US findings of Arena *et al.* (2008) and Ang *et al.* (2006).

As far as market microstructural effects in the UK are concerned, consistent with the US results of Lesmond *et al.* (2004), both Agyei-Ampomah (2007) as well as Li, Brooks and Miffre (2009) pointed out that the momentum strategies in the UK might not be as profitable as implied by the above studies after factoring in transaction costs.

The former paper examined the post-cost profitability of momentum investing on all common stocks traded on the LSE with data available on Datastream from 1988 to 2003. Having considered strategies with various ranking and holding periods, the authors found that accounting for transaction costs eliminates profits to all momentum portfolios based on time horizons of up to six months. Therefore, most average investors would not be able to trade profitably on those strategies as the cost of implementation dominates the return. However, for ranking and/or holding periods beyond six months the portfolio turnover decreases and, in consequence, so do the associated costs of trading, thereby allowing significantly positive net momentum profits (both raw and risk-adjusted). Since these results were also confirmed for a sub-sample of large-capitalisation stocks, the detected pattern is similar to the observations of both Weimin *et al.* (1999) in the UK as well as Korajczyk and Sadka (2004) in the US stock markets. Furthermore, in accordance with JT (2001) and Lesmond *et al.* (2004), most of the reported momentum returns come from short-selling the loser portfolio and, therefore, short-sale constraints may be an important factor preventing successful arbitrage trading. This suggestion is not, however, supported by Badreddine, Galariotis and Holmes (2012), who found evidence of statistically significant return momentum among optioned stocks, characterised by lower susceptibility to short-sale constraints, on the LSE for the period from 1989 to 2010.

The latter paper, by Li *et al.* (2009), also analysed the impact of transaction costs on momentum profitability using Datastream data for all LSPD stocks between 1985 and 2005. Complementing the results of Agyei-Ampomah (2007), it was found that losers, and to a lower extent winners, are small-capitalisation stocks with relatively low price and trading volume. Not surprisingly, therefore, the average round-trip transaction costs based on the quoted spread were estimated at a high of 3.76% and 2.21% for losers and winners, respectively. Once commissions, short-selling costs as well as stamp duties are also taken into account, the total trading costs rise to 3.77% for winners and 6.71% for losers, causing the documented momentum profits to disappear. While these figures seem to be consistent with the findings of Lesmond *et al.* (2004) and Badreddine *et al.* (2012) for the US and UK, respectively, they are notably higher than the estimates of Ellis and Thomas (2003), who assumed transaction costs not higher than 5.8% per year. Furthermore, the authors explained that the asymmetric pattern in trading costs between winners and losers is related to whether trades are buyer- or seller-initiated. Specifically, losers are more expensive than winners due to selling costs which are, on average, 2.3 times higher. Taking this into consideration, similarly to Ammann *et al.* (2011), Li *et al.* (2009) suggested implementing low-cost momentum strategies based on winners and losers that are cheapest to trade. In effect, the total transaction costs of standard momentum strategies based on actual turnover can be decreased by up to 60%, rendering the average returns to 35 out of 45 low-cost strategies positive and significant.

Therefore, although both raw and risk-adjusted returns to the UK momentum strategies match and exceed the corresponding US results, which is consistent with the earlier-discussed evidence for Europe at large, economy-level risk factors as well as transaction cost considerations appear to significantly affect the profitability of this type of investing in the UK. Considering the evidence presented above, it seems unclear whether any net momentum profits could still be observable after considering those variables, which underscores the need for more research. In the absence of clearly defined and theory-motivated macroeconomic risk variables that could fully capture return momentum, it is unlikely that much more could be achieved by searching for risk-based explanations of the studied phenomenon relating to the economy. However, more information would be useful in terms of transaction costs associated with momentum investing in the UK, especially considering the largely incompatible evidence of the only two academic studies in the area (*i.e.*, Agyei-Ampomah, 2007; and Li *et al.*, 2009).

2.3.3.1.2. OTHER EU COUNTRIES

The performance of momentum strategies has also been investigated in the individual EU stock markets of Ireland (*e.g.*, O'Donnell and Baur, 2009), Germany (*e.g.*, Glaser and Weber, 2003; Ryan and Overmeyer, 2003; 2004; Schiereck, De Bondt and Weber, 1999), Spain (*e.g.*, Muga and Santamaría, 2007b; 2009) and Sweden (*e.g.*, Parmler and González, 2007).

O'Donnell and Baur (2009), studying all stocks listed on the Irish Stock Exchange Quotient (ISEQ) between 1984 and 2007, reported that while unrestricted (or arbitrage-based) momentum strategies do not outperform the benchmark portfolio of the ISEQ Overall Index, all strategies based on the winner and loser portfolios alone produce abnormal returns which are both positive and statistically significant at a 95% confidence level. In particular, the excess return to winner strategies ranges from 2.1% per month, on average, for the 9-month/3-month strategy to 9.6% per month for the 6-month/12-month strategy. Dividing the sample period into episodes of low and high growth reveals that zero-cost momentum strategies yield positive excess returns only in the periods of high growth, whereas winner strategies seem to do well during both states of the economy. In 'bear markets', however, nine out of the 16 unconditional momentum trading strategies studied have significant returns above the market return per month, which contrasts with the findings of Chordia and Shivakumar (2002), and Cooper *et al.* (2004). Interestingly, controlling for heteroscedasticity including low- and high-volatility states using a GARCH model changes the results even further and now it appears that almost all zero-cost momentum strategies generate excess returns of up to 7.6% per month. Consequently, it seems that macroeconomic conditions, and therefore potentially macroeconomic risk factors, have a fundamental influence on the profitability of strategies exploiting return persistence in Ireland.

In Germany, Ryan and Overmeyer (2004) found that momentum strategies as proposed by JT (1993) can produce economically significant profits even when these are based on the largest capitalisation stocks in a national market. The authors studied monthly returns for all stocks in the DAX 100 index over the period 1990-1999.

Differently to the Irish results of O'Donnell and Baur (2009), all returns on the 16 arbitrage winner-loser portfolios considered are positive and statistically significant. The 3-month/3-month as well as the 12-month/3-month strategies are the most profitable, yielding 1.32 and 1.31 excess pps per month, respectively, which is consistent with the findings of JT (1993), Rouwenhorst (1998), and Weimin *et al.* (1999). The reported results are robust to lead-lag effects, as discussed by Lo and MacKinlay (1990), systematic risk measured by both beta and the Fama and French's (1996) model as well as reasonable levels of transaction costs. In addition, similarly to Weimin *et al.* (1999), while neither serial correlation in common factor realizations nor a delayed price reaction to a common factor can explain momentum profits, the evidence seems consistent with underreaction to firm- or industry-related news. However, unlike JT (1993), the authors did not observe price reversals beyond one year, but insignificant momentum profits instead.

In sharp contrast to the above-reported results, in a follow-up paper Ryan and Overmeyer (2003) found that for the constituents of DAX 30, strategies based on past price performance are not economically significant. The authors examined the market's response to past-accounting-based information using quarterly results published by the DAX 30 companies in the main German financial newspaper (*i.e., Handelsblatt*) over the period from 1995 to 2000. The reason for the discrepancy between the two studies, as suggested by the authors, might be that the profitability of momentum strategies is a function of size or investor characteristics, which are likely to be different for the DAX 100 and DAX 30 samples.

However, in line with Ryan and Overmeyer (2004), Glaser and Weber (2003) confirmed the viability of momentum investing in Germany on a larger sample of 446 firms listed on the Frankfurt Stock Exchange. The study was based on daily and monthly data derived from Datastream for the period 1988 to 2001.

Consistent with JT (1993), Schiereck *et al.* (1999) as well as Ryan and Overmeyer (2004), most zero-cost momentum portfolio returns are statistically significant and the 12-month/3-month strategy is the most profitable, yielding 1.07% per month. Interestingly, the momentum effect is still stronger among high-turnover stocks, which contrasts with the US findings of Lee and Swaminathan (2000). For example, focusing on the six-month/six-month strategy shows that high-turnover winners earn 0.78% per month more than low-turnover winners, while high-turnover losers have a 0.27% per month lower return than low-turnover losers. Thus, the documented relation is more pronounced for winners which, again, contradicts the observations of Lee and Swaminathan (2000), who found that this phenomenon is entirely driven by losers. The above-mentioned differences, nonetheless, can be explained by the use of distinct trading volume definitions. Lastly, robustness checks of the results reveal that the turnover effect is, to a large extent, a size-, book-to-market-, and industry-effect and that, consistent with Ryan and Overmeyer (2003), there is no momentum among large-capitalisation stocks in the German stock market.

In a study of the Spanish stock market based on monthly INTERTELL and Stock Market Association data for the period 1991-2000, Muga and Santamaría (2007b) reported that although momentum returns are, indeed, related to size, turnover and the turn of the year effects, neither of these factors is capable of explaining return continuation anomaly.

Using a methodology similar to JT (1993) as most of the earlier-discussed papers, the authors found that momentum is weaker in Spain as compared to the US, with the six-month/six-month strategy generating only 0.82% per month, which is lower than the corresponding figure of 1.39% per month from JT (2001). Although the presented evidence appears to be contrary to Forner and Marhuenda (2006, as cited in Muga and Santamaría, 2007b, p. 473), who documented no momentum in the Spanish stock market during the 1990s, momentum profits observed by Muga and Santamaría (2007b) proved to be unstable and begun to fade by 1997, coinciding with the onset of the stock market crisis of September 1997. This occurrence appears to be in accordance with Chordia and Shivakumar (2002), and Cooper *et al.* (2004). Furthermore, the authors rejected the suggestion that there may be a relation between earnings and past stock returns, thereby contradicting the findings of, *inter alios*, Ryan and Overmeyer (2003), and Chan *et al.* (1996; 1999).

However, in a follow-up study, Muga and Santamaría (2009) showed that the momentum effect is present in both up and down markets in the Spanish stock market between 1971 and 2004. The authors explained that the earlier-established relationship between momentum and market state might have altered as a result of accounting for the disposition effect[22], which increases the likelihood of momentum in both market states.

Now, the returns to the 16 momentum strategies considered range from 0.95% per month for the 3-month/3month strategy to 1.72% per month for the 12-month/3-month strategy, which is in line with JT (1993), Rouwenhorst (1998), and Weimin *et al.* (1999), among others. More importantly, as implied above, the results presented in this study are exactly opposite to those predicted by Chordia and Shivakumar (2002), and Cooper *et al.* (2004). Namely, momentum profits are higher in 'bear

[22] The disposition effect relates to the tendency of investors to hold on loser stocks longer than winner stocks (see *e.g.*, Shefrin and Statman, 1985; Odean, 1998).

markets' than in 'bull markets'. According to the authors, this phenomenon is driven by the fact that, when following up-markets (down-markets), momentum profitability declines (increases) over longer holding periods. Moreover, after 'bull markets', there is evidence of returns reversals. Overall, these results are consistent with investor overreaction caused by behavioural biases in up markets and underreaction due to the disposition effect in down markets.

The last paper to be discussed in this section is by Parmler and González (2007), who explored the profitability of momentum strategies in Sweden over the period 1979 to 2003 as based on monthly data obtained from the Trust database for all stocks traded on the Stockholm Stock Exchange.

The authors found that momentum strategies provide returns superior to a benchmark model, even after the effect of data-snooping has been taken into account. As in JT (1993), Rouwenhorst (1998), Weimin *et al.* (1999) and Muga and Santamaría (2009), among others, the most successful zero-cost strategy is based on a 12 month ranking period and a three month holding period and it generates 2.318% per month. These results, similarly to the UK study of Weimin *et al.* (1999), are robust across two subsamples and systematic risk. However, consistent with Moskowitz and Grinblatt (1999) and Lewellen (2002), Parmler and González (2007) documented only a very weak or no momentum effect when stocks are sorted by size, book-to-market and industry. Importantly, not controlling for the data-snooping bias resulted in almost always rejecting the null hypothesis of no momentum effect for the size, book-to-market and industry portfolios, which suggests that neglecting this problem may lead to very different conclusions.

Overall, the evidence from Ireland, Germany, Spain and Sweden conforms with the UK results and, thus, it would seem that even though momentum in stock returns is stronger in Europe than it is in the US in terms of magnitude, this effect is still influenced by firm-specific and macroeconomic variables, albeit apparently to a lesser extent than in the UK. The presented studies suggest, however, that none of these groups of factors can fully capture return continuation in European stock markets.

2.3.3.1.3. ASIA-PACIFIC

Only two multi-country papers have been published on the momentum effect in the Asia-Pacific region to date, those are by: Hameed and Kusnadi (2002), and Ryan and Curtin (2006).

Hameed and Kusnadi (2002), focusing on the six Asian stock markets of Hong Kong, Malaysia, Singapore, South Korea, Taiwan, and Thailand, reported no evidence of price momentum. The authors used monthly data obtained from the Pacific-Basin Capital Markets (PACAP) Database for the period 1979-1994.

It was found that the average monthly return on a zero-cost momentum strategy implemented on all stocks in all sample countries equals 0.53% per month, which although matches the findings of Rouwenhorst (1999) for 20 emerging markets, it remains to be a statistically insignificant return. Hameed and Kusnadi (2002) confirmed that this result is robust to the bid-ask bounce effect, calendar effects, return outliers, and different portfolio formation methods. To see if country effects influence the winner-loser portfolios, the authors considered country-neutral strategies and found that not only has this considerably reduced the volatility of momentum returns, but also the mean return of the arbitrage portfolio is now statistically significant and amounts to 0.37% per month. However, the US momentum portfolios, used as a benchmark here, generate 1.22% per month over the same period, which is consistent with JT (1993). Therefore, although, in line with Rouwenhorst (1999), the returns to momentum strategies in emerging markets are lower than in the US or European stock markets, contrary to Rouwenhorst (1998) and Nijman *et al*. (2004), country factors seem to meaningfully affect the overall results. Furthermore, when size and turnover effects are controlled for, the country-neutral profits dissipate, which coupled with the evidence showing no correlation between the US and Asian stock markets allowed the authors to suggest that the momentum effect may not hold across all markets.

These finding were strongly corroborated by Ryan and Curtin (2006) who, analysing monthly Datastream data for India, Indonesia, Hong Kong, Malaysia, Singapore, South

Korea, and Taiwan over 1991 through 2000, reported no exploitable momentum effect in these countries.

Using methodology similar to Hameed and Kusnadi (2002) and, by implication to JT (1993), the authors unexpectedly found that 14 out of 16 momentum strategies examined produce negative returns, meaning that past losers in fact outperform past winners. In ten of these cases the payoffs are statistically significant and this profitability tends to increase with the longer formation and holding periods. For example, within the 12-month/12-month strategy winners underperform losers by 2.7% per month. Whereas this evidence is clearly in contrast to the findings of all of the earlier-discussed studies on momentum investing, it seems to be in line with the short-term contrarian effect documented by, *inter alios*, JT (1995) and Lehmann (1990). Moreover, contrary to Hameed and Kusnadi (2002), the profits to country-neutral portfolios lack both economic and statistical significance, despite achieving reduction in return variability. Controlling for size does not alter the overall results.

In conclusion, both Hameed and Kusnadi (2002) as well as Ryan and Curtin (2006) confirmed and extended the earlier-mentioned observations of Griffin *et al.* (2003), Swinkels (2002) and Brush (2007) that the momentum effect is largely absent in the Far East region. Studies by Iihara, Kato and Tokunaga (2004) of the Japanese stock market as well as by Wang, Burton and Power (2004) of the Taiwanese stock market also add to this evidence. The existence of region-specific cultural factors seems to be the most likely explanation for the reported absence of the momentum anomaly (Brush, 2007; Chui, Titman and Wei, 2010). However, these results are only partly substantiated by the publications concerned with the Chinese and Indian stock markets, which are discussed next.

2.3.3.1.4. CHINA AND INDIA

In the context of China, Wang (2004) as well as Zhou, Geppert and Kong (2010) examined shares from the China Stock Market and Accounting Research Database that are listed on the Shanghai and Shenzhen Stock Exchanges for the periods 1994 – 2000 and 1995 – 2008, respectively. Importantly, while the former study was only based on A shares (*i.e.*, Chinese shares available exclusively to domestic investors in domestic currency), the latter study looked at both A shares and B shares (*i.e.*, Chinese shares available to foreign and, since 2001, also domestic investors in foreign currency).

The authors consistently found that, in the A-share market, momentum strategies generate statistically insignificant and, for most investment horizons, negative returns. What is more, the returns become more negative and statistically different from zero for longer formation and holding periods. Despite attenuating after the Fama and French's (1996) three-factor adjustment (Wang, 2004), this evidence of the contrarian effect corresponds closely with the earlier-discussed findings of Ryan and Curtin (2006). Similarly, for the B-share market, Zhou *et al.* (2010) documented statistically insignificant momentum profits for certain investment horizons below one year and statistically significant contrarian profits for investment horizons beyond one year.

However, the opposite conclusion to that of Wang (2004) as well as Zhou *et al.* (2010) was reached by Naughton, Truong and Veeraraghavan (2008), who evaluated the profitability of momentum investing by concentrating on monthly Shanghai Stock Exchange A-share market data for the period 1995 - 2005 as obtained from the Great China Database. The authors reported positive and significant momentum profits during the sample period covered for every combination of formation and holding periods. For instance, the 12-month/3-month and the six-month/six-month strategies yield 12.6% and 12.24% per year, respectively, which despite being some of the least profitable strategies, still match the average results of JT (1993). Additionally, consistent with JT (1993; 2001), the momentum effect lasts for about one year and, subsequently, converts into a reversal pattern from year two onwards. In accordance with Chan *et al.* (1996; 1999), although momentum strategies produce high intermediate-term payoffs around earning announcements, these returns constitute only a small component of the overall profits. However, the reported findings are inconsistent with Lee and Swaminathan (2000) as there seems to be no clear pattern in stock returns between high volume portfolios and low volume portfolios, having controlled for momentum.

Similarly, Sehgal and Balakrishnan (2004), studying monthly data obtained from Small Investor for 364 Indian companies traded on the Bombay Stock Exchange from 1989 to 1999, found a significant continuation effect in individual stocks as well as size and book-to-market sorted portfolios. The average monthly returns on all arbitrage momentum portfolios are statistically and economically significant, ranging from 1.26% per month for the 12-month/12-month strategy to 1.94 % per month for the 12-month/6-months strategy. These results, robust to month-of-the-year effects as well as risk-adjustment using CAPM, are notably higher than the corresponding figures from Hameed and Kusnadi (2002), Rouwenhorst (1999) or Naughton *et al.* (2008). Aside from this observation, it is also interesting to note that momentum profits in the Indian stock market seem to be partially explained by the Fama and French's (1996) three-factor model, which contrasts with the findings of, among others, Grundy and Martin (2001). In addition, consistent with an earlier study by Sehgal and Balakrishnan (2002), the post-holding period returns on zero-cost momentum portfolios continue to be positive, which suggest a weak or no reversal pattern and, therefore, appears to be against the implications of the behavioural models.

Thus, while the results for China[23] might be seen as inconclusive, raw and risk-adjusted momentum returns appear to be both statistically and economically significant in India, which contrasts with the findings for the other countries of the Far East region. Nevertheless, transaction costs, or other market microstructural effects, have not been considered here at all, which could have led to very different conclusions. Nonetheless, similar findings are reported for Australia, analysed next.

[23] Related to the earlier-discussed publications concerning the stock market(-s) of China is the research of, among others, Wang and Chin (2004); Zhou (2010); and Pan, Tang and Xu (2013). However, Wang and Chin (2004), similarly to Zhou (2010), studied the interaction between past returns and past trading volume, rather than past-return-based strategies *per se*, while Pan *et al*. (2013), unlike all other authors mentioned in this literature review, exanimated the momentum effect in weekly, rather than monthly, returns.

2.3.3.1.5. AUSTRALIA

Although the momentum anomaly has been extensively researched in Australia, only a brief overview of the evidence thereof is offered on account of the fact that the Australian studies are not immediately relevant to this research.

There are six academic papers that need to be mentioned here, *i.e.* that by Hurn and Pavlov (2003); Demir, Muthuswamy and Walter (2004); Durand, Limkirangkrai and Smith (2006); Brailsford and O'Brien (2008); Bettman, Maher and Sault (2009); and Galariotis (2010).

The first work examined monthly return data for the 200 largest Australian stocks from 1973 to 1998 and found cumulative raw returns to momentum strategies in the first year of trading to range from 4.79% to 7.13% per year, which is comparable to the results of Rouwenhorst (1999). The reported profits cannot be explained by industry effects, cross-sectional dispersion of unconditional mean returns or adjustment for the exposure to market-wide risk factors, which is broadly consistent with the US studies.

The main findings of Hurn and Pavlov (2003) were substantiated by Demir *et al.* (2004), analysing a larger sample of all Approved Securities observed daily on the ASX for the period 1990-2001, with the only consequential difference being that small stocks seem to exhibit stronger momentum than large stocks.

While, in a study of all 675 stocks listed on the Australian Stock Exchange during the period 1980-2001, Durand *et al.* (2006) reported very different results to both Hurn and Pavlov (2003) as well as Demir *et al.* (2004) at first, having replicated the study of Demir *et al.* (2004), the author confirmed the results of the previous paper, which suggest that the documented discrepancy is caused by the use of monthly instead of daily data as well as the inclusion of different stocks in the datasets. The findings presented by Durand *et al.* (2006), nonetheless, still remain at odds with the results of Hurn and Pavlov (2003).

Brailsford and O'Brien (2008) concluded that the above-identified discrepancy is a result of momentum being present only in the larger half of the Australian equity market. This finding, as Brailsford and O'Brien (2008) argued, casts doubt on the profitability of momentum investing, considering the relatively illiquid nature of medium capitalisation stocks in Australia as well as the fact that risk adjustments reduce the reported profits by roughly 25%.

Nonetheless, Bettman *et al.* (2009) found that the documented price continuation in the ASX is robust to the choice of an abnormal return metric, short selling restrictions, transaction costs in the form of bid-ask spreads, and liquidity constraints in the form of trading volume.

Galariotis (2010) controlled for the possibility that the findings of Hurn and Pavlov (2003) and Bettman *et al.* (2009) are sample specific by extending the earlier papers for two different samples of securities and two sample periods, confirming that the momentum anomaly is pervasive through time in the Australian stock market.

Overall, there seems to be strong evidence to suggest that the momentum strategies are profitable in the Australian stock market, even after controlling for risk, industry effects and market microstructure. The contrasting results of Durand *et al.* (2006) and, to some extent, Brailsford and O'Brien (2008) are likely to be a consequence of incompatible study designs.

2.3.4. SUMMARY AND CONCLUSION

Since the seminal work of JT (1993) documented that, in violation of the efficient market hypothesis, stocks yielding higher (lower) than average returns in one period will also yield higher (lower) than average returns in the following period over the intermediate term, numerous studies have investigated the profitability of strategies exploiting return continuation effect in the US as well as international stock markets.

Overall, although the existence of the momentum anomaly does not appear to be controversial and the overwhelming majority of scholars documented sizeable continuation profits, there seem to be several risk factors that are closely related to this effect.

In particular, an analysis of the US-stock-market-based papers revealed that momentum is associated with risk variables that can be broadly grouped into the firm-level and economy-level categories.

Firm-level risk factors in the form of beta, company size, cross-sectional dispersion in expected returns and book-to-market equity, despite having a notable influence on momentum profits, were found to be unable to fully account for the underlying effect.

At the economy level, inclusive of the industry level, variables related to industries, the business cycle and growth rates also could not fully rationalise the investigated anomaly, however, it was observed that momentum payoffs do vary with the business cycle. Whereas this may indicate excess exposure to a hitherto unidentified macroeconomic risk factor earning a risk premium, an equally likely explanation might be one based on investor irrationality, such as: (1) the mispricing of macroeconomic variables that impact the company performance, possibly capturing the market's aggregate overreaction or underreaction to corporate earnings (see *e.g.*, Chordia and Shivakumar, 2006); or (2) the overreaction induced by positive feedback trading strategies (see *e.g.*, De Long, Shleifer, Summers and Waldmann, 1990), where 'trend-chasers' reinforce movements in stock prices even in the absence of fundamental information, which also results in subsequent price reversals, such as those documented by DBT (1985) (see *e.g.*, Chan *et al.*, 1996; 1999). In fact, a number of scholars showed that momentum profitability varies counter-cyclically with the business cycle, which should not earn a positive risk premium (see *e.g.*, Asem and Tian, 2010; Avramov *et al.*, 2007; Chordia and Shivakumar, 2006).

Thus, even after controlling for the aforementioned two broad groups of risk factors, the momentum anomaly seems to be unaccounted for and momentum investing, as originally proposed by JT (1993), still remains a potentially profitable investment strategy, which is not explained by risk.

Moreover, this conclusion appears to be robust to direct transaction costs, liquidity risk premia, short-sale constraints and other microstructure effects.

In particular, while Ali and Trombley (2006) demonstrated that the proxy for loan fees used in their study is both stronger and incremental compared to the transaction cost measures employed by other scholars, Korajczyk and Sadka (2004), Ammann *et al.* (2011), and Hogan *et al.* (2004) showed that momentum strategies remain highly profitable even after accounting for short-sale constraints discussed by Ali and Trombley (2006). Similarly, momentum profits remain both statistically and economically significant once idiosyncratic volatility is considered (see *e.g.*, Arena *et al*., 2008; Ang *et al*., 2006).

As far as international papers on momentum are concerned, it is apparent that appreciably more research has been conducted on the momentum effect as compared to the contrarian effect. Nevertheless, over 90% of all studies still focus on developed markets.

The evidence from the developed European stock markets revealed that price momentum is stronger there than it is in the US and, as in the US, it seems to be related to firm-specific and macroeconomic risk factors.

In terms of idiosyncratic risk proxies, most authors agree that momentum cannot be explained by beta, size or book-to-market equity factors.

In terms of macroeconomic factors, while based on the results of Swinkels (2002) and Scowcroft and Sefton (2005) it is difficult to assess whether there are any industry components behind price momentum, industry momentum appears to be present in Europe alongside price momentum. This conclusion was substantiated by Nijman *et al*. (2004), who confirmed that European individual stock momentum is not subsumed by industry or country momentum. Additionally, Antoniou *et al.* (2007), using the Avramov and Chordia's (2006) model, confirmed the presence of business cycle patterns within momentum profits in Europe, thereby suggesting that an unidentified, business-cycle-related risk factor might be present. This conjecture is supported by the fact that incorporating behavioural variables into the model does not have a significant impact on the overall results, which seems to contradict the behavioural explanations of the momentum anomaly. However, such a conclusion would be in sharp contrast with, *inter alia*, the findings of Doukas and McKnight (2005) who, having studied 13 European stock markets, found evidence consistent with the gradual diffusion of firm-specific information hypothesis of Hong and Stein (1999).

Furthermore, Rouwenhorst (1998) observed that return persistence documented in Europe is not independent of the US experience, suggesting that momentum returns may have common components across markets. A similar effect was reported by Swinkels (2002), who found that European industries lag behind US industries. Van Dijk and Huibers (2002) suggested that this might be because analysts following European stocks behave similarly to analysts following US stocks. This explanation would be consistent with the existence of cultural factors as proposed by Brush (2007) and Chui *et al.* (2010) and constitute a realistic alternative to a global-risk-based rationalisation.

Therefore, the analysis of all pan-European studies revealed that although it seems clear that price persistence is stronger in Europe than it is in the US, more research is needed to evaluate the effects of risk and, more prominently, market microstructural factors on the momentum anomaly in those countries.

Weimin *et al.* (1999) confirmed that the above results for Europe in general also hold for the UK. The findings were argued to be robust across two sub-samples as well as to systematic risk, seasonal effects and skewness bias, discussed by Fuertes *et al.* (2009) in the US context. However, Hon and Tonks (2003) as well as Galariotis *et al.* (2007) showed that momentum investing in the UK is only profitable over certain time periods and Ellis and Thomas (2003) found most zero-cost momentum portfolios to have negative annual returns in stressed markets. These observations were supported by Chelley-Steeley and Siganos (2004; 2006) who, more specifically, suggested that momentum returns are influenced by a range of macroeconomic and market wide variables. Nonetheless, unlike Ellis and Thomas (2003), Chelley-Steeley and Siganos (2006) documented that momentum strategies are also profitable during recessions, which similarly to the US studies of, among others, Avramov *et al.* (2007) and Chordia and Shivakumar (2006), evidences momentum-business-cycle counter-cyclicality that should not earn a positive risk premium.

Furthermore, Agyei-Ampomah (2007), Li *et al.* (2009) and Badreddine *et al.* (2012) all pointed out that transaction cost considerations are important when assessing the profitability of momentum investing in the UK and found that only cost-efficient strategies yield meaningfully positive returns.

Therefore, it might be concluded that while both raw and risk-adjusted returns to the UK momentum strategies exceed the corresponding US results, similarly to the US experience, transaction costs as well as macroeconomic factors, especially those related to the business cycle, appear to significantly affect the profitability of momentum investing. Although it would seem that the momentum effect is still present after factoring in those two groups of variables, the exact impact remains largely unknown.

The evidence from other European stock markets discussed, *i.e.* Ireland, Germany, Spain and Sweden, conforms with the above-reported results for Europe in general and the UK, and, therefore, it will not be referred to in detail here.

By contrast, in the developed countries of the Asia-Pacific region, the momentum effect seems to be largely absent, with Australia being a notable exception. This finding, reported by Hameed and Kusnadi (2002) as well as Ryan and Curtin (2006), confirmed and extended the earlier-noted observations of Griffin *et al.* (2003), Swinkels (2002) and Brush (2007), who considered it to be consistent with the existence of cultural factors which are specific to the Asian nations.

Most importantly, though, very little research on momentum has been conducted for emerging economies. The only papers that considered developing countries are by: Rouwenhorst (1999) of 20 emerging markets; De Groot *et al.* (2012) of 24 emerging markets; Muga and Santamaria (2007a) of the Latin American countries; Wang (2004), Zhou *et al.* (2010) and Naughton *et al.* (2008) of China; and Sehgal and Balakrishnan (2002; 2004) of India. However, Rouwenhorst (1999) as well as De Groot *et al.* (2012) departed from JT's (1993) methodology in ways which could misrepresent the analysed effect, while the reported results for China and India are largely inconsistent with the evidence from other countries of the Far East region as presented by Hameed and Kusnadi (2002), Ryan and Curtin (2006), Griffin *et al.* (2003), Swinkels (2002), and Brush (2007). Furthermore, very little is known on the role of risk and market microstructural factors in the momentum anomaly in emerging nations.

Overall, having analysed the evidence on the momentum effect worldwide, it might be concluded that momentum investing, as originally proposed by JT (1993), is a profitable investment strategy, which cannot be fully explained by risk or microstructure effects. This conclusion holds for the US as well as international stock markets, with the exception of the developed Asian countries. The absence of momentum in those nations is likely to be due to cultural factors specific to the region (Brush, 2007; Chui *et al.*, 2010). Most importantly, though, it has been demonstrated that very little is known about the momentum effect in emerging economies. The extant literature in this field is scarce, conflicting and of questionable value for comparative purposes. In particular, no research on the momentum effect has been conducted for the EU12 countries, despite the fact that it is a region of growing importance internationally.

2.4. CONCLUSION

This literature review has provided an analysis of academic publications on the practical aspects of contrarian and momentum investment strategies.

While it would appear that neither contrarian nor momentum profits can be fully eliminated by accounting for risk and market microstructure effects in most stock markets examined, it is crucial to stress that research in this branch of finance is still conflicting and considerably underdeveloped in many areas.

In terms of the documented contradictory evidence, a substantial part of the problem appears to be related to methodological incompatibility between studies (*e.g.*, Rouwenhorst, 1999 and JT, 1993) and, frequently, narrow scope of individual studies (*e.g.*, DBT, 1985; 1987). This issue has been addressed in this thesis by, among others, consistently applying commonly used definitions of risk, market microstructure effects, portfolio formation and test horizon, portfolio size and stock weighting method.

As regards the areas of the subject matter that are still in their infancy, the main findings of this chapter underscore a pressing need to conduct more research for emerging economies. The international evidence on both contrarian and momentum investing is almost exclusively concerned with developed markets, with the only developing stock market analysed for the contrarian effect being Brazil (da Costa, 1994). Although more research has been done internationally on momentum, the overwhelming majority of studies still focused on developed markets (*i.e.*, 38 out of 43). The only academic publications that considered emerging economies are by: Rouwenhorst (1999) of 20 emerging markets; De Groot *et al.* (2012) of 24 emerging markets; Muga and Santamaria (2007a) of the Latin American countries; Wang (2004), Zhou *et al.* (2010) and Naughton *et al.* (2008) of China; and Sehgal and Balakrishnan (2004) of India. However, Rouwenhorst (1999) and De Groot *et al.* (2012) departed from JT's (1993) methodology in ways which could misrepresent the analysed effect, while the reported results for China and India are largely inconsistent with the evidence from other countries of the Far East region as presented by

Hameed and Kusnadi (2002), Ryan and Curtin (2006), Griffin *et al.* (2003), Swinkels (2002), and Brush (2007).

While both contrarian and momentum investing should be more profitable in less-developed markets, characterised by greater predictability as well as small and less sophisticated investors that may not instantaneously respond to information (see *e.g.*, Schatzberg and Reiber, 1992; Antoniou, Ergul and Holmes, 1997), the evidence on this issue is scarce and inconclusive.

In particular, there are no publications examining either contrarian or momentum profitability in the EU12 stock markets. Those economies are particularly interesting to study not only because of their growing economic importance resulting from increasingly integrated Europe, but also because those countries can be classified as both emerging and a part of the European community, which, considering the largely supportive evidence from both developing nations and Europe, suggests that the two investing methods might also be successful there.

Other limitations of the extant literature include the following aspects.

First, in addition to being very limited, the US-stock-market-based studies on contrarian investing have only covered sample periods of up to the late 1980s. Therefore, after over 30 years, it is not clear whether those strategies are still profitable or if the underlying anomaly has been fully countered by US arbitrageurs since. Moreover, given that all of the US-based publications considered almost identical sample periods, it is not clear whether the observed winner-loser effect is not a result of data snooping and, consequently, is not specific to the time period under analysis.

Second, although a substantial body of literature exists on the contrarian effect and on the momentum effect separately, to date there are virtually no studies of the combined contrarian and momentum effects for any of the 13 stock markets considered, except for US (NYSE-AMEX). In the case of the EU12 stock markets, as pointed out above, there are no studies on either the contrarian or the momentum effect in general. In the case of UK (LSE), there is one study by Galariotis *et al.* (2007)

that covers both the contrarian and the momentum effect, which was briefly mentioned in the 'Europe' part of this section. Importantly, the authors stated themselves that, to their knowledge, there are no other papers examining both the effects simultaneously for the UK stock market. In the case of the US stock markets, about seven studies have been published on the combined effect of contrarian and momentum strategies (see *e.g.*, Alwathainani, 2012; Asgharian and Hansson, 2009; Boynton and Oppenheimer, 2006; Figelman, 2007; Conrad and Kaul, 1998; JT, 2002; Yao, 2012), but none examined The NASDAQ Stock Market separately. However, of all the aforementioned papers, only two have focused on aspects that are immediately relevant to this thesis.

Third, it is not uncommon for international-stock-market-based publications to adopt a biased methodology, which further limits the effective scope and validity of the already scarce international evidence on the profitability of the two investment methods. For instance, Baytas and Cakici (1999) as well as Clare and Thomas (1995) adopted Conrad and Kaul's (1993) and Zarowin's (1990) methodologies, respectively, which were proved to be biased by Albert and Henderson (1995), and Loughran and Ritter (1996), respectively.

In consequence, it is clear that more research is needed to further investigate the economic viability and statistical significance of both contrarian and momentum investing approaches, especially in emerging stock markets, as the existing literature on this subject is incomplete and, frequently, inconsistent, thereby leaving many crucial issues unresolved.

3. METHODOLOGY

3.1. INTRODUCTION

The main purpose of this chapter is to provide an explanation of the methodology employed by this study of the contrarian and momentum effects in the stock markets of the US, UK and EU12 countries. There are three sections to follow excluding the 'Summary' section at the end of the chapter: 'Research questions'; 'Data sources'; and 'Data processing'.

To begin with, the 'Research questions' section formalises and elaborates on the two principal objectives of this thesis. The first question is concerned with the existence of the contrarian and momentum effects in the stock markets studied, whereas the second question looks at the characteristics of extreme past-performance[24] and arbitrage portfolios.

Subsequently, the 'Data sources' section contains comprehensive information on the data collected for the purposes of this research, which were obtained from two independent sources: the Thomson Reuters Datastream Database and the CRSP/Compustat Merged Database. The first two subsections of the 'Data sources' section, *i.e.* 'Creating lists of company shares' and 'Time period under analysis', discuss the stock selection criteria and the overall timeframe adopted for this study, respectively, which information is equally applicable to both data sources. Then, the 'Thomson Reuters Datastream Database' subsection that follows deals with the data obtained from Thomson Reuters Datastream Advance 4.0, whilst the 'CRSP/Compustat Merged Database' subsection deals with the data generated through CRSPSift Enterprise 4.2.

Finally, the 'Data processing' section discusses the empirical procedures that are applied on the data with the aim of results generation and analysis. The first

[24] 'Extreme past-performance' (or 'extreme past-return') portfolios is a collective term for the highest past-return portfolio (also referred to as the 'winner' portfolio) and the lowest past-return portfolio (also referred to as the 'loser' portfolio). In addition, 'past-return-based portfolios' is a collective term, used extensively in the 'Empirical results and analysis' chapter, for extreme past-performance and arbitrage portfolios.

subsection, titled: 'Portfolio return calculation procedures', focuses on the calculation methods pertaining to the most important variable in this research, *i.e.* the total stock return. The empirical procedures relating to the other variables of interest are then covered in the 'Portfolio investment characteristics calculation procedures' subsection. Last of all, the 'Statistical and economic significance tests' subsection provides information on all of the tests of statistical and economic significance employed in the study, which are either parametric or non-parametric.

With this chapter design the reader will have the opportunity to first understand the questions that this study aims to address, then to familiarise themselves with the pertinent data and, lastly, to appreciate the breadth of methods that were applied to answer each research question.

Concurrently with fulfilling the main objective stated in the beginning, this chapter also delivers information and clarification with regard to three significant contributions of the present research to the development of the discipline.

The first contribution relates to the detection and assistance in the rectification of a number of errors and inconsistencies within the two data sources used (*i.e.*, the Thomson Reuters Datastream database and the Center for Research in Security Prices database). This is discussed in detail in 'The reliability of the Datastream data' and 'The reliability of the CRSP/Compustat data' subsubsections.

The second contribution is a result of compliance with the most important guidelines provided by, among others, the American Psychology Association, which institution sets editorial standards for more than 1000 journals in the social and behavioural sciences (Fidler, Geoff, Mark and Neil, 2004). The above-mentioned compliance relates to the, largely disregarded in finance and economics, practice of conducting, reporting and interpreting effect size tests for the variables studied. This is discussed in the 'Statistical and economic significance tests' subsection, particularly in the 'Parametric tests' part.

The third contribution, outlined in the 'Portfolio investment characteristics calculation procedures' subsection, relates to the application of two practical, and arguably more appropriate as compared to conventional, measures of risk not previously considered in the context of contrarian and momentum investing. These are downside standard deviation and downside beta.

3.2. RESEARCH QUESTIONS

The two main research questions that this thesis aims to answer are formulated in terms of null hypotheses ($H_{0(1,2)}$) and alternative hypotheses ($H_{1(1,2)}$) in the two following subsections. All hypotheses relate to the time period under analysis, which spans from 01/01/2000 to 30/12/2011 (for more information see the 'Time period under analysis' subsection). In addition to specifying the hypotheses, each subsection provides brief information on the tests that are conducted, so as to either accept or reject the null hypothesis.

3.2.1. IS EITHER THE CONTRARIAN OR THE MOMENTUM EFFECT PRESENT IN THE US, UK OR EU12 STOCK MARKETS?

The first research question is designed to investigate whether the contrarian or the momentum effect is present in the US, UK or EU12 stock markets. It is essential to emphasise at this point that studying the pervasiveness of the contrarian and momentum effects is, in essence, equivalent to studying the feasibility of the contrarian and momentum investing approaches, which are investment strategies aimed to exploit the aforementioned effects.

Tests of the contrarian effect as well as tests of the momentum effect are invariably based on formation- (F) and test- (T) period stock return calculations, whereby stocks are first classified into portfolios as determined by the formation-period performance and then, in the test period, forward performance is evaluated. The number of months in both the formation period and the test period is usually given in the literature on the subject to range from 24 months to 60 months for the former effect and from one month to 12 months for the latter effect. Due to the fact that multiple combinations of portfolio formation and test periods (henceforth referred to as timeframes) are possible, each effect needs to be further annotated to allow differentiation and this is achieved by using the following expression: F-month/T-month, where F is the number of formation-period months and T is the number of test-period months. Importantly, the present study is limited to the six-month/six-month timeframe exclusively.

Another issue to note is that contrarian strategies and momentum strategies, as originally proposed by DBT (1985) and JT (1993) respectively, involved the lowest past-return portfolio, the highest past-return portfolio as well as the arbitrage portfolio to simultaneously demonstrate statistically significant returns. This study considers the possibility that only one of the three above-mentioned portfolio types may be associated with a statistical (and economic) significance of returns. As presented in the 'Empirical results and analysis' chapter, not only is it possible to observe the contrarian effect or the momentum effect for the highest past-return portfolio, the lowest past-return portfolio or the arbitrage portfolio alone, but in fact it is a relatively common occurrence. Therefore, in order to preserve accuracy, the term ‘strategy’ in its singular form is used herein to refer to **individual** portfolios that belong to the subset of extreme past-return and arbitrage portfolios, rather than, as in most previous studies, to **collectively** refer to an entire group of extreme past-return and arbitrage portfolios that belong to the same F-month/T-month timeframe.

The first null hypothesis ($H_{0(1)}$) and the first alternative hypothesis ($H_{1(1)}$), for each stock market covered by this research, are formulated as follows:

> $H_{0(1)}$: The six-month/six-month contrarian strategy and the six-month/six-month momentum strategy generate (1) returns that are not both statistically significant (with $p > 0.05$) and economically significant (with Δ or $\delta < 0.5$)[25]; or (2) CAPM alphas that are not both positive and statistically significant (with $p > 0.05$);
>
> $H_{1(1)}$: The six-month/six-month contrarian strategy or the six-month/six-month momentum strategy generates (1) returns that are both statistically significant (with $p \leq 0.05$) and economically significant (with Δ or $\delta \geq 0.5$) as well as (2) CAPM alphas that are both positive and statistically significant (with $p \leq 0.05$);

Alternatively, $H_{0(1)}$and $H_{1(1)}$ may be expressed in mathematical notation (see Equation 1).

[25] The Greek upper case letter delta (*i.e.*, ‘Δ’) represents the result of the Glass’s Effect Size Test for economic (or practical) significance. The Greek lower case letter delta (*i.e.*, ‘δ’) represents the result of the Cliff’s Effect Size Test for economic (or practical) significance. The former test is applicable to Gaussian distributions, whereas the latter test is applicable to non-Gaussian distributions. For more information see the ‘Statistical and economic significance tests’ subsection.

EQUATION 1. HYPOTHESES $H_{0(1)}$ AND $H_{1(1)}$ PRESENTED IN MATHEMATICAL NOTATION.

$H_{0(1)}$: $\forall i \in I \; \forall (t-1,t) \in T^2 \; \left(P\{E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] \neq 0\} > 0.05 \vee \Delta \vee \delta\{E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] \neq 0\} < 0.5 \vee \alpha_{i,t} \leq 0 \; \vee \; P\{\alpha_{i,t}\} > 0.05\right)$[26]

$H_{1(1)}$: $\exists i \in I \; \exists (t-1,t) \in T^2 \; \left(P\{E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] \neq 0\} \leq 0.05 \wedge \Delta \vee \delta\{E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] \neq 0\} \geq 0.5 \wedge \alpha_{i,t} > 0 \wedge P\{\alpha_{i,t}\} \leq 0.05\right)$

with I = {P1L, P1S, P10L, P10S, P1L/P10S, P1S/P10L}; T = {6 months};

where I is the set of all past-return-based portfolios, and the corresponding long-short configurations, studied (see 'Portfolio return calculation procedures' for more information); T is the set of all formation-period and test-period horizons studied; $\bar{R}_{i,t-1}$ and $\bar{R}_{i,t}$ are the arithmetic mean returns of past-return-based portfolio i in the formation and test period, respectively; $\alpha_{i,t}$ is the Sharpe-Lintner Capital Asset Pricing Model (or CAPM) alpha of past-return-based portfolio i in the test period;

To test the first (1) part of the aforementioned hypothesis, monthly buy-and-hold compounded returns to the highest past-return (or 'winner'), the lowest past-return (or 'loser') and the arbitrage portfolios are calculated, and statistical tests of significance are conducted. As far as the former aspect is concerned, portfolios are constructed in a manner similar to DBT (1985), with the arithmetic mean compounded returns being calculated for extreme past-performance, arbitrage and market portfolios. In terms of the latter aspect, there are two types of tests of statistical significance implemented: (1) parametric tests; and (2) non-parametric tests. Parametric statistical tests, at the Hypothesis One level, will take the form of the Student's One-Sample t-Tests assuming a mean return of zero and apply to the US, UK and (collective) EU12 populations. Non-parametric statistical tests are, at this point, limited to a Student's One-Sample t-Test equivalent for non-Gaussian distributions, *i.e.* the Wilcoxon Signed-Ranks Test, and apply to the individual EU12 populations. In

[26] *N.B.* The expression $\{E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] \neq 0\}$ is logically equivalent to $\{E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] > 0 \vee E[(\bar{R}_{i,t-1}-0)(\bar{R}_{i,t}-0)] < 0\}$.

the case of both parametric and non-parametric tests, the arbitrary threshold of p = 0.05 is used as the criterion for the identification of statistical significance. In addition to statistical tests, effect size computations using Glass's (1981) or Cliff's (1993) definitions will verify whether the results are of any economic (or practical), as opposed to statistical, significance. The arbitrary threshold value of Δ or δ = 0.5 is used as the criterion for the identification of economic significance. It should be noted, however, that although the adoption of arbitrary threshold values for both statistical and economic significance tests is the *condicio sine qua non* for formal hypothesis acceptance or rejection, whenever it is possible the exact p-values as well as Δ- or δ-values will be reported.

To test the second (2) part of Hypothesis One, CAPM ordinary least squares (or OLS) regressions are estimated using standard OLS covariance matrix estimators as well as heteroscedasticity- and autocorrelation-consistent covariance matrix estimators (often called HAC or Newey-West estimators), as described by Newey and West (1987). HAC estimators are calculated at all lags up to three, *i.e.* at lag zero, one, two and three, which total value has been determined by considering the periodicity and number of observations. The reported p-values (*i.e.*, p_{NW}) relate to the lag that is associated with the largest p-value. At lag zero, Newey-West estimators are the same as heteroscedasticity-consistent covariance matrix estimators (also known as robust or White's estimators). The relevant parameter estimate here is, of course, CAPM alpha (or, more precisely, CAPM alpha 'hat').

It should be pointed out, however, that HAC is only used in this thesis as a supporting procedure and, therefore, it is referred to exclusively on the occasions when the standard OLS estimates are accompanied by p-values (*i.e.*, p_{OLS}) that indicate statistical significance, for the purpose of assessing the potential impact of heteroscedasticity and/or autocorrelation. This practice is recommended by, *inter alios*, Wallace and Silver (1988) as well as Gujarati and Porter (2009).

The test of statistical significance for CAPM alpha is the Student's Regression Coefficient t-Test, with the arbitrary threshold of p = 0.05 being used as the criterion for the identification of significance. Considering that there are no standardised effect sizes for regression intercepts *per se*, economic significance is not reported for this statistic. Importantly, although standardised regression coefficients are often used in the academic literature as a measure of effect size, the intercept of a regression involving standardised regressand and regressor(-s) will always be zero and, therefore, this method cannot be used as a measure of economic significance for CAPM alphas. However, it should be noted that *R*-squared, reported for all portfolios *vis-à-vis* Hypothesis Two, is a proportion-of-variance-explained measure of economic significance frequently employed by researchers in the regression analysis context.

3.2.2. ARE CONTRARIAN OR MOMENTUM STRATEGIES ASSOCIATED WITH UNFAVOURABLE INVESTMENT CHARACTERISTICS?

This research question is concerned with the investment characteristics of the highest past-return, the lowest past-return and the market portfolios. Specifically, it explores whether winners or losers differ in terms of time-constant or time-varying risk, or market microstructure from the market as a whole, as determined by quantitative analysis based on tests of statistical and economic significance as well as qualitative analysis. It is important to stress at this point that the use of the market portfolio as the benchmark in this study is grounded in both finance theory and finance practice, most prominently by virtue of the Modern Portfolio Theory (see *e.g.*, Markowitz, 1952; 1959).

The second null hypothesis ($H_{0(2)}$) and the second alternative hypothesis ($H_{1(2)}$), for each stock market covered by this research, are defined below.

> $H_{0(2)}$: Relative to the market portfolio, either the highest past-return portfolio or the lowest past-return portfolio has unfavourable time-constant or time-varying risk profile, or market microstructure characteristics, as indicated by quantitative analysis based on tests of statistical significance (with $p < 0.05$) and tests of economic significance (with Δ or $\delta > 0.5$) as well as qualitative analysis;

> $H_{1(2)}$: Time-constant and time-varying risk profile, and market microstructure characteristics of the highest past-return portfolio and the lowest past-return portfolio are not unfavourable relative to the market portfolio, as indicated by quantitative analysis based on tests of statistical significance (with $p > 0.05$) and tests of economic significance (with Δ or $\delta < 0.5$) as well as qualitative analysis;

The quantitative part of the above hypotheses is evaluated through a parametric (for the US, UK and collective EU12 populations) or non-parametric (for the individual EU12 populations) test of statistical and economic significance, applied on a range of variables that proxy for risk and market microstructure. In the first instance, the tests take the form of either the Student's Two-Sample (Unequal Variance) *t*-Test or the Student's Paired *t*-Test for statistical significance, depending on whether the independent variables are assumed to be constant in time or time-varying, and the Glass's Effect Size Test for economic significance. Analogously, in the second instance, the tests are either the Kolmogorov-Smirnov Two-Sample Test or the Wilcoxon Matched-Pairs Signed-Ranks Test for statistical significance and the Cliff's Effect Size Test for economic significance. As was the case with the first hypothesis, the arbitrary threshold values of $p = 0.05$ and Δ or $\delta = 0.5$ are used as criteria for the identification of statistical significance and economic significance, respectively. However, whenever it is possible the exact p values as well as Δ or δ values will be reported.

The qualitative part of the hypotheses principally relates to the need for good judgement involved in weighting the entirety of the quantitatively-assessed evidence, mentioned earlier, as well as the non-quantitatively-assessed evidence.

As a final point it should be added that although testing the arbitrage portfolios in the context of Hypothesis Two would be, in the case of most proxy variables, inappropriate due to the fact that those portfolios essentially represent a combination of two different long-short investment positions in two different portfolios, the return volatility measures can still be, and indeed are, successfully applied. While insofar as standard deviations are concerned the results will be exactly the same for both types of arbitrage portfolios, the CAPM-related statistics (including CAPM alphas and the *p*-values thereof) are likely to be slightly different in terms of absolute value, on account of the fact that the 'risk-free' rates, and not returns alone, are involved in their derivation.

3.3. DATA SOURCES

This section of the 'Methodology' chapter provides detailed information on the database of company stocks, time period studied, data characteristics and data extraction methods used in this research. All core data qualifies as secondary monthly quantitative financial information and is either obtained from the Thomson Reuters Datastream Database for the European populations or the CRSP/Compustat Merged Database for the US populations.

The organisation of this section is as follows. To begin with, it is discussed how the lists of company shares are created and how the timeframe for this study is determined, which topics are equally applicable to the two above-mentioned data sources. Subsequently, data characteristics as well as data extraction methods for the Thomson Reuters Datastream Database and the CRSP/Compustat Merged Database are considered separately.

3.3.1. CREATING LISTS OF COMPANY SHARES

The entire database of the European company stocks used for the purposes of this research is constructed from the information obtained from Datastream Advance 4.0. That part of the database covers the following populations: Bulgaria (Sofia Stock Exchange), Cyprus (Cyprus Stock Exchange), Czech Republic (Prague Stock Exchange), Hungary (Budapest Stock Exchange), Lithuania (Vilnius Stock Exchange), Poland (Warsaw Stock Exchange), Romania (Bucharest Stock Exchange), Slovakia (Bratislava Stock Exchange), Slovenia (Ljubljana Stock Exchange) and the UK (London Stock Exchange). All of the above populations, excluding UK (LSE) stocks, are used to form a collective EU12 population.

Differently, all information on the US stocks is derived from CRSPSift Enterprise 4.2, which population is divided into two groups: US (NYSE-AMEX) and US (NASDAQ). The rationale behind this operation is to account for the different characteristics of the US (NYSE-AMEX) and US (NASDAQ) stock populations as well as to make the US (NYSE-AMEX), US (NASDAQ), UK (LSE) and collective EU12 populations of stocks more of an equal size.

This study employs the Dow Jones Indexes Country Classification System (S&P Dow Jones Indexes, 2011) as the basis for determining stock market maturity. Consequently, the EU12 stock populations constitute herein the sample of less-developed stock markets, whereas the US (NYSE-AMEX), US (NASDAQ) and UK (LSE) stock populations constitute herein the sample of developed stock markets[27].

[27] It should be noted that the Dow Jones Indexes Country Classification System (S&P Dow Jones Indexes, 2011), in addition to the concepts of 'developed markets' and 'emerging markets', also introduced the concept of 'frontier markets', which are markets considered by the source to be even less accessible to foreign investors and less developed than 'emerging markets'. However, this study does not discriminate between 'emerging markets' and 'frontier markets', which is for two main reasons. First, as explained in the introduction to this thesis, upon the accession to the EU the EU12 countries were required to adjust their level of openness to foreign investors to the EU standard. Therefore, it seems questionable to differentiate the EU markets on those grounds. Second, the basic distinction between developed markets and less-developed markets is sufficient and, more importantly, preferential in terms of comparability with previous studies. In consequence, as mentioned in footnote 3 on page 26, the terms 'less-developed', 'underdeveloped', 'developing' and 'emerging' are used interchangeably in this thesis to describe 'less-than-developed' stock markets, economies or countries.

Furthermore, in the case of each population, not the entire universe of stocks is studied, but only ordinary shares of both domestic and foreign companies for which the total return index (*i.e.*, *RI*, discussed later) is available; no global depository receipts (GDRs), American depository receipts (ADRs), CREST depository interests (CDIs), depository interests (DIs), investment trusts (ITs), exchange traded funds (ETFs), equity investment instruments, mutual funds, subscription shares, preference shares or warrants are included. The reasons for excluding each of the above-listed types of equity are presented in Table 1 on the next page.

TABLE 1. THE REASONS FOR THE EXCLUSION OF CERTAIN EQUITY TYPES.

GDRs, ADRs, CDIs, DIs	GDRs, ADRs, CDIs and DIs are financial instruments which represent ownership in foreign companies and trade much like domestic shares. Nonetheless, any changes in the value of those instruments necessarily go in line with changes in the value of foreign underlying securities (otherwise, simple arbitrage would take place). Therefore, including the aforementioned types of equity would render the contrarian and momentum effects being measured mainly in home markets of the companies and not the host markets (*i.e.*, the markets were the instruments were issued; the markets under analysis).
ITs, ETFs, mutual funds, equity investment instruments	ITs, ETFs, mutual funds and equity investment instruments are another type of financial instruments that trade like common shares. One of their shared characteristics is that any changes in the value of those instruments, to a large extent, reflect changes in the value of the underlying assets, which are usually shares of other companies. Including the above-listed instruments may create a potentially undesirable situation, whereby the contrarian and momentum effects are amplified, masked or attenuated in the stock market under consideration as a direct result of the high correlation with the underlying securities which may or may not exhibit the studied effects.
Preference shares	Preference shares are excluded from the analysis on the grounds of not being a part of the CRSP/Compustat universe. Although CRSP collects and stores information on those shares internally, there is no database available to subscribers. Therefore, to ensure Thomson Reuters Datastream and CRSP/Compustat data comparability, all preferred shares are excluded from the Thomson Reuters Datastream populations of stocks.
Subscription shares, partly-paid shares, warrants	Subscription shares, partly-paid shares and warrants are all quite distinct financial instruments which, however, share one feature that is consequential to this research. Namely, in all cases there is effectively an expiration date that may lead to an artificially inflated turnover of shares in some portfolios.

Having examined information in Table 1, one might wonder why foreign companies are included in the database, whilst GDRs, ADRs, CDIs and DIs are excluded. The rationale for this is simple.

The information investors rely on when valuing shares of a company on any given stock exchange is the same regardless of whether the company was incorporated in the stock market domestic to the investors or foreign to the investors. However, when a company is listed (*i.e.*, issues shares) on an stock exchange outside its home market, then the changes in the value of shares of that company are not directly linked with the changes in the value of the company's shares in its home market as it is the case with GDRs, ADRs, CDIs and DIs.

In other words, the valuation of an ordinary share of a foreign company is determined by the supply and demand of those shares in the country where they were issued - it does not matter that they were issued outside the home market of the company. In the case of GDRs, ADRs, CDIs and DIs, this valuation is established by the supply and demand in the country where the company is listed (that is, in its home market) and, thus, any price changes of those financial instruments reflect the changes in share valuation in the home country and not the host country (*i.e.*, the country were the financial instruments are listed; the country under analysis). This result would be ensured by arbitrage in case of disequilibrium.

Omitting GDRs, ADRs, CDIs, DIs and equity investment instruments also serves the purpose of creating a relatively homogeneous database of exclusively ordinary shares, which potentially makes any inferences from test results more reliable as the contrarian and momentum effects might affect different types of equity to a different extent, *e.g.* due to the clientele effect or different risk properties. In addition, the US, UK and individual EU12 stock populations are now, arguably, more comparable as the aforementioned financial instruments mainly appear in the first two cases.

However, it should be mentioned that although investment trusts as a group are excluded from the database constructed for the purposes of this research, real estate investment trusts (REITs) are included. The reason for this is that, unlike most investment trusts, REITs do not usually invest in other companies that might be listed on the same stock exchange as the shares of the investment trust which, as discussed in Table 1, would potentially create problems with the amplification or attenuation of the contrarian and momentum effects in the stock market under consideration. Instead, REITs invest in and own properties and/or property mortgages, depending on whether a REIT is an equity REIT, a mortgage REIT or a hybrid REIT, which renders them no different than other firms as far as investigating the contrarian and momentum effects is concerned.

The number of active, suspended and delisted qualifying companies for the entire time period studied, *i.e.* from 01/01/2000 to 30/12/2011, can be seen on a logarithmic scale in Figure 1 and, more accurately, in Table 2 and Table 3.

FIGURE 1. NO. OF ACTIVE, SUSPENDED AND DELISTED COMPANIES IN THE US, UK AND EU12 STOCK MARKETS FROM 01/01/2000 TO 30/12/2011.

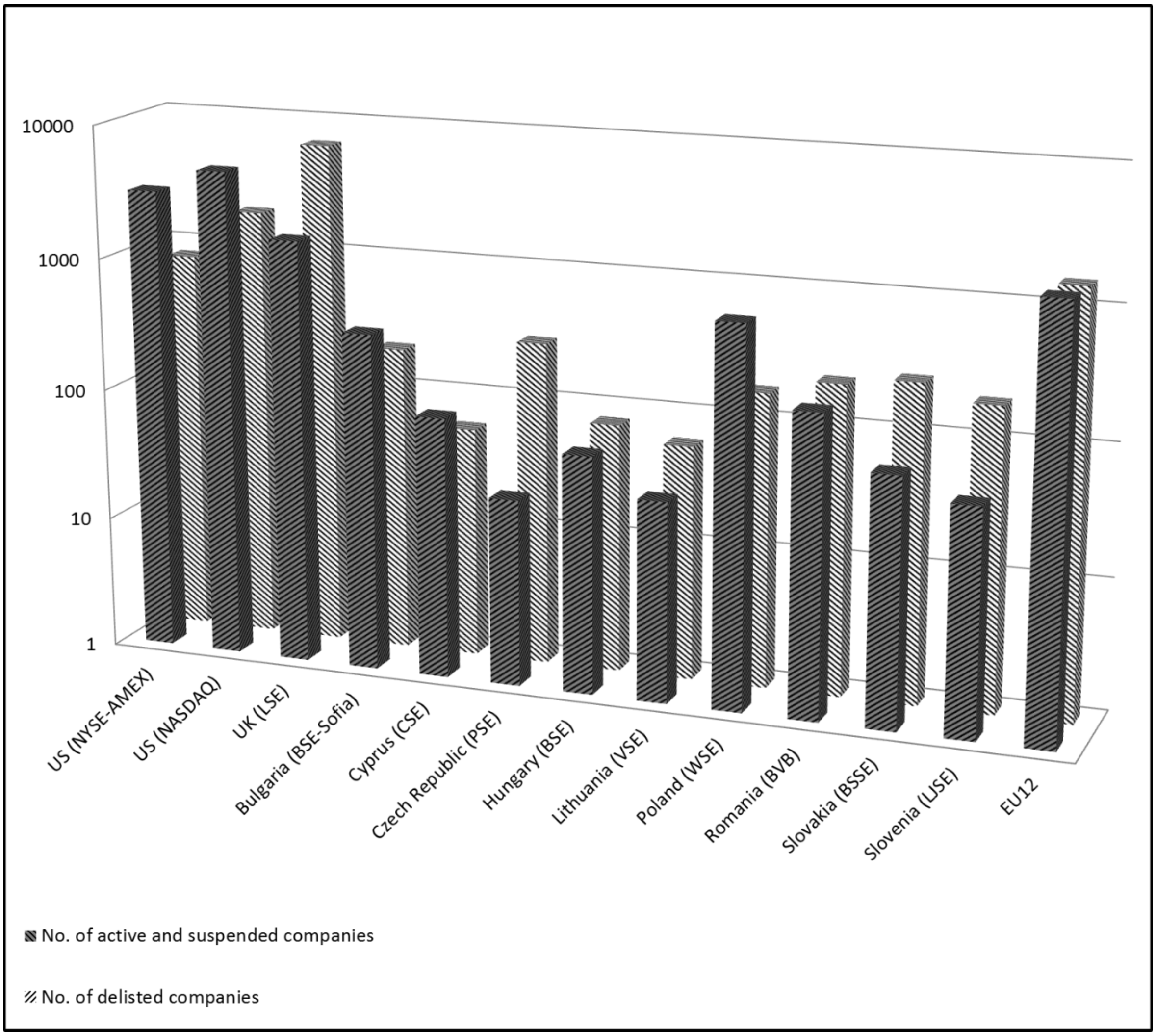

TABLE 2. NO. OF ACTIVE, SUSPENDED AND DELISTED COMPANIES IN THE US, UK AND EU12 STOCK MARKETS FROM 01/01/2000 TO 30/12/2011. PART 1.

	US (NYSE-AMEX)	US (NASDAQ)	UK (LSE)	Bulgaria (BSE-Sofia)	Cyprus (CSE)	Czech Republic (PSE)	Hungary (BSE)
Active and suspended companies	3182	4838	1617	360	95	26	63
Delisted companies	794	1878	6544	206	56	283	77
Total	**3976**	**6716**	**8161**	**566**	**151**	**309**	**140**

TABLE 3. NO. OF ACTIVE, SUSPENDED AND DELISTED COMPANIES IN THE US, UK AND EU12 STOCK MARKETS FROM 01/01/2000 TO 30/12/2011. PART 2.

	Lithuania (VSE)	Poland (WSE)	Romania (BVB)	Slovakia (BSSE)	Slovenia (LJSE)	EU12
Active and suspended companies	33	739	189	76	52	1678
Delisted companies	60	169	221	254	194	1575
Total	**93**	**908**	**410**	**330**	**246**	**3253**

From Figure 1, Table 2 and Table 3, one can easily verify that, during the entire time period studied, the number of active and suspended companies in the European populations ranges from a low of 33 for Lithuania to a high of 1678 for the EU12, which number is roughly equal to the size of the UK population of 1617. The corresponding US populations are two to three times larger than that of the EU12 or UK, which statistics underscore the US stock market's greater size and maturity. As for the delisted companies at the end of 30/12/2011, the numbers are as low as 56 for Cyprus and as high as 6556 for the UK.

It is important to emphasise, nevertheless, that the above-reported figures refer to the entire time period studied, that is active and suspended companies are companies that were either still in operation or classified as suspended as at 30/12/2011, whereas delisted companies are companies that were delisted from a given exchange at any point from 01/01/2000 to 30/12/2011. The actual month to month variation in the number of stocks for a given stock exchange depends on the overall availability of the total return index (or RI) for that month, which is discussed in the 'Identifying variables of interest' subsections.

3.3.2. TIME PERIOD UNDER ANALYSIS

As mentioned in the preceding section, the time period under analysis spans from 01/01/2000 to 30/12/2011, which is equal to 144 months or 12 years. The reason for specifying the research timeframe as stated above is related to the lower and upper bound limiting factors.

The limiting factor for the lower bound is the first trading session date of the individual stock exchanges of the EU12 region, which for many countries that comprise the EU12 was in the mid- to late-1990s. Therefore, it seems sensible to start the analysis a few years later, at which point most of the stock exchanges should have reached reasonable operational efficiency as well as number of listings. This time lag is the more justified considering the troublesome history of the 12 stock markets, which issue is briefly discussed in the 'Empirical results and analysis' chapter. In addition, as it will become clearer later, marking the start of the timeframe earlier would achieve little as seen from the power analysis perspective. Specifically, for the momentum strategies, whose non-overlapping data requirements typically range from two months to two years, the number of samples for each population should be sufficient regardless of whether three to four additional years are considered. Similarly, for the contrarian strategies, whose non-overlapping data requirements typically range from six to ten years, adding three to four years of data would increase the number of samples by only two.

In terms of the upper bound limiting factor, this was determined by both the practical consideration of the need to establish a cut-off point as well as the end of the York Management School's subscription to the CRSP/Compustat Merged Database, which is essential to produce a comparative study with the Thomson Reuters Datastream Database data.

3.3.3. THOMSON REUTERS DATASTREAM DATABASE

Thomson Reuters claims to be the leading source of intelligent information for the world's businesses and professionals, serving customers primarily in the sectors of financial services, legal, tax, accounting, intellectual property and science (Thomson Reuters, 2011). Datastream Advance is one of the company's products. It is a client-based software that runs as an independent interface with the Thomson Reuters Datastream Database in London and offers, among others, access to historical financial content for 175 countries in 60 global markets (*ibid*.).

The next subsection provides information on data characteristics as well as data extraction methods for the 11 populations of stocks obtained from the Thomson Reuters Datastream Database.

3.3.3.1. IDENTIFYING VARIABLES OF INTEREST

The database created for the purposes of this research project contains monthly observations on six variables of interest: return (R), the market value of equity (ME), volume (VO), price (P), the ask price (PA) and the bid price (PB), where the ask price (PA) and the bid price (PB) are used to compute the bid/ask spread (BA). Each of those variables will now be discussed in turn.

The stock (total) return (R) can be defined as the sum of two components: (1) net income received from the security in the form of dividends; and (2) net capital gain/loss resulting from a change in price of the security. It is usually expressed in relative terms, that is as a percentage change in value over a specified period of time, and, in the stock trading context, it is also known as the rate of return (ROR), return on investment (ROI), the rate of profit or simply return.

In Datastream Advance, the total return of a stock, ignoring tax and reinvestment charges, can be computed in a number of ways, as shown in Equation 2.

EQUATION 2. DATASTREAM ADVANCE TOTAL STOCK RETURN CALCULATIONS.

$$R_{i,t} = \left[\frac{\left(UP_{i,t+1} + UDD_{i,t+1}\right) * AF_{i,t+1}}{UP_{i,t} * AF_{i,t}} - 1\right] * 100\% = \left(\frac{P_{i,t+1} + DD_{i,t+1}}{P_{i,t}} - 1\right) * 100\%$$
$$= \left(\frac{RI_{i,t+1}}{RI_{i,t}} - 1\right) * 100\%$$

where $R_{i,t}$ is the total return of stock i in month t expressed as a percentage; UP is the unadjusted price, *i.e.* the closing price as it was historically determined on the stock exchange; $UP_{i,t}$ is the unadjusted price for stock i in month t; $UP_{i,t+1}$ is the unadjusted price for stock i in month $t+1$; UDD is the individual unadjusted cash income dividend payment; $UDD_{i,t+1}$ is the unadjusted dividend for stock i in month $t+1$; AF is the adjustment factor, *i.e.* the factor by which unadjusted variables need to be multiplied by to take into account capital operations of companies; $AF_{i,t}$ is the adjustment factor for stock i in month t; $AF_{i,t+1}$ is the adjustment factor for stock i in month $t+1$; P is the adjusted price, *i.e.* the official closing price adjusted for capital operations of companies and the default data type in Datastream Advance (if no data type is specified, Datastream Advance will return P); $P_{i,t}$ is the adjusted price for stock i in month t; $P_{i,t+1}$ is the adjusted price for stock i in month $t+1$; DD is the individual adjusted cash income dividend payment; $DD_{i,t+1}$ is the adjusted dividend for stock i in month $t+1$; RI is the return index, *i.e.* the theoretical growth (inclusive of dividends) in the value of a notional stock holding, assuming that dividends are reinvested to purchase additional units of equity at the closing price of the ex-dividend date; $RI_{i,t}$ is the return index for stock i in month t; $RI_{i,t+1}$ is the return index for stock i in month $t+1$;

If no dividends are paid during a period of time, then Equation 2 is numerically equal to Equation 3 for that period.

EQUATION 3. DATASTREAM ADVANCE TOTAL STOCK RETURN CALCULATIONS WHEN NO DIVIDENDS ARE PAID.

$$R_{i,t} = \left(\frac{UP_{i,t+1} * AF_{i,t+1}}{UP_{i,t} * AF_{i,t}} - 1\right) * 100\% = \left(\frac{P_{i,t+1}}{P_{i,t}} - 1\right) * 100\%$$

where the variables are defined as per Equation 2;

In this research project, stock return is calculated using the return index variables in months $t + 1$ and t, as shown in Equation 2, where $t + 1$ and t are month end and beginning dates, respectively. RI itself is constructed using one of two methods: (1) annualised dividend yield (see Equation 4); (2) ex-dividend date (see Equation 5 and Equation 6). In most cases, the latter method is used, in which more realistically the discrete quantity of dividend paid is added to the price on the ex-date of the payment. However, when dividend payment data contains a mixture of dividends marked as net and gross, the former method continues to be used.

EQUATION 4. DATASTREAM ADVANCE ANNUALISED DIVIDEND YIELD METHOD FOR CALCULATING *RI*.

$$RI_{i,t} = RI_{i,t-1} * \frac{PI_{i,t}}{PI_{i,t-1}} * \left(1 + \frac{DY_{i,t}}{100} * \frac{1}{N}\right)$$

where RI is the return index; $RI_{i,t}$ is the return index for stock i in month t; $RI_{i,t-1}$ is the return index for stock i in month $t - 1$; PI is the price index, *i.e.* the theoretical growth (exclusive of dividends) in the value of a notional stock holding, also known as capital appreciation index; $PI_{i,t}$ is the price index for stock i in month t; $PI_{i,t-1}$ is the price index for stock i in month $t - 1$; DY is the dividend yield percentage, *i.e.* the total dividend amount expressed as a percentage of the market value of a company; $DY_{i,t}$ is the dividend yield percentage for stock i in month t; N is the number of working days in the year (taken to be 260);

EQUATION 5. DATASTREAM ADVANCE EX-DIVIDEND DATE METHOD A FOR CALCULATING RI (APPLIES WHEN $t \neq$ EX-DATE OF THE DIVIDEND PAYMENT D_t).

$$RI_{i,t} = RI_{i,t-1} * \frac{P_{i,t}}{P_{i,t-1}}$$

where $P_{i,t-1}$ is the adjusted price for stock i at $t-1$; and the rest of the variables are defined as per Equation 2 and Equation 4;

EQUATION 6. DATASTREAM ADVANCE EX-DIVIDEND DATE METHOD B FOR CALCULATING RI (APPLIES WHEN $t =$ EX-DATE OF THE DIVIDEND PAYMENT D_t).

$$RI_{i,t} = RI_{i,t-1} * \frac{P_{i,t} + DD_{i,t}}{P_{i,t-1}}$$

where the variables are defined as per Equation 2 and Equation 5;

The total return of a stock, R, may be considered to be the most important variable in this study as it is central to the calculations of extreme past-performance and arbitrage portfolios' return, on the basis of which the contrarian and momentum effects are essentially measured.

As far as the second variable of interest is concerned, *i.e.* the market value of equity (ME), it is also known as market capitalisation or simply size (as in 'company size') and can be defined as the share price multiplied by the number of ordinary shares in issue. The amount of ordinary shares in issue is updated whenever new tranches of stock are issued or after a capital change. If a company has more than one class of equity capital, ME is expressed according to the individual issue. It is interesting to note that Thomson Reuters refers to this data type as 'market value', which term is commonly used to refer to the total market value of a company and is equal to the market capitalisation **plus** the market value of debt. Nonetheless, the definition accompanying the discussed data type leaves no doubt that it is, in fact, the market value of equity that is being computed, as shown in Equation 7.

EQUATION 7. DATASTREAM ADVANCE MARKET-VALUE-OF-EQUITY CALCULATION.

$$ME_{i,t} = P_{i,t} * N_{i,t}$$

where $ME_{i,t}$ is the market value of equity for company i in month t expressed in millions of units of local currency; $P_{i,t}$ is the adjusted price for company i in month t; N is the number of ordinary shares in issue for company i in month t;

The market value of equity, similarly to volume (VO), price (P) and the bid/ask spread (BA), is used in this research to produce point estimates of those variables for extreme past-performance portfolios as well as the market portfolio, in order to allow statistical inferences to be drawn with respect to the investment characteristics of the aforementioned portfolios.

The remaining four variables: volume (VO), price (P), the ask price (PA) and the bid price (PB), are much less complex in nature as compared to R or even ME and do not involve any formulae for their derivation.

Volume (VO), also referred to as 'turnover by volume', is the single counted (sell side only) number of shares traded for a stock adjusted for capital events and always expressed in thousands. Price (P) represents the official closing price for a stock adjusted for all capital actions and, as mentioned in the key to Equation 2, it is the default data type in Datastream. P is expressed in primary units of currency, at the time, for the country to which it relates (except in the case of the UK, where price is given in pence).

Finally, the ask price (PA) and the bid price (PB) are the asking price (or the offer price) and the bid price of a stock quoted at close of market, respectively. Similarly to P, both PA and PB are expressed in primary units of currency, at the time, for the country to which they relate (except in the UK). As mentioned earlier, the ask price and bid price are used for the sole purpose of obtaining a point estimate of the bid/ask spread (BA) for each portfolio, which procedure is discussed in the 'Portfolio investment characteristics calculation procedures' subsection.

To summarise, the six variables of interest are: return (R), the market value of equity (ME), volume (VO), price (P), the ask price (PA) and the bid price (PB), where the ask price (PA) and the bid price (PB) are used to compute the bid/ask spread (BA). The first variable, R, is used for the purposes of evaluating portfolio performance, whereas ME, VO, P and BA are required to produce point estimates of portfolios' investment characteristics.

It is now important to consider the actual month to month variation in total stock returns per EU stock market and in the number of observations for each variable, including total stock returns, per EU stock market (see Table 4, Table 5 and Table 6). Insofar as the variable R is concerned, this examination is critical from a statistical point of view as the total number of shares in any month will directly affect the number of shares that are allocated to extreme past-performance portfolios in that month, which in turn shall fundamentally impact the statistical assumptions regarding the distribution of portfolio returns. In the case of the other variables, looking at the monthly variation of observations might be interesting insofar as the accuracy of statistics is concerned.

TABLE 4. CHARACTERISTICS OF MONTHLY TOTAL STOCK RETURNS FOR DATASTREAM ADVANCE DATA.

	R[28]						
	Minimum	**Maximum**	**Average**	**Median**	**Standard deviation**	**Skewness**	**Kurtosis**
UK (LSE)	-1.0000	3570.4246	0.0045	0.0000	3.65	938.12	912450.41
Bulgaria (BSE-Sofia)	-0.9996	1161.5000	0.0855	0.0000	5.84	179.73	35387.36
Cyprus (CSE)	-0.9756	93.8186	0.0029	0.0000	0.73	118.50	15141.57
Czech Republic (PSE)	-0.6364	1.5569	0.0056	0.0000	0.06	5.13	89.88
Hungary (BSE)	-1.0000	10.2093	0.0091	0.0000	0.22	20.02	713.20
Lithuania (VSE)	-0.8606	11.6667	0.0152	0.0000	0.22	25.80	1176.62
Poland (WSE)	-1.0000	107.5639	0.0056	-0.0038	0.50	181.46	38955.68
Romania (BVB)	-1.0000	98.2903	0.0414	-0.0007	0.94	69.83	6261.40
Slovakia (BSSE)	-1.0000	500.9914	0.0714	0.0000	4.18	100.23	10973.77
Slovenia (LJSE)	-0.9881	123.5413	0.0315	0.0000	1.27	75.55	6531.93
EU12	-1.0000	1161.5000	0.0322	0.0000	2.68	322.31	128758.79

[28] As the caption explains, the data in this table refers to monthly total stock returns and not monthly total stock **index** returns. This means that, for example, the minimum return for the UK (LSE) of -100% is the lowest monthly total stock return for **a stock** from UK (LSE) during the studied time period, which should be interpreted as the bankruptcy of the company that issued the stock. The characteristics of monthly total stock **index** returns are available in Appendix C.

TABLE 5. MONTH TO MONTH VARIATION IN THE NUMBER OF OBSERVATIONS FOR DATASTREAM ADVANCE DATA. PART 1.

	R			**ME**			**VO**		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
UK (LSE)	5353	7908	6992	5231	7802	6858	1329	2572	1957
Bulgaria (BSE-Sofia)	117	514	308	6	415	183	11	216	78
Cyprus (CSE)	56	142	123	57	151	135	48	124	100
Czech Republic (PSE)	155	303	294	276	292	283	14	130	41
Hungary (BSE)	69	116	90	75	130	94	37	60	45
Lithuania (VSE)	38	76	59	61	83	74	29	44	40
Poland (WSE)	191	860	390	190	895	391	175	671	299
Romania (BVB)	169	406	325	192	325	270	122	220	186
Slovakia (BSSE)	80	260	178	5	173	96	6	64	23
Slovenia (LJSE)	92	179	151	90	205	164	42	136	74
EU12	1198	2593	1988	1002	2767	1769	769	1324	930

TABLE 6. MONTH TO MONTH VARIATION IN THE NUMBER OF OBSERVATIONS FOR DATASTREAM ADVANCE DATA. PART 2.

	P			**PA**			**PB**		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
UK (LSE)	5509	8156	7187	0	2604	1997	0	2604	1998
Bulgaria (BSE-Sofia)	116	566	329	0	285	109	0	312	113
Cyprus (CSE)	57	151	135	0	115	51	0	108	42
Czech Republic (PSE)	293	309	300	0	0	0	0	0	0
Hungary (BSE)	75	140	99	0	58	32	0	55	31
Lithuania (VSE)	61	93	83	0	44	20	0	43	19
Poland (WSE)	192	908	397	0	428	221	0	430	223
Romania (BVB)	194	410	352	0	111	36	0	107	38
Slovakia (BSSE)	110	330	248	0	62	15	0	50	18
Slovenia (LJSE)	94	246	201	0	88	31	0	92	28
EU12	1242	3253	2224	0	1037	532	1	1028	530

Table 4 on page 143 provides Datastream Advance data on the characteristics of monthly total stock returns for the time period under analysis (*i.e.*, 01/01/2000 - 30/12/2011), which show significant deviations from normality. Most importantly, the skewness and the kurtosis of monthly returns for all EU stock markets examined strongly suggests that the distribution of R is heavily left-skewed (or negatively skewed) and extremely leptokurtic. This interpretation is clearly substantiated by the remaining statistics in Table 4. First, average returns are consistently higher than median returns, with the difference ranging from as little as 0.29% per month for Cyprus (CSE) to as much as 8.55% per month for Bulgaria (BSE-Sofia). Second, while the lowest monthly return on a stock is, as expected, not less than -100% in all cases considered, the highest monthly return on a stock varies enormously across the stock markets, *i.e.* from 155.69% for Czech Republic (PSE) to 357042.46% for UK (LSE). It is crucial to note at this point that all monthly returns above 1500%, of which there were 68 instances, have been verified by the Thomson Reuters Customer Support as correct.

Furthermore, it can be seen from Table 5 and Table 6 that the minimum monthly variation of R for the individual EU12 countries ranges from 38 to 191, which means that, potentially, for the shortest of momentum strategies there might be anywhere between four and 19 stocks in a decile portfolio, although on average one should expect between nine and 39 stocks in a decile portfolio. For ME, VO, P, PA and PB, the average monthly number of observations ranges from 74 to 391, 23 to 299, 83 to 397, 15 to 221 (excluding Czech Republic) and 18 to 223 (excluding Czech Republic), respectively. In the case Czech Republic, there are no observations for PA and PB, and, hence, no point estimates of BA are given for those countries.

The above results underscore the need for non-parametric tests of statistical (and economic) significance as, given the potentially very small sample sizes, it cannot be assumed that the sampling distribution of the mean for any of the six variables follows a Gaussian distribution under the Central Limit Theorem. This conclusion is supported by the normality-test-led empirical analysis of a random sample of the present research results as well as the extensive empirical literature suggesting that return distributions deviate from normality (see *e.g.*, Affleck-Graves and MacDonald, 1989; Fama, 1965; Officer, 1972; Richardson and Smith, 1993). If monthly stock returns do not follow a Gaussian distribution, then a sampling distribution of the mean monthly stock return based on a small sample cannot be guaranteed to follow that distribution under the Central Limit Theorem as well. The same problem is likely to apply to the distributions of the remaining five variables.

In the case of the EU12 as a group, however, the average monthly variation in the number of observations per decile portfolio of R, ME, VO, P, PA and PB is 199, 177, 93, 222, 53 and 53, respectively. For the UK, those figures are 699, 686, 196, 719, 200 and 200, respectively. Therefore, in the case of the EU12 as a group and the UK, the sample size is sufficiently large (with the number of observations being greater than 40 in all cases and greater than 100 in most cases) to safely assume that the sampling distribution of the mean for all the six variables follows a Gaussian distribution under the Central Limit Theorem.

Three side notes are also in order here.

First, in the case of all populations, there is an upward trend in the number of observations, which is to be expected as both the number of new listings as well as the coverage of stocks by Thomson Reuters Datastream increase over time substantially, especially for the individual EU12 countries.

Second, the implementation of non-parametric tests for samples of a small size and parametric tests for samples of a very large size also allows bypassing the rather complicated process of managing extreme values, in particular outliers. In the former case, the reason is that non-parametric tests are distribution independent and thus, in general, they are not affected by extreme values. In the latter case, the reason is that, for samples containing more than 100 observations[29], the sampling distribution of the mean will follow a Gaussian distribution, even in the presence of extreme outliers, skewness or multimodal population distributions (LeBlanc, 2004). This

[29] Even though the number of observations for PA and PB does not exceed 100, as explained later, the method used for the construction of the BA variable considerably increases this number in the case of most strategies. Moreover, with a sample size of over 40 observations, only data points as large as 100 times the median would cause concern as to whether the sampling distribution of the mean is still Gaussian (LeBlanc, 2004).

circumvention is very beneficial, especially considering that there are no universally applicable rules insofar as the process of managing extreme values is concerned. 'Outlier tests' can only help to identify unusual data points in the dataset, but they are incapable of identifying errors. For this reason, no data point should be removed from a dataset on statistical grounds alone. Furthermore, managing extreme values would be all the more complicated in the present case as the focus here is on extreme performance portfolios, which groups of stocks, from a statistical point of view, may be considered extreme values by definition.

Third, the reader might wonder why the BA variable is not constructed in a manner analogous to the R variable, that is why as in the case of transforming the return index, RI, provided natively by Datastream into the total stock return, R, the PA and PB variables are not used to form the BA variable straight away. The reason for this could also be deduced from Table 5 and Table 6. Namely, unlike the case of R, the construction of BA requires both PA and PB. With the number of observations for PA and PB varying largely independently over time, as it is evident from Table 5 and Table 6, this means that if there was either only PA or PB available in any month, then there would be no point estimate for BA. However, with the BA variable being formed at the stage of portfolio formation, it is sufficient to have only one observation of PA and PB in any month to obtain an estimate for BA.

Perhaps an example will make the above-described case clearer. Let us consider an instance whereby we wanted to derive a point estimate of BA for the test period of the six-month/six-month momentum strategy, with the first figure as always denoting the number of months in the formation period and the second figure the number of months in the test period. Assuming that PA was only available in month one of the test period and PB was only available in month two of the test period, BA would not be available if it was calculated at the data entry level, like R. This would not be an uncommon situation considering the quality of Datastream database (see *e.g.*, 'The reliability of the Datastream data' part further on). However, with point estimates of BA being computed at the portfolio formation stage, as it is the case in this study, BA can be calculated using average values for PA and PB over the entire six-month period, which in the present example would mean the value of PA from month one of the test period and the value of PB from month two of the test period. More information on the BA variable is provided in the 'Portfolio investment characteristics calculation procedures' subsection.

All of the above-discussed variables except volume, *i.e.* R, ME, P, PA and PB, are converted to a single currency, euro. The conversion process is covered in depth in the next part of this subsection.

3.3.3.2. CURRENCY CONVERSION

There are 11 distinct populations of common shares that comprise the universe of securities studied in this thesis, *i.e.* that of the US, UK and nine emerging countries of the European Union. As it was explained in the preceding part of this subsection, monthly information is gathered on six variables of interest for each of those populations to create a database. In the case of four out of six of those variables, *i.e.* ME, P, PA and PB, observations are recorded in primary units of currency, at the time, for the country to which they relate. Although R is reported in relative terms, it is computed through RI which, in turn, is computed through P that is also recorded in the domestic currency for the country to which it relates.

This situation poses a problem from a comparative analysis point of view as not only are the variables for each population denominated in a different currency, but also the variables for certain individual EU12 populations are expressed in more than one currency due to, among others, the joining of the Economic and Monetary Union (EMU) by those countries. Therefore, in order to maintain consistency within each population, enable direct comparisons of all populations and construct the EU12 index of stocks, the variables R, ME, P, PA and PB are converted from domestic currencies to euros.

For the European populations, the conversion process is carried out using a custom developed expression for average monthly exchange rate which is not readily provided by Thomson Reuters Datastream Advance. Applying average monthly rates, instead of mid-monthly rates (*i.e.*, as of the 15th of every month) provided natively by Datastream, should generate much more reliable estimates. In addition, what is of significance is the fact that the part of the data that is already in euros, *e.g.* as it is the case with Slovenia, Slovakia or Cyprus, does not undergo the conversion process, which would contaminate the results. The custom developed expression, as confirmed by experts at Thomson Reuters Client Support, uses daily (4pm London) WM/Reuters closing spot rates for the currency transformation and it reads as shown in Figure 2.

FIGURE 2. EXPRESSION 1 FOR DATASTREAM DATA CURRENCY CONVERSION.

$$X(\Theta)/CMA\#(X(\Theta)/(X(\Theta){\sim}E),I,P)$$

where X is a symbolic placeholder replaced by either a single series or a constituent of a list that one selects; Θ is the variable of interest; *CMA#* is the calendar month average function that is a part of Datastream functionality; *I* is the parameter for ignoring N/A values (the default mode is to pad values within, but not between months); P is the parameter for incomplete start month (*e.g.*, if start date is not the beginning of month date);

Using the expression in Figure 2, instead of that in Figure 3 below, ensures that the scale of the variable of interest does not change in addition to the currency transformation.

FIGURE 3. EXPRESSION 2 FOR DATASTREAM DATA CURRENCY CONVERSION.

$$X(\Theta)/CMA\#(X/X{\sim}E,I,P)$$

where the variables are to be interpreted as in Figure 2;

Volume, being always displayed in thousands of shares, clearly does not require currency conversion.

Importantly, though, the process of converting domestic currencies to euros introduces the foreign exchange (FOREX) rate factor into all calculations, fluctuations of which constitute another source of variation in stock returns. It is worth pointing out, however, that this development is *de facto* desirable in terms of accounting for exchange rate risk. Indeed, with the international investor in mind, it is essential to verify whether the contrarian and momentum effects still exist once FOREX rates are considered.

3.3.3.3. THE RELIABILITY OF THE DATASTREAM DATA

Datastream is one of the largest, if not the largest, historical financial database in the world, which aims to serve tens of thousands of portfolio managers, investment bankers, research analysts, economists, hedge fund managers and strategists across the world (Thomson Reuters, 2011). Yet, the literature on the reliability of Datastream data is scarce and in the process of data extraction, unexpectedly, a number of unprecedented consequential problems with the Thomson Reuters database transpired.

All the errors within Datastream uncovered by this study have been officially confirmed by the Thomson Reuters Customer Support and Quantitative Team in writing and, considering the potentially enormous number of affected users, those findings constitute an important contribution of this research.

To begin with, the coverage of stocks by Datastream is frequently much lower than the actual number of stocks traded on a stock exchange. For instance, there are currently over 2,400 domestic and foreign companies listed on the UK main market and AIM (London Stock Exchange, 2013), while fewer than 1,800 active companies are covered by Datastream in the UK research list 'FBRIT'.

Furthermore, less-developed markets appear to have lower coverage than more developed markets. For example, while Datastream holds comprehensive data on UK stocks from both the main market as well as the AIM market, in the case of Poland, the coverage of the alternative market ('New Connect') is less than 15%. Therefore, there seems to be a database bias, whereby more developed markets are more thoroughly covered.

Another, related, problem with the database which is of considerable significance is to do with the quality of the Datastream research lists. Thomson Reuters provides users with lists of companies for most equity markets, which one is **recommended** to use when analysing data for an entire country. Examples of those lists include the 'FBRIT' list mentioned earlier or the 'DEADUK' list, which represent the lists of all active and delisted UK companies, respectively. The two lists, due to their considerable length, have been broken down into six (*i.e.*, 'GRP1-6') and seven (*i.e.*, 'DEADUK1-7') parts, respectively. In the former versions of Datastream Advance, one could not, for example, download data for the 'DEADUK' list directly, containing around 7,000 entries, but had to extract data in seven blocks. During the analysis of the extracted data, it emerged that the total number of companies recorded in the seven 'DEADUK1-7' lists did not match the number of companies from the 'DEADUK' list. The difference was substantial and amounted to roughly 1,000 companies, which is more or less 13% of all companies. As it came to light later, not only were the 'DEADUK1-7' lists incomplete, but also the main 'DEADUK' list itself was missing approximately 300 major companies, which suggested irregular and infrequent updating. Importantly, this incident was not isolated to the above-mentioned example, but also affected other populations studied, *e.g.* the Lithuanian 'FLUTHU' and 'LITHCM' lists or the Polish 'FPOL' and 'DEADPO' lists.

The Thomson Reuters Customer Support explained that these were historical errors and "henceforth analyst(-s) will be more vigilant to avoid this type of errors in future". Be that as it may, what this effectively means is that researchers all around the world have been working with meaningfully smaller populations of stocks for a number of countries for the last few years.

In addition to the company coverage, missing stocks and updating issues mentioned earlier, there were also issues with the quality of data, both that found in the official research lists as well as in the database at large.

To start with, it seems that Datastream sometimes fails to correctly recognise different types of equity. For instance, in the case of UK stocks, the listings by the Bank of Georgia (*i.e.*, database entry 'JSC BK.OF GEORGIA 144A GDR') or the company Powertech (*i.e.*, database entry 'POWERTECH TECH.GDRS (XSQ)') were marked as equity and not GDRs as they should be. Those and other similar errors were later rectified by Thomson Reuters upon formal request.

Furthermore, Datastream contains a considerable number of, generally speaking, erroneous entries, such as un-updated entries, duplicates of companies not marked as duplicates or entries with no data.

The case of un-updated entries is probably best exemplified by the UK stocks which are marked as duplicates of other stocks. Clearly, a label 'duplicate', which means 'exactly like something else', a 'copy', suggests that the two pertinent entries show the same data. Unfortunately, this is never the case. Again, upon a formal written inquiry into this matter, containing a comprehensive sample of the problematic stocks, the Thomson Reuters Data Team was first "(…) unable to determine how these DS codes were marked as duplicates" and subsequently concluded that "those codes [were] created incorrectly and [they] do not have any maintenance activity (name change, pricing data, capital adjustment etc.) or do not change any attributes, hence the client will not find any similarity in duplicate codes if they compare [those] with the actual codes (primary code).". Interestingly, those and other 'incorrectly created codes' still continue to exist in the database, waiting for the unwary researcher.

As far as unmarked duplicates of companies and entries with no data are concerned, those issues can be plainly seen in the example of the Polish population of stocks. For instance, database entries 'Wistil' (DSCode: 673455) and 'Wistil SA' (DSCode: 67678L) or 'Powszechny Zaklad Ubezpieczeniowy' (DSCode: 68819E) and 'PZU Group' (DSCode: 69231H) refer to the same stock. Furthermore, entries: 'Wealth Bay SA' (DSCode: 749920), 'Telestrada SA' (DSCode: 68319X) and 'Stark Development' (DSCode: 67939X), are all showing no data as at February 2012 and March 2013.

In the light of all of the above-mentioned problems associated with the Datastream database, it becomes clear that in order to ensure consistency and reliability of data, company lists need to be constructed manually, rather than downloaded from the selection of the readily available recommended official lists, and still numerous categories of errors need to be filtered out, as was done for the purposes of this research project.

3.3.4. CRSP/COMPUSTAT MERGED DATABASE

CRSP/Compustat is a database of merged historical market and fundamental information for the US companies, which is perhaps a less commercially successful invention than Thomson Reuters Datastream, with only just over 500 subscribers worldwide (Center for Research in Security Prices, 2013a). Nonetheless, the firm's commitment to providing data with high level of accuracy, the depth and breadth of stock history and the use of permanent identifiers (*i.e.*, PREMNOs and PERMCOs) are probably the reasons why CRSP is considered by many academics and finance practitioners to offer the most expansive and clean historical financial data in the market. The superiority of CRSP/Compustat over Datastream for the US data has been noted by a number of academics (see *e.g.*, Ince and Porter, 2006) and is the prime motivation here for choosing the former database to study the US population of stocks, rather than the latter. In addition, as shown by Chakrabarty and Trzcinka (2006) for the context of the contrarian and momentum effects specifically, the choice of a database can make a fundamental difference, large enough to affect the statistical significance of results, and, therefore, it is critical to use the most reliable source. Unfortunately, as of March 2013, CRSP does not have international data, but "(…) [it] is currently reviewing data from several sources for the likelihood of commencing a project to build an international product over the next few years." (Center for Research in Security Prices, 2013b).

The equivalent of the Advance tool provided by Thomson Reuters for CRSP is the Microsoft Windows interface called CRSPSift (or CRSP's Security Information Filtering Tool), which is basically CRSP's suite of data access utilities. It is with the assistance of that tool that the relevant data are extracted for the six CRSP variables of interest, which are covered at length in the next part of this subsection.

3.3.4.1. IDENTIFYING VARIABLES OF INTEREST

Identically to the case of the Thomson Reuters Datastream Database discussed earlier, the information obtained from the CRSP/Compustat Merged Database also involves monthly observations on six variables of interest: return (R), the market value of equity (ME), volume (VO), price (P), the ask price (PA) and the bid price

(PB), where the ask price (PA) and the bid price (PB) are used to compute the bid/ask spread (BA).

Nonetheless, it is important to stress that CRSP provides users with many versions of one variable and the versions utilised are the ones best matching both the Datastream data and the requirements of this study. The variable definitions as well as the necessary variable manipulations are discussed below.

The total monthly stock return, denoted by CRSP as $MRET$, is defined here as the change in the month-end to month-end total value of a stock per dollar of initial investment, with the ordinary dividends reinvested at month-end. $MRET$ is, therefore, equivalent to Equation 2, *i.e.* R obtained from Datastream, when expressed in a percentage. When a return is missing, CRSPSift reports a special missing return code, which specifies the reason the return is missing.

As regards the market value of equity, unlike Thomson Reuters, CRSP labels it correctly as capitalisation, abbreviated as $MTCAP$, and it is the closing price multiplied by the number of shares outstanding in thousands. In consequence, the procedure for calculating ME is the same for Datastream and CRSPSift (as shown in Equation 7), however, for the data to be comparable, the latter figures need to be divided by a factor of 1,000,000 as ME is expressed in millions of units of local currency in Datastream.

Similarly, volume, named $MADJVOL$ at CRSP, represents the total one-sided turnover of shares traded within the selected output calendar and, as with ME, requires an adjustment to match Datastream VO variable, such that the CRSP value is divided by a factor of 1,000.

The three variables: P (CRSP's $MPRC$), PA (CRSP's $MADJASK$) and PB (CRSP's $MADJBID$), do not need to be adjusted to be in agreement with Datastream variables and are respectively defined as: (1) the closing price of a security for the last trading day of the month (if unavailable, a bid/ask average is provided); (2) closing ask on the last trading date of the month, adjusted for distributions; and (3) closing bid on the last trading date of the month, adjusted for distributions. The bid/ask spread is also calculated in accordance with the Datastream procedures, which matter is discussed in the 'Portfolio investment characteristics calculation procedures' subsection.

To summarise, the above-presented six variables, plus the bid/ask spread (BA) variable, are consistent with the earlier-discussed Datastream variables, which in the case of R, ME and VO necessitated certain simple mathematical manipulations. As mentioned at the beginning of this section, the Datastream data together with the CRSP/Compustat data are the sole two components of the database on which this research is based, with the variable R being used for the purposes of evaluating portfolio performance and variables: ME, VO, P and BA, being used to produce point estimates of the portfolios' investment characteristics.

In correspondence with the statistical considerations from the 'Thomson Reuters Datastream Database: Identifying variables of interest' subsection, Table 7, Table 8 and Table 9 demonstrate the actual month variation in total stock returns per US stock market and in the number of observations for each variable, including total stock returns, per US stock market.

TABLE 7. CHARACTERISTICS OF MONTHLY TOTAL STOCK RETURNS FOR CRSPSIFT DATA.

	R[30]						
	Minimum	**Maximum**	**Average**	**Median**	**Standard deviation**	**Skewness**	**Kurtosis**
US (NYSE-AMEX)	-1.0000	16.1088	0.0120	0.0076	0.17	5.48	282.64
US (NASDAQ)	-1.0000	14.0045	0.0095	-0.0009	0.23	4.22	93.70

TABLE 8. MONTH TO MONTH VARIATION IN THE NUMBER OF OBSERVATIONS FOR CRSPSIFT DATA. PART 1.

	R			ME			VO		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
US (NYSE-AMEX)	1918	2644	2228	1923	2642	2226	1923	2642	2226
US (NASDAQ)	2451	4660	3221	2446	4668	3209	2448	4671	3209

TABLE 9. MONTH TO MONTH VARIATION IN THE NUMBER OF OBSERVATIONS FOR CRSPSIFT DATA. PART 2.

	P			PA			PB		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
US (NYSE-AMEX)	1923	2642	2226	319	2409	2129	319	2409	2129
US (NASDAQ)	2446	4668	3209	2446	4668	3209	2446	4668	3209

[30] As with Table 4 (p. 143), the data in this table refers to monthly total stock returns and not monthly total stock **index** returns. This means that, for example, the minimum return for US (NYSE-AMEX) of -100% is the lowest monthly total stock return for **a stock** from US (NYSE-AMEX) during the studied time period, which should be interpreted as the bankruptcy of the company that issued the stock. The characteristics of monthly total stock **index** returns are available in Appendix C.

The CRSPSift data presented in Table 7 suggest that, for the time period under analysis (*i.e.*, 01/01/2000 - 30/12/2011), the distribution of monthly total stock returns deviated from normality, albeit the degree of this deviation for the US stock markets appears to be smaller than the earlier-noted deviation for most EU stock markets (see Table 4 on page 143). Still, in line with the Datastream Advance data, the skewness and the kurtosis of monthly returns for both US (NYSE-AMEX) and US (NASDAQ) indicate that the distribution of R is left-skewed (or negatively skewed) and leptokurtic. Average returns are consistently higher than median returns, with the difference ranging from 0.44% per month for US (NYSE-AMEX) to 1.04% per month for US (NASDAQ). The lowest and highest monthly return on a stock are -100% and approximately 1500%, respectively, in both cases considered.

Furthermore, the minimum monthly variations of R, ME, VO and P for both the US (NYSE-AMEX) and US (NASDAQ) populations range from 1918 to 2451 and from 319 to 2446 for PA and PB (see Table 8 and Table 9). Considering that for samples containing more than 100 observations the sampling distribution of average monthly total stock returns will follow a Gaussian distribution even in the presence of extreme outliers, skewness or multimodal population distributions (LeBlanc, 2004), this evidence justifies the implementation of parametric statistical procedures for the two subpopulations, despite the aforementioned departure from normality.

Incidentally, one may easily notice just how consistent the CRSP/Compustat Merged Database is in terms of reporting data by looking at the corresponding number of observations for each variable within each population. With the exception of PA and PB in the US (NYSE-AMEX) population, the deviation of the number of observations for each variable is extremely small and this is indicated by the nearly equal averages. It should be mentioned, however, that the observation count for both populations decreases over time, which is unlike the case of Datastream, and may be a result of a rising number of company delistings during the studied period.

3.3.4.2. CURRENCY CONVERSION

As was the case with the European part of this study's database of stocks, data extracted from the CRSP/Compustat Merged Database need to be converted into euros. However, the procedure to be followed is slightly different from the one described in the 'Thomson Reuters Datastream Database: Currency conversion' part of the section. There, the pertinent financial information is already obtained in the desired currency, owing to the utilisation of the custom developed expression in Figure 2. Under the current circumstances, this is not possible as all US data is extracted from CRSPSift, which does not have the option to perform automatic currency conversion. Thus, data were first obtained in the default currency of CRSPSift, *i.e.* US dollars, and then converted to euros using average monthly USD/EUR exchange rates derived from Datastream via the application of expression in Figure 4 below.

FIGURE 4. USD/EUR EXCHANGE RATE EXPRESSION.

$$CMA\#(USEURSP, I, P)$$

> where *CMA#* is the calendar month average function that is a part of Datastream functionality; USEURSP is the expression for the US/EUR exchange rate; I is the parameter for ignoring N/A values (the default mode is to pad values within, but not between months); P is the parameter for incomplete start month (*e.g.*, if start date is not the beginning of month date);

3.3.4.3. THE RELIABILITY OF THE CRSP/COMPUSTAT DATA

The reliability of CRSP/Compustat data was already briefly commented on in the introduction to this subsection. Overall, the CSRP/Compustat Merged Database seems to be a high-quality source for empirical research in finance and, beyond reasonable doubt, the best database for the US stock market. This has been substantiated by a number of researchers (see *e.g.*, Chan, Jegadeesh and Lakonishok, 1995; Ince and Porter, 2006), yet some have reported the presence of biases (see *e.g.*, Rosenberg and Houglet, 1974; Breen and Korajczyk, 1994; Kothari, Shanken and Sloan, 1995; Shumway, 1997).

Two important findings should, however, be noted, the second of which constitutes another important database-related contribution of this thesis.

To begin with, as was mentioned in Table 1, unlike Thomson Reuters, CRSP does not provide subscriber access to information on preference shares, which clearly limits the scope of security analysis as well as affects data comparability with other databases unless preference shares are excluded from all sources.

More significantly, though, some considerable problems arise when one intends to extract monthly data with non-month-end dates through the use of a custom calendar. On such occasions, monthly data is taken into a daily series and different variables behave differently, leading to severe inconsistencies. In the case of volume, monthly volume pulled into a daily series will return the average volume for the month, *e.g.* a January 1st date will pull in the average volume calculated for the month of January. Similarly, monthly returns pulled into a daily series will return the geometric average of the returns for the month to which the date belongs. However, in the instances of price and market capitalisation, the closing price on the last day of the previous month or previous month's capitalisation is carried through the full month, *e.g.* a January 1st or January 25th date will provide information on price or market capitalisation calculated as at December 31st. Therefore, some items, like volume and returns, are forward looking, whereas some items, like prices and market capitalisations are backward looking. Upon a formal inquiry into this issue, CRSP Senior Director at Client Services confirmed the aforementioned inconsistency, admitted that this issue is not well documented and assured that the necessary changes will soon be introduced.

3.4. DATA PROCESSING

This section of the 'Methodology' chapter provides essential information regarding portfolio return calculation procedures, portfolio investment characteristics calculation procedures as well as tests of statistical and economic significance.

The next subsection, titled: 'Portfolio return calculation procedures', discusses, among others, the formulae for computing returns, the portfolio size limit used, portfolio specification, the weighting method used and data overlap procedure. The prime focus of that subsection is, therefore, on the procedures relating to the foremost, as seen through the prism of this study's objectives, variable R. The second subsection, *i.e.* 'Portfolio investment characteristics calculation procedures', on the other hand, complements the preceding subsection by adding information concerning the computation of statistics for (1) the remaining four variables, *i.e.* ME, VO, P and BA; (2) as well as portfolio standard deviations (σ), downside standard deviations ($D\sigma$), betas (β), downside betas ($D\beta$), alphas ($\propto$), adjusted R-squared (R^2) and idiosyncratic volatilities ($IVol$) per strategy. Finally, the 'Statistical and economic significance tests' subsection provides details concerning the tests of statistical and economic significance utilised in this thesis for the purposes of evaluating the two main hypotheses stated in 'Methodology: Research questions'.

All the calculations discussed in this section are performed using the Microsoft Excel 2010 spreadsheet application, with the assistance of Microsoft Excel 2010 Visual Basic for Applications and Stata 12 software packages.

3.4.1. PORTFOLIO RETURN CALCULATION PROCEDURES

The six-month/six-month contrarian and momentum strategies examined in this study require monthly total stock returns to be aggregated over six-monthly formation and test periods.

Although Loughran and Ritter (1996) argued that cumulating returns, following the empirical procedures originally proposed by DBT (1985), gives rise to similar conclusions as compounding returns, many academics agree that the latter method provides a more realistic, if not, indeed, an unbiased, investment experience (see *e.g.*, Conrad and Kaul, 1993; Dissanaike, 1994). In consequence, the aggregation process in this study takes the form of compounding as shown in Equation 8 and Equation 9 for the formation and test periods, respectively.

EQUATION 8. FORMATION-PERIOD RETURN CALCULATION.

$$R_{F_i} + 1 = \prod_{t=1}^{F} \left(R_{i,t} + 1\right)$$

> where R_{F_i} is the formation-period total compounded return for stock i expressed as a decimal; F is the number of months in the formation period for the strategy under consideration; $R_{i,t}$ is the total return of stock i in month t expressed as a decimal (see Equation 2);

EQUATION 9. TEST-PERIOD RETURN CALCULATION.

$$R_{T_i} + 1 = \prod_{t=1}^{T} \left(R_{i,t} + 1\right)$$

> where R_{T_i} is the test-period total compounded return for stock i expressed as a decimal; T is the number of months in the test period for the strategy under consideration; $R_{i,t}$ is the total return of stock i in month t expressed as a decimal (see Equation 2);

Only stocks with no missing returns in the formation period enter the calculations of R_F and once the qualifying formation-period returns are compounded, as per

Equation 8, stocks are assigned to decile (10%) portfolios. The stocks with the highest R_F, *i.e.* the best performing stocks or winners, are allocated to the first portfolio, *i.e.* P1, whereas the stocks with the lowest R_F, *i.e.* the worst performing stocks or losers, are allocated to the last portfolio, *i.e.* P10. Consequently, 10% of the best performing stocks comprise portfolio P1 and 10% of the worst performing stocks comprise portfolio P10. Additionally, a portfolio of all stocks called 'the market portfolio', denoted as Pm, is created for benchmarking purposes. The use of Pm as the benchmark in this study is grounded in both finance theory and finance practice, most prominently by virtue of the Modern Portfolio Theory (see *e.g.*, Markowitz, 1952; 1959).

While all stocks are assigned to portfolios on the basis of formation-period returns (*i.e.*, R_F) on what essentially is a long, unleveraged investment position in a given stock, both formation-period and test-period portfolio returns can be reported for either a long investment position (annotated with the letter L) or a short investment position (annotated with the letter S) in a given portfolio. The returns on the market portfolio (*i.e.*, Pm), which invariably relate to a long position in the market portfolio (denoted as PmL), are the only exception from this convention. Thus, a long (short) position in the highest past-return portfolio is denoted as P1L (P1S) and a long (short) position in the lowest past-return portfolio is denoted as P10L (P10S). The winner portfolio (*i.e.*, P1) and the loser portfolio (*i.e.*, P10), based on the opposite long-short investment positions, are also used to create arbitrage portfolios, denoted as P1/P10, P1L/P10S or P1S/P10L.[31]. To avoid confusion, only the portfolios based on the long-short positions that generate positive test-period returns are presented, analysed and discussed in the 'Empirical results and analysis' chapter.

Having compounded total stock returns and grouped stocks into portfolios on the basis of R_F, weighted portfolio returns are then calculated for the formation and test

[31] To reiterate, the portfolio comprising 10% of the best performing stocks in the formation period is referred to as the highest past-return portfolio, the winner portfolio or P1, whereas the portfolio comprising 10% of the worst performing stocks in the formation period is referred to as the loser portfolio, the lowest past-return portfolio or P10. The two portfolios are referred to collectively as extreme past-performance or extreme past-return portfolios and, together with the arbitrage portfolio (*i.e.*, P1/10), simply as past-return-based portfolios.

periods following the formulae presented in Equation 10 and Equation 11, respectively.

EQUATION 10. FORMATION-PERIOD WEIGHTED PORTFOLIO RETURN CALCULATION.

$$R_{P_i} = \frac{\sum_{j=1}^{N} R_F}{N}$$

where R_{Pi} is the total portfolio return for portfolio i expressed as a decimal; R_F is the formation-period compounded return calculated as per Equation 8; N is the total number of stocks in portfolio i;

EQUATION 11.TEST-PERIOD WEIGHTED PORTFOLIO RETURN CALCULATION

$$R_{P_i} = \frac{\sum_{j=1}^{N} R_T}{N}$$

where R_{Pi} is the total portfolio return for portfolio i expressed as a decimal; R_T is the test-period compounded return calculated as per Equation 9; N is the total number of stocks in portfolio i;

Two crucial facts with regard to Equation 10 and Equation 11 need to be stressed.

First, it can be easily noticed that the compounded return in the formulae is equal-weighted within a portfolio. This weighting method, as the name suggests, assigns each observation an equal weight and by doing so it allows to easily control the absolute investment-risk exposure to individual companies by investing an equal amount of funds into each company's stocks. However, it is important to note that, in the world of practice, investors may not always be able to achieve exactly equal weights in a large portfolio as this could require the purchase of a large quantity of stocks on account of the fact that individual securities are indivisible.

The second important fact about Equation 10 and Equation 11 is that the formulae thereof implicitly assume a buy-and hold investing approach, whereby investors buy a portfolio of stocks and simply hold it for the entire duration of the strategy exercised. While other investing approaches have also been studied in the literature, most prominently the rebalancing method, the buy-and-hold approach may be considered to be the most suitable for the purposes of this research for a number of reasons, *e.g.* : (1) its implementation does not introduce any new effects, such as that of monthly rebalancing; (2) its logic is the most consistent with the concept underlying both the contrarian and the momentum effect that extreme past performers are temporarily mispriced as it should be possible to exploit that mispricing by a one-off decision to buy or sell stocks; (3) it usually involves lower transaction costs and tax benefits; (4) it is less affected by problems related to infrequent trading.

If a security is delisted or a security's return is missing in any month of the test period, then the buy-and-hold return is calculated from the available data. This procedure does not introduce a survivorship bias, owing to the fact that in the event of delisting the last return figure reflects the proceeds available to stockholders, which if equal to zero, set the entire test period buy-and-hold return to zero as all returns are compounded. Importantly, in both the Thomson Reuters Datastream Database and the CRSP/Compustat Merged Database numerous observations are missing which, however, should not be uniformly interpreted as a company delisting, because the reason for the missing observation might equally likely be, *e.g.* incomplete information, infrequent trading or temporary suspension from trading. Indeed, in the case of a large number of securities, some observations are missing in the middle of a series, which suggest one of the latter explanations, and dropping such securities from a portfolio would inevitably lead to an attrition bias.

Once portfolio total returns are computed for the first calculation period, *i.e.* for the $F + T$ months starting from January 2000, the entire procedure is repeated for the next calculation periods, beginning at $F_n + 1$, where F_n is the last month of the preceding calculation period. The aforementioned succession of calculation periods may be considered to be semi-overlapping[32] as the preceding test period fully overlaps with the subsequent formation period. For a six-month/six-month strategy starting in January 2000, the first calculation period extends from January 2000 to December 2000 (12 months), the second one from June 2000 to June 2001 (12

[32] *N.B.* DBT (1985; 1987) labelled this procedure as 'non-overlapping'.

months), the third one from January 2001 to December 2001 (12 months) and so on until no more complete semi-overlapping six-month/six-month combinations can be created before 31st December 2011. Given the timeframe of the present study, extending from the beginning of January 2000 to the end of December 2011, the total number of calculation periods for a six-month/six-month strategy is equal to 23. Importantly, with the above-described procedure, no adjustments need to be made to the standard error element in the statistical significance formulae as no data are used twice for the purposes of the same calculation.

3.4.2. PORTFOLIO INVESTMENT CHARACTERISTICS CALCULATION PROCEDURES

As it was discussed in the two 'Identifying variables of interest' parts of this chapter, the five variables studied in addition to R are ME, VO, P, PA and PB, with the last two variables being used for the sole purpose of constructing the BA variable. The ultimate four variables, together with portfolio standard deviations (σ), downside standard deviations ($D\sigma$), betas (β), downside betas ($D\beta$), alphas ($\propto$), adjusted R-squared (R^2) and idiosyncratic volatilities ($IVol$) per strategy, constitute the basis for examining portfolio investment characteristics in this thesis.

Although R is the only variable necessary to measure the contrarian and momentum effects, the ME, VO, P and BA variables are used to provide point estimates for the market value of equity, volume, price and the bid/ask spread, respectively, for all the portfolios studied, so as to see if there are any statistically significant differences across the portfolios in terms of the investment characteristics for which those variables proxy. Importantly, both formation and test period statistics are considered, given that investment characteristics may either be time-constant or time-varying.

The market value of equity, *i.e.* ME, is commonly used in finance as a measure of the size of a company and has been considered by many academics, especially the proponents of the efficient market hypothesis, to be a proxy for investment risk. Therefore, in this study, it is investigated whether the average company size in the loser portfolio is significantly different from the average company size in the winner and market portfolios. Specifically, first, the arithmetic mean ME is computed from the available data for each security for the formation and test periods and then the results are used to calculate the arithmetic mean portfolio ME per calculation period. The arithmetic mean portfolio MEs from all calculation periods form the basis for the reported ME statistic per strategy as well as the tests of statistical significance.

Additionally to ME, to the end of assessing investment risk differences across portfolios, portfolio standard deviations (σ), downside standard deviations ($D\sigma$), betas (β), downside betas ($D\beta$), alphas ($\propto$), adjusted R-squared (R^2) and idiosyncratic volatilities ($IVol$) per strategy are also examined.

The standard deviation of actual returns from expected returns (see Equation 12) is the most general measure of risk in finance, which implicitly assumes, in line with the efficient market hypothesis, that risk is symmetric, *i.e.* that upside risk must inevitably create potential for downside risk. This assumption, however, may be considered to be highly problematic, especially in the context where one intends to measure risk for portfolios which are suspected of generating above-average returns as, in that case, risk estimates may be artificially inflated. Therefore, to address this limitation, downside standard deviation is used alongside the conventional (unconditional) standard deviation, which allows measuring only the downside risk of an investment by examining exclusively fluctuations in negative portfolio returns (see Equation 13). Despite the measure's usefulness and intuitiveness, it has been rarely explicitly considered in the finance literature on the contrarian and momentum effect and, thus, the current application should be regarded as contributory to the development of the discipline.

EQUATION 12. PORTFOLIO STANDARD DEVIATION CALCULATION.

$$\sigma_{P_i} = \sqrt{\frac{\sum_{t=1}^{N}\left(R_{P_{i,t}} - \bar{R}_{P_i}\right)^2}{N-1}}$$

where σ_{P_i} is the standard deviation of returns for portfolio i; $R_{P_{i,t}}$ is the return on portfolio i at time t; $\bar{R}_{P_i}$ is the arithmetic mean return on portfolio i; N is the number of observations for portfolio i[33];

[33] All variance-related formulae (*i.e.*, formulae for variance, standard deviation and downside standard deviation) in this thesis utilise Bessel's correction, whereby $N-1$ is used instead of N in the computation of sample statistics, in order to reduce estimation bias.

EQUATION 13. PORTFOLIO DOWNSIDE STANDARD DEVIATION CALCULATION.

$$D\sigma_{P_i} = \sqrt{\frac{\sum_{R_{P_{i,t}}<0}^{N}\left(R_{P_{i,t}} - 0\right)^2}{N-1}}$$

where $D\sigma_{P_i}$ is the downside standard deviation of returns for portfolio i; $R_{P_{i,t}}$ is the return on portfolio i at time t; N is the number of observations for portfolio i whose return is below zero;

Beta, on the other hand, is the sole risk factor in the most long-standing risk-return model in finance, *i.e.* the Sharpe-Lintner Capital Asset Pricing Model (CAPM), and it measures the exposure of an asset (in this case, a portfolio) to the non-diversifiable market risk, by examining the standardised excess return covariance of the decile portfolio with the market portfolio (see Equation 14). As with standard deviation, it is necessary to distinguish between conventional (unconditional) beta and downside beta as otherwise erroneous conclusions may be drawn insofar as estimates of relative risk are concerned. Computing the downside beta of portfolio returns allows ascertaining the expected change in the value of a portfolio relative to the expected change in the value of all stocks (*i.e.*, the market portfolio) during a falling market[34] (see Equation 15).

EQUATION 14. PORTFOLIO BETA CALCULATION.

$$\beta_{P_i} = \frac{\sigma\left(R_{P_i} - R_f, R_{P_m} - R_f\right)}{\sigma_m^2}$$

with $\quad \sigma\left(R_{P_i} - R_f, R_{P_m} - R_f\right) = \frac{\sum_{t=1}^{N}\left(R_{P_{i,t}} - \bar{R}_{P_i} - R_{f_t}\right) * \left(R_{P_{m,t}} - \bar{R}_{P_m} - R_{f_t}\right)}{N-1};$

$$\sigma_m^2 = \frac{\sum_{t=1}^{N}\left(R_{P_{m,t}} - \bar{R}_{P_m} - R_{f_t}\right)^2}{N-1};$$

[34] A falling market (also known as a 'bear market') is defined as the market condition in month t whereby the market return in month t declines below zero.

where β_{P_i} is the beta of portfolio i; $\sigma(R_{P_i} - R_f, R_{P_m} - R_f)$ is the covariance between the excess return on portfolio i (*i.e.*, the rate of return on portfolio i minus the rate of return on a 'risk-free' asset) and the excess return on the market portfolio (*i.e.*, the rate of return on the market portfolio minus the rate of return on a 'risk-free' asset); σ_m^2 is the variance of the excess returns on the market portfolio; $R_{P_{i,t}}$ is the return on portfolio i in month t; $\bar{R}_{P_i}$ is the arithmetic mean return on portfolio i; $R_{P_{m,t}}$ is the return on the market portfolio in month t; $\bar{R}_{P_m}$ is the arithmetic mean return on the market portfolio; R_{f_t} is the return on a 'risk-free' asset in month t; N is the number of observations for portfolio i and the market portfolio;

EQUATION 15. PORTFOLIO DOWNSIDE BETA CALCULATION.

$$D\beta_{P_i} = \frac{D\sigma(R_{P_i} - R_f, R_{P_m} - R_f)}{D\sigma_m^2}$$

with $\quad D\sigma(R_{P_i} - R_f, R_{P_m} - R_f) = \frac{\sum_{\mathrm{R}_{P_m} < 0}^{N}(R_{P_{i,t}} - 0 - R_{f_t}) * (R_{P_{m,t}} - 0 - R_{f_t})}{N-1};$

$$D\sigma_m^2 = \frac{\sum_{\mathrm{R}_{P_m} < 0}^{N}(R_{P_{m,t}} - 0 - R_{f_t})^2}{N-1};$$

where $D\beta_{P_i}$ is the downside beta of portfolio i; $D\sigma(R_{P_i} - R_f, R_{P_m} - R_f)$ is the downside covariance between the excess return on portfolio i (*i.e.*, the rate of return on portfolio i minus the rate of return on a 'risk-free' asset) and the excess return on the market portfolio (*i.e.*, the rate of return on the market portfolio minus the rate of return on a 'risk-free' asset); $D\sigma_m^2$ is the downside variance of the market portfolio returns; $R_{P_{i,t}}$ is the return on portfolio i in month t; $R_{P_{m,t}}$ is the return on the market portfolio in month t; R_{f_t} is the return on a 'risk-free' asset in month t; N is the number of observations for the market portfolio whose return is below zero;

Importantly, the mathematical equations for both types of beta as well as the CAPM Ordinary Least Squared regression, discussed later in this section, require a 'risk-free' rate of return, which is an interest rate that **comes closest** to being risk free, but, strictly speaking, is never completely risk free[35]. In the case of the US and UK stock populations, the ‘risk-free’ rate is the semi-annualised yield on the respective government’s three-month treasury bill, whereas in the case of all EU12 stock populations the ‘risk-free’ rate is the semi-annualised yield on the Euro Interbank Offered Rate (or Euribor). This choice of the financial instruments with minimal credit risk is in line with the recommendations of Thomson Reuters (2013).

Furthermore, the interpretations of different values of downside beta are not exactly the same as those of unconditional beta. This can be seen in Table 10.

[35] Treasury bonds issued by local governments have traditionally been used as the ‘risk-free’ assets in many risk-return models in finance. However, over the course of history, numerous governments have defaulted, particularly to foreign creditors (*e.g.*, Tomz, 2007; but also see Reinhart and Rogoff, 2011). In fact, during the ongoing Eurozone Crisis (see Section 4.2.), Greece confronted the very real possibility of defaulting on part of its debts, and some would argue that this danger still exists. Additionally, it should be noted that an interbank rate, such as Euribor, also bears a very limited credit risk inherent to the banks active in the market (Thomson Reuters, 2013).

TABLE 10. INTERPRETATIONS OF DIFFERENT VALUES OF BETA.

Value of beta	Interpretation (unconditional beta)	Interpretation (downside beta)
$\beta < 0$	The movement of portfolio *i* returns relative to the average portfolio *i* return is in the opposite direction as the movement of the market portfolio returns relative to the average market portfolio return; this value of beta is unlikely for portfolio *i* as most portfolio *i* returns move in the same direction as the market portfolio returns;	The movement of portfolio *i* returns relative to zero is in the opposite direction as the movement of the market portfolio returns relative to zero; more specifically, portfolio *i* returns are, on average, positive while the market portfolio returns are, on average, negative; unlike the case of unconditional beta, this value of downside beta would be expected for, for example, the loser portfolios in the formation period;
$\beta \cong 0$	The movement of portfolio *i* returns relative to the average portfolio *i* return is almost uncorrelated with the movement of the market portfolio returns relative to the average market portfolio return; this value of beta is unlikely for portfolio *i* as most portfolio *i* returns show positive correlation with the market portfolio returns;	The movement of portfolio *i* returns relative to zero is almost uncorrelated with the movement of the market portfolio returns relative to zero; unlike the case of unconditional beta, this value of downside beta would be expected for, for example, the middle decile portfolios in the formation period;
$0 < \beta < 1$	The movement of portfolio *i* returns relative to the average portfolio *i* return is in the same direction as the movement of the market portfolio returns relative to the average market portfolio return, but it is smaller in magnitude; this value of beta would be expected for a portfolio of stable companies, such as that of utility companies;	The movement of portfolio *i* returns relative to zero is in the same direction as the movement of the market portfolio returns relative to zero, but it is smaller in magnitude; more specifically, both portfolio *i* returns and the market portfolio returns are negative, but portfolio *i* returns are, on average, less negative than the market portfolio returns;
$\beta \cong 1$	The movement of portfolio *i* returns relative to the average portfolio *i* return is in the same direction as the movement of the market portfolio returns relative to the average market portfolio return and approximately of the same magnitude; this value of beta would be expected for a portfolio that is a strong contributor to the market portfolio in terms of returns;	The movement of portfolio *i* returns relative to zero is in the same direction as the movement of the market portfolio returns relative to zero and approximately of the same magnitude; more specifically, both portfolio *i* returns and the market portfolio returns are negative and approximately equal;
$\beta > 1$	The movement of portfolio *i* returns relative to the average portfolio *i* return is in the same direction as the movement of the market portfolio returns relative to the average market portfolio return, but it is greater in magnitude; this value of beta would be expected for a portfolio of volatile stocks, such as that of technology companies;	The movement of portfolio *i* returns relative to zero is in the same direction as the movement of the market portfolio returns relative to zero, but it is greater in magnitude; more specifically, both portfolio *i* returns and the market portfolio returns are negative, but portfolio *i* returns are more negative than the market portfolio returns;

In addition to the above, the alpha ($\propto$) of the regression presented in Equation 16 determines the rate of return on a portfolio, as predicted by CAPM, that remains after accounting for its exposure to market risk. Two related issues should be noted at this point. First, the value of the beta estimated in Equation 16 will be equal to the value of the conventional beta in Equation 14. Second, the reason for focusing on CAPM alpha in this study rather than, for instance, the alpha of the three-factor model developed by Fama and French (1996) is that the data necessary for calculating the value factor[36] are mostly unavailable for the EU12 stock markets. Specifically, during the entire time period under consideration by the present research, companies' book values **in any form** are available for **one month or more** only in the case of about 40% of all EU12 stocks. This fact may, however, be seen as inconsequential, since the return on all strategies investigated in Chapter Four can be fully explained by a combination of robustness tests that are already employed.

EQUATION 16. THE CAPM ORDINARY LEAST SQUARES REGRESSION.

$$R_{P_{i,t}} - R_{f_t} = \propto_{P_i} + \beta_{P_i}(R_{P_{m,t}} - R_{f_t}) + \varepsilon_{P_{i,t}}$$

where $R_{P_{i,t}}$ is the return on portfolio i in month t; R_{f_t} is the return on a 'risk-free' asset in month t; $\propto_{P_i}$ is the CAPM alpha for portfolio i; β_{P_i} is the beta of portfolio i; $R_{P_{m,t}}$ is the return on the market portfolio in month t; $\varepsilon_{P_{i,t}}$ is the error term for portfolio i in month t;

The adjusted R-squared (R^2) of the regression based on CAPM provides an estimate of the proportion of portfolio risk that can be attributed to market risk, whereas the balance $1 - R^2$ provides an estimate of the proportion of portfolio risk that can be attributed to firm-specific, or idiosyncratic, risk.

Nevertheless, a more accurate measure of firm-specific risk was proposed in the literature on contrarian and momentum investing by Arena *et al.* (2008) who, drawing on the methodology of, *inter alios*, Ali, Hwang and Trombley (2003),

[36] The value factor (also called the 'high-minus-low' or HML factor) is computed as the difference in returns between the portfolio of stocks with the highest book-to-market ratio and the portfolio of stocks with the lowest book-to-market ratio.

calculated idiosyncratic volatility (*IVol*) as the standard deviation of market model residuals estimated from the regression in Equation 16[37]. With the research on the subject being largely limited to the US studies of Arena *et al.* (2008) and Ang *et al.* (2006), the aforementioned firm-specific risk proxy is also examined in this thesis.

The calculation procedures for VO and P are identical to the case of ME. Volume point estimates are used to investigate the differences in volume between portfolios, which form the basis for statistical inferences in relation to relative liquidity and the problem of infrequent trading. Price statistics, on the other hand, help to assess whether the loser portfolios are composed of stocks whose price is significantly different, from a statistical point of view, from that of the winner portfolios or the market portfolios. In particular, on the basis of P point estimates it is determined whether low-priced stocks may drive the contrarian and momentum effects.

As regards the BA statistic per strategy, in accordance with the previous variable-based investment characteristics, it is derived from the arithmetic mean portfolio BAs from all calculation periods. The arithmetic mean portfolio BA itself is constructed from the arithmetic mean ask price (PA) and bid price (PB), which are computed from the available data for each security for the formation and test periods (see Equation 17).

EQUATION 17. BID-ASK SPREAD CALCULATION.

$$\overline{BA}_{P_i} = \sum_{i=1}^{N} \frac{\frac{\overline{PA}_i - \overline{PB}_i}{\frac{\overline{PA}_i + \overline{PB}_i}{2}} * 100\%}{N}$$

with $\overline{PA}_i = \sum_{t=1}^{M} \frac{PA_{i,t}}{M}; \overline{PB}_i = \sum_{t=1}^{Q} \frac{PB_{i,t}}{Q};$

where $\overline{BA}_{P_i}$ is the arithmetic mean bid/ask spread for portfolio i expressed as a percentage; $\overline{PA}_i$ is the arithmetic mean ask price for stock i ; $\overline{PB}_i$ is the

[37] Strictly speaking, the main model of Arena *et al.* (2008) included a lagged value of the market return to account for the effects of possible non-synchronous trading following Dimson (1979), however, the authors concluded that the results are similar when the factor is excluded.

arithmetic mean bid price for stock i; N is the total number of stocks in portfolio i; $PA_{i,t}$ is the PA for stock i in month t; $PB_{i,t}$ is the PB for stock i in month t; M is the total number of non-missing observations for PA corresponding to stock i; Q is the total number of non-missing observations for PB corresponding to stock i;

Assuming approximately equal brokerage fees, on average, for all categories of stocks, the bid/ask spread gives an accurate indication of the relative transaction costs associated with stock trading, which knowledge is essential to decide whether trading in stocks exhibiting extreme past performance involves higher than the market-average transaction costs. In addition, given that brokerage fees may be assumed constant for the time taken to complete a transaction, BA also complements VO in that it provides an estimate of the liquidity premium.

3.4.3. STATISTICAL AND ECONOMIC SIGNIFICANCE TESTS

To formally investigate whether the observed differences in both performance as well as investment characteristics across the studied portfolios of stocks are significant, several tests of statistical and economic significance are conducted. The purpose of this section is to provide details of the statistical procedures employed in this study, starting with parametric procedures through non-parametric procedures to other procedures and considerations.

3.4.3.1. PARAMETRIC TESTS

There are four types of parametric tests of significance used in this study: (1) the One-Sample *t*-Test; (2) the Paired-Sample *t*-Test; (3) the Two-Sample Unequal Variance *t*-Test; and (4) the Glass's (delta) Effect Size Test. The aforementioned tests are applied to populations whose sampling distribution of the mean may be assumed to be normal under the Central Limit Theorem and, as explained in the two 'Identifying variables of interest' parts of this chapter, this condition is satisfied by four out of the 13 populations studied, *i.e.* US (NYSE-AMEX), US (NASDAQ), UK and EU12.

To begin with, One-Sample *t*-Tests (also known as Single-Sample *t*-Tests) are only carried out on the test-period sample results for the variable R. The aim is to establish whether the test-period R point estimate for a portfolio of interest is statistically different from zero. Considering that past-return-based portfolios, which constitute the basis for all contrarian and momentum strategies, are stratified by past (or formation-period) returns by design, formation-period tests are not justified for this variable. The relevant test statistic is calculated as shown in Equation 18.

EQUATION 18. TEST STATISTIC (t) FOR COMPARING THE MEAN OF A SINGLE SAMPLE TO THE VALUE OF ZERO, WITH POPULATION VARIANCE UNKNOWN.

$$t = \frac{\bar{R}_{P_i} - 0}{\frac{\sigma}{\sqrt{N}}}$$

with $\sigma = \sqrt{\frac{\sum_{t=1}^{N}(R_{i,t})^2 - N*\left(\frac{\sum_{t=1}^{N}(R_{i,t})}{N}\right)^2}{N-1}}; t \sim t_{df,\frac{\propto}{2}}; df = N-1;$

where $\bar{R}_{P_i}$ is the arithmetic mean return on portfolio i; σ is the standard deviation of returns for portfolio i; $R_{i,t}$ is the return on portfolio i at time t; N is the number of observations for portfolio i;

Furthermore, in order to verify whether investment characteristics change over time, *i.e.* whether they are time-constant or time-varying, a Paired-Sample t-Test (also known as the Dependent t-Test or the Repeated Measures t-Test) is implemented to statistically compare formation and tests period sample results for the ME, VO, P and BA variables (see Equation 19).

EQUATION 19. TEST STATISTIC (t) FOR COMPARING THE MEANS OF PAIRED SAMPLES, WITH POPULATION VARIANCES UNKNOWN AND ASSUMED TO BE EQUAL.

$$t = \frac{\bar{D}_{X_{P_{i,t-1}}, X_{P_{i,t}}}}{\frac{\sigma_D}{\sqrt{N}}}$$

with $\bar{D}_{X_{P_{i,t-1}}, X_{P_{i,t}}} = \frac{\sum^{N}_{\substack{t=1 \\ t-1=1}} (X_{i,t-1} - X_{i,t})}{N};$

$$\sigma_D = \sqrt{\frac{\sum^{N}_{\substack{t=1 \\ t-1=1}} (X_{i,t-1} - X_{i,t})^2 - N*\left(\frac{\sum^{N}_{\substack{t=1 \\ t-1=1}} (X_{i,t-1} - X_{i,t})}{N}\right)^2}{N-1}}; t \sim t_{df,\frac{\propto}{2}}; df = N-1;$$

where $\bar{D}_{X_{P_{i,t-1}}, X_{P_{i,t}}}$ is the arithmetic mean difference between the formation $(t-1)$ and test (t) period measurements on portfolio i for variable X; σ_D is the standard deviation of $\bar{D}_{X_{P_{i,t-1}}, X_{P_{i,t}}}$; N is the number of paired observations;

$X_{i,t-1}$ is the formation-period i-th sample result for variable X; $X_{i,t}$ is the test-period i-th sample result for variable X;

Considering the fact that the Paired-Sample t-Tests in this study are 'before and after' measurements on the same subjects and variables, the assumption of the homogeneity of variances is unlikely to be violated.

Furthermore, Two-Sample Unequal Variance t-Tests (also known as Welch-Satterthwaite Tests) are conducted on the sample results for the ME, VO, P and BA variables within both formation and test periods, so as to ascertain if the ME, VO, P and BA point estimates are statistically different across portfolios. The tests follow the procedure depicted in Equation 20.

EQUATION 20. TEST STATISTIC (t) FOR COMPARING THE MEANS OF TWO INDEPENDENT SAMPLES, WITH POPULATION VARIANCES UNKNOWN AND NOT ASSUMED TO BE EQUAL.

$$t = \frac{\bar{X}_i - \bar{X}_j}{\sqrt{\frac{\sigma_i^2}{N_i} + \frac{\sigma_j^2}{N_j}}}$$

$$\text{with } \sigma^2 = \sqrt{\frac{\sum X^2 - N * \left(\frac{\sum X}{N}\right)^2}{N-1}};\ t \sim t_{df,\frac{\alpha}{2}};\ df = \frac{\left[\left(\frac{\sigma_i^2}{N_i}\right) + \left(\frac{\sigma_j^2}{N_j}\right)\right]^2}{\frac{\left(\frac{\sigma_i^2}{N_i}\right)^2}{N_i - 1} + \frac{\left(\frac{\sigma_j^2}{N_j}\right)^2}{N_j - 1}};$$

where $\bar{X}_i$ and $\bar{X}_j$ are the arithmetic means of variable X for portfolios i and j, respectively; σ_i^2 and σ_j^2 are the variances of variable X for portfolios i and j, respectively; N_i and N_j are the number of portfolio i and j samples, respectively;

There are two crucial facts that need to be stressed at this point.

First, the Two-Sample Unequal Variance t-Test involves a corrected df value, often referred to as Satterthwaite's degrees of freedom (see Satterthwaite, 1946), that is smaller than if the two population variances were assumed equal. Generally speaking, it is recommended to always use the Two-Sample Unequal Variance t-Test, rather than the Two-Sample Equal Variance t-Test based on a pooled variance, since the former test is valid whether or not the two population variances are equal and, in real-world applications, it is almost always more accurate (Ruxton, 2006; Moore, Notz and Flinger, 2011). There is also another reason why it would be incorrect to use the Two-Sample Equal Variance t-Test in the present case and, therefore, assume that the true variance of the winner, loser and market populations is equal. The financial interpretation of such an assumption would be that the above-mentioned three groups of stocks have the same risk characteristics insofar as the volatility of the sample results for the ME, VO, P and BA variables is concerned. Considering the fact that both contrarian and momentum strategies have been documented by some academics to consistently earn above-average returns and that the cornerstone of modern financial theory, the efficient market hypothesis, states that, in the long-run, investors can earn above-market returns only by holding a portfolio that has above-market riskiness and/or market microstructure frictions, it seems unreasonable to assume from the very beginning that the variances of the winner, loser and market portfolio populations are equal and, hence, that the risk and market microstructure characteristics of the three groups are the same. DBT (1985; 1987) as well as other prominent academics often used Two-Sample Equal Variance t-Tests with pooled variances to parametrically compare the loser portfolios to the winner portfolios. Although this practice might be seen as incorrect for the aforementioned reasons, it is admittedly less of a concern if the winner and loser portfolios have the same number of stocks, as it is often the case. In the context of parametrically comparing portfolios where the sample sizes are equal, the results obtained from the Two-Sample Equal Variance t-Test and the Two-Sample Unequal Variance t-Test will be similar (Moser and Stevens, 1992).

Second, the Two-Sample Unequal Variance t-Tests employed in this study are used to compare extreme past-performance portfolios to the market portfolio. Since the market portfolio contains all stocks traded on a stock market during a given period of time, including all the highest past-return and the lowest past-return stocks, the above-described statistical test will inevitably involve the incidence of shared observations across groups. This raises the question of statistical independence and suggests that the reported *t*-statistics thereof should only be treated as an approximation. The conventional statistical remedy for the above-described problem would be to remove the winner and loser stocks from the market portfolio. Yet, not only would this render the used-to-be market portfolio meaningless from a financial point of view, but, more importantly, it seems that this operation would be entirely superfluous. The reason for this is that statistical independence can hardly be seen as the prime consideration in the present context, given that all stock returns exhibit some degree of both spatial and temporal dependence. Spatial dependence can be exemplified by the documented higher stock returns for low market-value-of-equity companies and lower stock returns for high market-value-of-equity companies (see *e.g.*, Banz, 1981; Fama and French, 1996). Temporal dependence, on the other hand, is reflected by the fact that all stock prices respond to common market factors, to a lesser or greater extent, and, thence, all stock returns are necessarily serially correlated, to a smaller or larger degree. Therefore, the fact that, for example, the highest past-return portfolio and the lowest past-return portfolio do not share observations does not mean that the two samples are, indeed, independent. The implication is that performing statistical comparisons between any portfolios of stocks is inherently tainted by some degree of spatial and temporal dependence, which cannot always be easily identified and accounted for.

Furthermore, it should be noted that, regardless of whether there are any shared observations across portfolios or not, in the case of comparing either the highest past-return or the lowest past-return portfolio to the market portfolio, the sample sizes are unlikely to be equal and, hence, it would be incorrect to use the Two-Sample Equal Variance *t*-Test. This could increase the Type I error rate by five to 60 times the Two-Sample Unequal Variance *t*-Test Type I error rate (Coombs, Algina and Oltman, 1996).

The One-Sample *t*-Test, the Paired-Sample *t*-Test as well as the Two-Sample Unequal Variance *t*-Test are standard hypothesis testing tools used for the purpose of verifying whether a phenomenon exists or not. However, the two tests do not necessarily provide any information about the magnitude of the phenomenon, that is about its economic (or practical) significance. With a sufficiently large sample size, even a minute difference in sample means, which would normally be considered negligible in practice, may generate a statistically significant result. This fact was used as the basis for many academics to argue that tests of statistical significance are not generally useful (see *e.g.*, Carver, 1978; 1993; Cohen, 1994; Hunter, 1997; Johnson, 1999; Kirk, 1996; Schmidt, 1992). For this reason, researchers, especially from the disciplines of the social and behavioural sciences, are increasingly encouraged to conduct effect size tests alongside the classical statistical tests as a means of quantifying the degree to which a phenomenon exists or, in other words, as a means of quantifying the economic (or practical), rather than statistical, significance of a phenomenon (see *e.g.*, American Psychology Association, 1994; American Psychology Association, 2001; American Psychology Association, 2009; Ellis, 2012; Thompson, 2004)[38]. To that end, Glass's (1981) (delta or Δ) Effect Size Tests are performed for all variables under investigation. The extensive relevance of those procedures to the present research stems from both the practical orientation of this thesis as well as the paucity of academic studies on the subject of contrarian and momentum investing which would consider the economic impact of the results. In fact, there have been virtually no publications of effect sizes based on standardised mean difference for the phenomena examined here to date and, resultantly, this constitutes another meaningful contribution of this thesis.[39]

Effect size tests invariably compute the difference between the means of the two groups considered and divide the result by the standard deviation of the population from which the two groups were sampled. The problem, however, is that the population standard deviation is often unknown and some approximate value needs

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[38] It is important to note that the American Psychology Association Publication Manuals set editorial standards for over 1000 journals in the social and behavioural sciences (Fidler *et al.*, 2004). According to the American Psychology Association Task Force on Statistical Inference, reporting and interpreting effect sizes is "essential to good research" (Wilkinson, 1999, p. 599). More strongly still, American Psychology Association (2001, p. 5) considers failure to report effect sizes as a "defect in the design and reporting of research".

[39] The only measures related to effect size used in the contrarian and momentum literature are the coefficient of determination (also known as R-squared) and the Pearson's product-moment correlation coefficient (also known as Pearson's r). However, as pointed out by Olejnik and Algina (2000) as well as Coe (2002), such 'proportion of variance' measures suffer from a number of limitations, such as sensitivity to violation of assumptions, large standard errors for small sample sizes, unidirectionality or no explicit claim of causality between variables. Indeed, on account of that last shortcoming alone, it is difficult to classify the aforementioned measures as 'effect' sizes, which term has an inherent implication of causality.

to be used instead. There are three such values proposed by the literature and the corresponding effect size tests are named: Cohen's *d*, Hedges' *g* and Glass's delta (Ellis, 2012). The first and the second tests are based on the assumption of roughly equal variance, which assumption, as it was already discussed, cannot be used for the winner and loser groups. Glass's delta, on the other hand, is commonly used when the assumption of the homogeneity of variances is violated and it is based on the standard deviation of the group which is least tainted by the investigated effects and, hence, most closely reflects the population standard deviation. In the context of the winner, loser and market portfolios, the best estimate of the population standard deviation would evidently be the standard deviation of the market portfolios and, hence, the test is defined as in Equation 21.

EQUATION 21. TEST STATISTIC (DELTA) FOR COMPARING THE MEANS OF TWO GROUPS, WITH THE POPULATION STANDARD DEVIATION ASSUMED TO BE EQUAL TO THE MARKET PORTFOLIO STANDARD DEVIATION.

$$\Delta = \left|\frac{\bar{X}_i - \bar{X}_j}{\sigma_m}\right|$$

with $\sigma_m = \sqrt{\frac{\sum_{t=1}^{N}(X_{m,t}-\bar{X}_m)^2}{N-1}}$;

where $\bar{X}_i$ and $\bar{X}_j$ are the arithmetic means of variable X for portfolios i and j, respectively; σ_m is the standard deviation of variable X for the market portfolio; N is the number of portfolio samples;

Given that the use of effect sizes in the discipline of finance is still very rare, the set of conventions (or operational definitions) offered by Cohen (1988) are adopted, whereby an effect size of 0.2 is considered a 'small' effect, 0.5 a 'medium' effect and 0.8 to infinity a 'large' effect. The reader is referred to Cohen (1988, pp. 8-14, pp. 24-27, pp. 284-288) for a comprehensive review of the considerations leading to the setting of the aforementioned conventions, and the advantages and disadvantages inherent therein.

3.4.3.2. NON-PARAMETRIC TESTS

There are four types of non-parametric tests of significance used in this study: (1) the Wilcoxon Signed-Ranks Test; (2) the Wilcoxon Matched-Pairs Signed-Ranks Test; (3) the Kolmogorov-Smirnov Two-Sample Test; and (4) the Cliff's (delta or δ) Effect Size Test. The aforementioned tests are used for populations whose sampling distribution of the mean cannot be assumed to be normal under the Central Limit Theorem. As explained in the two 'Identifying variables of interest' parts of this chapter, this applies to all individual EU12 populations of stocks.

The Wilcoxon Signed-Ranks Test and the Wilcoxon Matched-Pairs Signed-Ranks Test serve herein as the non-parametric counterparts to the One-Sample t-Test and the Paired-Sample t-Test, respectively. The former Wilcoxon test is employed to perform a statistical comparison between the test-period sample results for the variable R and the median value of zero, in order to verify whether portfolio returns are statistically different from zero. In the case of the latter Wilcoxon test, a statistical comparison is made between formation and test period sample results for ME, VO, P and BA, so as to assess whether portfolio investment characteristics are time-constant or time-varying.

Three steps are involved in calculating the test statistic (W) for either one of the two non-parametric tests discussed. First, it is necessary to measure the differences between pairs of observations, eliminating any differences equal to zero and reducing the number of pairs accordingly. As mentioned before, in the case of the Wilcoxon Signed-Ranks Test test-period sample results are compared to the (constant) median value of zero, whereas in the case of the Wilcoxon Matched-Pairs Signed-Ranks Test formation-period sample results are compared to test-period sample results. Second, the absolute values of the differences are ranked in an ascending order, with tied observations being assigned the average of their ranks. Third, the sum of both the negative and positive differences is calculated, where the smaller of the two constitutes the sought test statistic W for a two-tailed test. Critical values of W are obtained from statistical tables for sample sizes of up to 50, while the normal approximation is used for W for samples of more than 50 (see Equation 22).

EQUATION 22. NORMAL APPROXIMATION FOR THE WILCOXON SIGNED-RANKS TEST AND THE WILCOXON MATCHED-PAIRS SIGNED-RANKS TEST.

$$z = \left| \frac{W - \frac{N * (N+1)}{4}}{\sqrt{\frac{N * (N+1) * (2N+1)}{24}}} \right|$$

where z is the z-statistic for a two-sided significance test; W is the statistic for the Wilcoxon Signed-Ranks Test and the Wilcoxon Matched-Pairs Signed-Ranks Test; N is the number of paired observations;

When the normal approximation for the Wilcoxon Signed-Ranks Test is applied, the exact p-value is always reported. This is obviously not the case on occasions when the tables of critical values need to be used and it is important to note that, unlike with most other statistical tests, the test statistic W needs to be less or equal to the critical value to reject the null hypothesis.

In accordance with the case of the two Wilcoxon tests, the Kolmogorov-Smirnov Two-Sample Test is employed in this study as a non-parametric analogue to the Two-Sample Unequal Variance t-Test for the purpose of ascertaining whether the ME, VO, P and BA point estimates are statistically different across portfolios within both formation and test periods.

The Kolmogorov-Smirnov Two-Sample Test examines a single maximum difference between two empirical distribution functions and, hence, it is not based on a measure of central tendency, such as mean or median (see Equation 23).

EQUATION 23. TEST STATISTIC (D) FOR COMPARING THE MEANS OF TWO GROUPS, ASSUMING NON-GAUSSIAN DISTRIBUTIONS AND UNEQUAL VARIANCES.

$$D = sup|F_1(X) - F_2(X)|$$

where D is the Kolmogorov-Smirnov D-statistic; $F_1(X)$ is the empirical distribution function of the first sample; $F_2(X)$ is the empirical distribution function of the second sample;

For sample sizes below 100, the tables of critical values are used to obtain the *D*-statistic. If the sample size is greater than 100, then an approximate *D*-statistic is calculated using the formula in Equation 24 (for two-sided test; $\propto$ = 0.05) or Equation 25 (for two-sided test; $\propto$ = 0.01).

EQUATION 24. THE APPROXIMATION FOR THE KOLMOGOROV-SMIRNOV *D*-STATISTIC FOR SAMPLES SIZES OF ABOVE 100 (TWO-SIDED TEST; ALPHA = 0.05).

$$D = 1.36 * \sqrt{\frac{2}{N}}$$

where D is the Kolmogorov-Smirnov D-statistic; N is the sample size;

EQUATION 25. THE APPROXIMATION FOR THE KOLMOGOROV-SMIRNOV *D*-STATISTIC FOR SAMPLES SIZES OF ABOVE 100 (TWO-SIDED TEST; ALPHA = 0.01).

$$D = 1.63 * \sqrt{\frac{2}{N}}$$

where the variables are defined as per Equation 24;

In terms of quantifying the economic (or practical), rather than statistical, significance of the observed portfolio returns and investment characteristics, the non-parametric equivalent of the Glass's (delta) Effect Size Test is the Cliff's (1993) (delta) Effect Size Test, which is calculated by enumerating the number of occurrences when an observation from one group has a higher value than an observation from the second group, and the number of occurrences of the reverse situation. This procedure can be presented in mathematical notation as shown in Equation 26, assuming equal sample sizes.

EQUATION 26. TEST STATISTIC (DELTA) FOR COMPARING THE MEANS OF TWO GROUPS, ASSUMING NON-GAUSSIAN DISTRIBUTIONS AND UNEQUAL VARIANCES.

$$\delta = \left| \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} sign\left(X_{P_i} - X_{P_j}\right)}{N^2} \right|$$

where δ is the Cliff's delta statistic for a two-sided significance test; X_{P_i} is the observation for portfolio i on variable X; X_{P_j} is the observation for portfolio j on variable X;

When Cliff's delta is approaching the value of zero, then this implies a small effect size, whereas when the statistic is approaching the value of one, then this implies a large effect size.

3.4.3.3. OTHER TESTS AND CONSIDERATIONS

As mentioned in Section 3.4.2., portfolio σ, $D\sigma$, β, $D\beta$ and $IVol$ per strategy, similarly to portfolio ME, VO, P and BA per strategy, are computed from the arithmetic mean portfolio returns from all calculation periods. However, given that the former investment characteristics are, in effect, measures of variability, only one point estimate can be obtained per portfolio, per strategy, thereby rendering any tests of statistical or economic significance impossible to conduct in most cases.

Although, as far as statistical significance tests are concerned, the F-test, or its non-parametric equivalent (*e.g.*, the Kruskal–Wallis H-test or the Non-Parametric Levene Test), could be used for σ and the t-Test for Linear Regression Coefficients[40] could be used for β, those tests would not be appropriate for $D\sigma$, $D\beta$ and $IVol$. While this should not be surprising when it comes to $IVol$ as there are no dedicated statistical tests to determine the significance of the standard error of a regression *per se*, the unsuitability of the aforementioned tests might not be as clear in the case of $D\sigma$and $D\beta$, which measures are essentially variants of σ and β. It should be stressed, however, that the adopted definitions of $D\sigma$ and $D\beta$ are based on the deviation of observations from zero, while the above-mentioned statistical tests for σ and β assume that the deviation of observations is calculated from the mean. Although the formulae for the downside measures could be changed so as to be based on the mean by simply applying the conventional measures on a restricted dataset, it might be argued that the present definitions provide much more informative statistics from a practical point of view. The main reasons for this are as follows.

If the conventional beta were calculated only for observations where the market is 'going down', then it would be possible for an investment portfolio to have positive beta, even if all its returns during that period were non-negative. This is because the variability of the hypothetical investment portfolio's returns would be measured

[40] *N.B.* The F-test for the overall significance of a regression as well as the t-Test for Linear Regression Coefficients can be used for both normal and non-normal populations as the Gauss-Markov conditions, which relate to both the linear regression model as well as the t-Test for the model's coefficients, make no assumptions about the distribution of the variables. Both those tests are employed in this study to determine the overall statistical significance of the CAPM regressions and the statistical significance of CAPM alphas, respectively.

relative to the average return of that portfolio during a 'bear market' and not relative to zero. The 'downside' average portfolio return could be influenced by extreme positive values, which would render most of the demeaned portfolio returns negative and result in positive beta as described above. Similarly, in the case of the conventional standard deviation computed only for negative returns, the potential extent of a financial loss would not be reflected by the result as it would only measure variability around a point equal to the 'downside' average return of the portfolio and not relative to zero. All these issues, which may be seen as misleading to investors, can be avoided by employing the present definitions of $D\sigma$and $D\beta$ that are based on the deviation of observations from zero.

At first sight it would seem that the implementation of a non-parametric bootstrap technique (see *e.g.*, Efron and Tibshirani, 1994; Davison and Hinkley, 1997) could circumvent the problem of statistical and economic significance testing for σ, $D\sigma$, β, $D\beta$ and $IVol$. The technique, adopted for the purposes of this research, would involve randomly generating 10,000 resamples of the arithmetic mean portfolio returns with replacement for each portfolio and then performing non-parametric tests of statistical and economic significance, since the distributions of σ, $D\sigma$, β, $D\beta$ and $IVol$ are unknown, on all the resamples. Nevertheless, a non-parametric bootstrap generates erroneous results in the above-described context, which conclusion was empirically confirmed in the course of the present study. The primary reason for the experiment's failure is that portfolio outcomes are not simulated correctly as resampling individual data points destroys spatial and temporal dependence. Although a block bootstrap, either overlapping or non-overlapping, would normally be able to replicate correlations between variables by resampling blocks of data (see *e.g.*, Carlstein, 1986; Hall, 1985; Kunsch, 1989), the exogenously constrained time period under analysis prevents its effective application.

Importantly, while statistical and economic significance tests are not performed for portfolio σ, $D\sigma$, β, $D\beta$ and $IVol$ for the aforementioned reasons, the F-test, based on a right-tailed F distribution, (see Equation 27) is used as a test of the overall statistical significance of the CAPM regression and the t-Test for Linear Regression Coefficients, based on the two-tailed t distribution, (see Equation 28) is used as a test of statistical significance for portfolio $\propto$.

EQUATION 27. TEST STATISTIC (F) FOR THE OVERALL SIGNIFICANCE OF THE CAPM REGRESSION LINE.

$$F = \frac{MS_R}{MS_E}$$

with $MS_R = \frac{\sum_{t=1}^{N}(\hat{R}_{i,t}-\bar{R}_i)^2}{df_1}$; $MS_E = \frac{\sum_{t=1}^{N}(R_{i,t}-\hat{R}_{i,t})^2}{df_2}$; $F \sim F_{df_1,df_2,\propto}$; $df_1 = 1$; $df_2 = N - 2$;

where MS_R and MS_E are the error mean square and the regression mean square of the CAPM regression (see Equation 16), respectively; $\hat{R}_{i,t}$ is the estimated return on portfolio i at time t; $\bar{R}_i$ is the arithmetic mean return on portfolio i; $R_{i,t}$ is the (observed) return on portfolio i at time t; N is the number of observations for portfolio i;

EQUATION 28. TEST STATISTIC (t) FOR COMPARING THE INTERCEPT OF THE CAPM REGRESSION LINE TO THE VALUE OF ZERO

$$t = \frac{\hat{\propto}_i - 0}{\sqrt{\frac{\frac{\sum_{t=1}^{N} {e_{i,t}}^2}{N-2}}{\sum_{t=1}^{N}(R_{i,t} - \bar{R}_i)^2}}}$$

with $t \sim t_{df,\frac{\propto}{2}}$; $df = N - 2$;

where $\hat{\propto}_i$ is the estimated CAPM alpha of portfolio i; $e_{i,t}$ is the residual i at time t; $\bar{R}_i$ is the arithmetic mean return on portfolio i; $R_{i,t}$ is the (observed) return on portfolio i at time t; N is the number of observations for portfolio i;

Insofar as CAPM alphas are concerned, CAPM ordinary least squares (or OLS) regressions are estimated using standard OLS covariance matrix estimators as well as heteroscedasticity- and autocorrelation-consistent covariance matrix estimators (often called HAC or Newey-West estimators), as described by Newey and West (1987). HAC estimators are calculated at all lags up to three, *i.e.* at lag zero, one, two and three, which total value has been determined by considering the periodicity and number of observations. The reported p-values (*i.e.*, p_{NW}) relate to the lag that is associated with the largest p-value and are evaluated against the statistical significance threshold of $p = 0.05$. At lag zero, Newey-West estimators are the same as heteroscedasticity-consistent covariance matrix estimators (also known as robust or White's estimators).

It is important to mention at this point that HAC is only used in this thesis as a supporting procedure to verify if heteroscedasticity and/or autocorrelation could potentially be a serious problem, which leads to different conclusions. This practice is recommended by, *inter alios*, Wallace and Silver (1988) as well as Gujarati and Porter (2009). However, both Newey-West as well as White's variances and standard errors are, strictly speaking, only valid in large samples and may perform worse in small samples, such as those examined in the present study, than the usual OLS variances and standard errors (see *e.g.*, Rao and Griliches, 1969). Therefore, only the estimates based on the latter estimators are reported in this thesis systematically. The estimates based on the former estimators are referred to exclusively on the occasions when the standard OLS estimates are found to be statistically significant (*i.e.*, $p_{OLS} \leq 0.05$) for the purpose of assessing the potential impact of heteroscedasticity and/or autocorrelation.

3.5. SUMMARY

The principal purpose of this chapter has been to outline the methodology employed by this study, which objective was achieved in three steps.

First, in the 'Research questions' section, the two main hypotheses of this thesis were formalised and discussed. Hypothesis One enquires into the existence of the contrarian and momentum effects in the stock markets studied. Hypothesis Two looks at the investment characteristics of the winner and loser portfolios.

Second, in the 'Data sources' section, essential information was provided on data characteristics as well as data extraction methods for the 11 populations of stocks obtained from the Thomson Reuters Datastream Database and the two populations of stocks obtained from the CRSP/Compustat Merged Database. Once the two elements common to both data sources were discussed, *i.e.* the stock selection criteria and the time period under analysis, each of the two data sources was analysed in more depth, which involved identifying variables of interest, currency conversion and data reliability analysis.

Third, in the 'Data processing' section, the adopted terminology as well as all empirical procedures applied on the data with the aim of results generation and analysis were discussed. The empirical procedures involved: (1) calculation methods pertaining to the most important variable in this research, *i.e.* the total stock return, and this was covered in the 'Portfolio return calculation procedures' part of the section; (2) calculation methods relating to the other variables of interest and this was covered in the 'Portfolio investment characteristics calculation procedures' subsection; and (3) statistical and economic tests of significance, and this was covered in the 'Statistical and economic significance tests' subsection.

In addition to the above, this chapter also provided essential information and clarification with regard to four significant contributions of this thesis to the development of the discipline.

First, the present research helped to improve the quality and reliability of two major data sources used by thousands of professionals worldwide (*i.e.*, the Thomson Reuters Datastream database and the Center for Research in Security Prices database). This was discussed in 'The reliability of the Datastream data' and 'The reliability of the CRSP/Compustat data' parts of this chapter.

Second, unlike any other research in the field, this study carried out effect size tests based on standardised mean difference for all variables studied, which enabled the analysis of the economic (or practical), rather than merely statistical, significance of the observed phenomena. This practice is line with, among others, the American Psychology Association guidelines, which represent editorial standards for more than 1000 journals in the social and behavioural sciences (Fidler *et al.*, 2004).

Third, the 'Portfolio investment characteristics calculation procedures' subsection introduced two practical, and arguably more appropriate as compared to conventional, measures of risk not previously considered in the context of contrarian and momentum investing. These measures are downside standard deviation and downside beta.

Fourth, the scope of this research is more comprehensive than that presented in any single study or a series of studies on the subject of contrarian and momentum investing to date. This is not only reflected by investigating the contrarian effect and the momentum effect simultaneously, but also by considering, among others, multiple stock markets, risk proxies, market microstructure proxies, statistical significance tests and economic significance tests.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. INTRODUCTION

This chapter provides a report, an analysis and a discussion of the empirical results generated for the purpose of evaluating the two main hypotheses of the present research. Information on the data used to produce the above-mentioned results as well as on the methodological design and procedures of the study can be found in, *inter alia*, the preceding chapter, titled: 'Methodology'.

There are three more sections to follow excluding the 'Conclusion' section at the end of this chapter.

The next section, *i.e.* 'Background information on the US, UK and EU12 investment environments', discusses the fundamental characteristics of the examined countries' investment environments, with an explicit emphasis on the stock trading aspect. All data presentation, analysis and discussion thereof have been organised into two interrelated subsections: 'Qualitative information' and 'Quantitative information'. The principal objective of that part of the chapter is to clearly delineate the context in which the contrarian and momentum effects are studied.

In the subsequent two sections, each of the two main hypotheses is formally addressed consecutively.

The first of the two sections, *i.e.* Section 4.3., investigates the returns on past-return-based portfolios, which constitute the basis for contrarian and momentum investment strategies, in all of the 13 stock markets of interest, *i.e.* in the stock markets of: US (NYSE-AMEX), US (NASDAQ), UK (LSE), Bulgaria (BSE-Sofia), Cyprus (CSE), Czech Republic (PSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania (BVB), Slovakia (BSSE), Slovenia (LJSE) and the EU12. This section is divided into 13 separate subsections, thereby one subsection corresponds to one individual stock market.

The second of the two sections, *i.e.* Section 4.4., examines the investment characteristics of the past-return-based portfolios studied in the previous section. While similarly to Section 4.3. there are 13 subsections corresponding to the 13 stock markets analysed in this section, the subsections in Section 4.4. are further separated into two parts: risk characteristics and market microstructure characteristics. The first part looks into the risk profile of the contrarian and momentum strategies by considering seven statistics for both the formation and test periods. Those statistics are the following: (1) the standard deviation of returns; (2) the downside standard deviation of returns; (3) beta; (4) downside beta; (5) the standard error of the Capital Asset Pricing Model (CAPM) regression; (6) *R*-squared; as well as (7) the market value of equity. All of the seven variables, as mentioned in the 'Methodology' chapter, are recognised in the finance literature as proxies for risk and, hence, the corresponding statistics will help to explore whether the past-return-based portfolios differ significantly from the benchmark portfolio of all stocks traded in a given stock market in terms of risk. The second part of each subsection is concerned with the market microstructure characteristics of the past-return-based portfolios. Here, three statistics will be examined: (1) price; (2) volume; and (3) bid-ask spread. The aim of this examination is to determine if the portfolios are composed of stocks with significantly lower price, lower trading volume and/or higher bid-ask spread as compared to the stock market average.

For the reader's convenience as well as to preserve high accuracy of a relatively large volume of data, most empirical results in this chapter have been presented in the form of tables. The investigated contrarian and momentum investment strategies can be easily located and inspected by following the information in the 'List of tables' on page 8. Furthermore, for calculation purposes, it is assumed that investment returns and characteristics are distributed evenly throughout the pertinent, formation or test, period. All calculations involving market figures always assume a long position in the market portfolio.

4.2. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS

This section provides information on the US, UK and EU12 trading environments with the aim of defining the context in which the contrarian and momentum effects are studied.

All core data for each of the 14 countries[41] (16 stock markets) have been divided into five tables, two of which contain qualitative data (*i.e.*, Table 11 and Table 12) and three of which contain quantitative data (*i.e.*, Table 13, Table 14 and Table 15). The presentation, analysis and discussion of the two types of data has been organised into two subsections: 'Qualitative information' and 'Quantitative information'. In addition, comprehensive data have been collected on taxation for the countries of interest which although is relevant to the present, practice-orientated research, has only been presented in Appendix F. The primary reason for this is that the information on taxation cannot be used in a rigorous analysis, on account of individual circumstances of each taxpayer which influence the amount of tax due, such as personal allowance or marital status.

As noted in each of the two ensuing subsections, the qualitative data are for the year 2011 and the quantitative data are for the year 2009, which constitutes the most up-to-date information available on the date of writing this chapter that is obtainable for all the stock markets studied for the same period of time. The qualitative data, including categories such as national currency or the largest shareholder of the main regulated secondary stock markets, represent the more current information of the two types, on account of the fact that it is usually legally bound to be released more often in the form of government announcements, official bulletins or financial statements. The quantitative data, on the other hand, represent statistics which in most cases take much more time to be prepared and published, especially for the smaller of the stock markets considered, and are usually not legally required to be released as they serve informational purposes of investors only. Whereas it would be

[41] *N.B.* The EU12 does not appear as a separate entry in the tables containing qualitative data, *i.e.* in Table 11 and Table 12, as these tables only show information relating to sovereign countries. To enable the computation of the aggregate EU12 figures, this section provides figures for Estonia, Latvia and Malta (but see footnote 2 on page 24).

possible to obtain more up-to-date data for some stock markets, it is absolutely crucial that all data analysed are for the same time period as otherwise inter-country comparisons would not be valid, due to, *inter alia*, changing global economic circumstances.

Despite the fact that all data in this section are time-period consistent within the two individual data-type groups considered, it is still important to be mindful of the global economic and financial environment dynamics during the time period under analysis. In particular, two events are of cardinal importance: the Global Financial Crisis and the Eurozone Crisis. The global investment environment of the 21st century has been most adversely affected by the Global Financial Crisis of 2007-2008, which is regarded by many economists as the worst financial crisis since the Great Depression (see *e.g.*, Pendery, 2009). One of the major, pertinent to this study, effects of that difficult episode have been downturns in economic activity, evidenced by the currently on-going global recession, and downturns in stock markets around the world, which is clearly reflected in the absolute values of all economic and financial metrics employed. As the world's financial sector was on its slow way to recovery from the financial crisis of 2007-2008, since 2011 Europe has been faced with three interlocking crises, involving a sovereign debt crisis, a banking crisis and a growth crisis (Shambaugh, Reis and Rey, 2012; Brown, 2012). The three-dimensional Eurozone crisis has no doubt put the UK and the EU12 economies and stock markets in an unfavourable light as compared to the US investment environment, which has been improving steadily and at a credible rate, with American stock market indices reaching consecutive all-time high records in 2013.

Therefore, considering that the two main global economic and financial events of the 21st century coincide with the present research's timeframe and that these crises have a number of pertinent implications, it is important for the reader to view the following analysis and discussion in the light of the above-described circumstances.

In particular, while a typical, post-World War II business cycle can be characterised by an average of 58.4 months of expansion and 11.1 months of contraction, thereby suggesting an expansion/contraction ratio of 5.26, the time period from 2000 to 2011 has a ratio of 4.53 for the US and 3.97 for the EU by conservative estimates (Eurostat, 2013c; National Bureau of Economic Research, 2013). This information coupled with compelling evidence of increasingly stable business cycles over time, both domestically and internationally, (see *e.g.*, Bergman, Bordo and Jonung, 1998; Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Stock and Watson, 2003) means that the timeframe of this study can be considered to portray realistic investment conditions for the foreseeable future, while being well on the conservative side. It is also important to point out that whereas there have been a number of studies investigating the profitability of contrarian and momentum strategies in the up and down market states (see *e.g.*, Chen and Sauer, 1997; Chordia and Shivakumar, 2002; Cooper *et al.*, 2004; DBT, 1987), the information thereof might be regarded as not very helpful for the typical investor, who is unable to reliably predict changes in the aggregate economic activity. Therefore, research with an emphasis on a realistic business cycle can be arguably more informative and useful for investment practice than research focusing on periods of either expansion or contraction.

Notwithstanding the above considerations, in order to gain a better understanding of the short-term and long-term implications of the Global Financial and Eurozone Crises on the contrarian and momentum effects, the present study's time period, which extends from 01/01/2000 to 31/12/2011, has been divided into two sub-periods in a series of robustness tests that are separate from the main analysis. The first time sub-period (spanning 90 months, from 01/01/2000 to 29/06/2007) covers the months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis, whereas the second time sub-period (spanning 54 months, from 01/07/2007 to 31/12/2011) covers the months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis. The results of the aforementioned auxiliary tests suggest that the main findings of this research are robust across time periods. For more information the reader is referred to Appendix E.

4.2.1. QUALITATIVE INFORMATION

In this subsection, all primary qualitative information on the investment environments of the 14 countries studied is presented, analysed and discussed. The emphasis is on the stock trading environment, although a number of relevant, general, economic metrics are also considered. There are only two figures containing qualitative data, *i.e.* Table 11 and Table 12, and these can be found on pages 200-201. All information in the two tables is as at 31/12/2011 and, with the exception of sovereign credit ratings, it was obtained on 10/01/2012 directly from the official website of each stock exchange, *i.e.*: NYSE (www.nyse.com), NASDAQ (www.nasdaqomx.com), LSE (www.londonstockexchange.com), BSE-Sofia (www.bse-sofia.bg), CSE (www.cse.com.cy), PSE (www.pse.cz), TSE (www.nasdaqomxbaltic.com), BSE (www.bse.hu), RSE (www.nasdaqomxbaltic.com), VSE (www.nasdaqomxbaltic.com), MSE (www.borzamalta.com.mt), WSE (www.wse.com.pl), BVB (www.bvb.ro), BSSE (www.bsse.sk), LJSE (www.ljse.si). In the case of sovereign credit ratings, the information was acquired on the same date, but the source was the official websites of the three credit rating agencies considered, *i.e.* S&P's (www.standardandpoors.com), Fitch Ratings (www.fitchratings.com) and Moody's (www.moodys.com).

TABLE 11. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. QUALITATIVE DATA (AS AT 31/12/2011). PART 1.

Country	Sovereign credit rating for bonds in foreign currency (S&P's / Moody's/ Fitch)	National currency	National currency changes since 01/2000	Largest national stock exchange by market capitalisation	Foundation date of the largest national stock exchange (first trading session)
US	AA+/AAA/Aaa	US dollar (USD)	-	New York Stock Exchange (NYSE)	03/1817 (03/1817)
UK	AAA/AAA/Aaa	pound sterling (GBP)	-	London Stock Exchange (LSE)	03/1801 (03/1801)
Bulgaria	BBB/BBB-/Baa2	Bulgarian lev (BGN)	-	Bulgarian Stock Exchange (BSE-Sofia)	12/1995 (10/1997)
Cyprus	BBB/BBB/Baa3	euro (EUR)	Cypriot pound (CYP) was replaced by euro (EUR) in 01/2008	Cyprus Stock Exchange (CSE)	04/1993 (03/1996)
Czech Republic	AA-/A+/A1	Czech crown(CZK)	-	Prague Stock Exchange (PSE)	11/1992 (04/1993)
Estonia	AA-/A+/A1	euro (EUR)	Estonian kroon(EEK) was replaced by euro (EUR) in 01/2011	Tallinn Stock Exchange (TSE)	04/1995 (06/1996)
Hungary	BBB-/BBB-/Baa3	Hungarian forint (HUF)	-	Budapest Stock Exchange (BSE)	06/1990 (06/1990)
Latvia	BB+/BBB-/Baa3	Latvian lat (LVL)	-	Riga Stock Exchange (RSE)	12/1993 (07/1995)
Lithuania	BBB/BBB/Baa1	Lithuanian lita (LTL)	-	Vilnius Stock Exchange (VSE)	05/1993 (09/1993)
Malta	A/A+/A2	euro (EUR)	Maltese lira (MTL) was replaced by euro (EUR) in 01/2008	Malta Stock Exchange (MSE)	11/1990 (01/1992)
Poland	A-/A-/A2	Polish zloty (PLN)	-	Warsaw Stock Exchange (WSE)	04/1991 (04/1991)
Romania	BB+/BBB-/Baa3	Romanian leu (RON)	-	Bucharest Stock Exchange (BVB)	04/1995 (11/1995)
Slovakia	A+/A+/A1	euro (EUR)	Slovak crown (SKK) was replaced by euro in 01/2009	Bratislava Stock Exchange (BSSE)	03/1991 (04/1993)
Slovenia	AA-/AA-/A3	euro (EUR)	Slovenian tolar (SIT) was replaced by euro in 01/2007	Ljubljana Stock Exchange (LJSE)	12/1989 (10/1993)

TABLE 12. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. QUALITATIVE DATA (AS AT 31/12/2011). PART 2.

Country	Main regulated secondary stock markets	Largest shareholder of the main regulated secondary stock markets	Leading stock index	Main stock trading platform
US	NYSE Euronext US consisting of: NYSE; AMEX (as of 05/2012 known as NYSE MKT LLC); NYSE Arca[42]	NYSE Euronext Group (100%)	NYSE AMEX Composite (as of 05/2012 known as NYSE MKT Composite)	UTP
	The NASDAQ Stock Market (commonly known as NASDAQ)	NASDAQ OMX Group (100%)	NASDAQ Composite	INET
UK	LSE consisting of: Main Market; AIM	London Stock Exchange Group (100%)	FTSE All-Share	TradElect; Millennium Exchange
Bulgaria	BSE-Sofia consisting of: Official Equities Market 'A'; Official Equities Market 'B'; Unofficial Equities Market 'A'; Unofficial Equities Market 'B'	Government of Bulgaria (50.05%)	SOFIX	XETRA
Cyprus	CSE consisting of: Main Market; Parallel market, Alternative Market; Investment Companies Market; Special Category Market; Special Characteristics Market; Shipping Companies Market	Government of Cyprus (100%)	CSE General	OASIS
Czech Republic	PSE consisting of: Main Market; Free Market	CEE Stock Exchange Group (92.74%)	PX	SPAD; KOBOS
Estonia	TSE consisting of: Baltic main list; Baltic secondary list	NASDAQ OMX Group (100%)	OMX Tallinn	INET; SAXESS
Hungary	BSE consisting of: BSE Category A; BSE Category B; BETa Market	CEE Stock Exchange Group (68.8%)	BUX	MMTS
Latvia	RSE consisting of: Baltic main list; Baltic secondary list	NASDAQ OMX Group (92.98%)	OMX Riga	INET
Lithuania	VSE consisting of: Baltic main list; Baltic secondary list	NASDAQ OMX Group (96.34%)	OMX Vilnius	INET; SAXESS
Malta	MSE consisting of: Official List; Alternative Companies List	Government of Malta (100%)	MSE Share	XETRA
Poland	WSE consisting of: Main List; NewConnect	Government of Poland (35%)	WIG	WARSET
Romania	BVB consisting of: BSE (main); RASDQ; ATS	Templeton Asset Management Ltd (<5%)	BET	ARENA XT
Slovakia	BSSE consisting of: Listed main market; Listed parallel market; Regulated free market	Government of Slovakia (75.94%)	SAX	ORACLE
Slovenia	LJSE consisting of: Prime Market; Standard Market; Entry Market	CEE Stock Exchange Group (83.41%)	SBI TOP	BTS

[42] NYSE Arca is not a part of this study's database and analysis. Please see the remaining part of this section for more details.

As can be seen from Table 11 and Table 12, there are nine categories of data for each country. The first and most important category in Table 11, 'Sovereign credit rating for bonds in foreign currency (S&P's / Fitch / Moody's)'[43], provides information on the credit worthiness of the bond issuing government as determined by the three most renowned credit rating agencies of Standard and Poor's, Fitch Ratings and Moody's. The rating itself may be considered to represent the level of risk associated with the investment environment of a given country[44].

The rationale for using sovereign credit ratings as a proxy for macroeconomic risk of an investment is, at least, twofold. First, credit rating agencies weigh numerous economic, social, and political factors pertaining to a specific economy, which are based on information that is both qualitative/quantitative and public/non-public in nature (Moody's Investor Service, 1995; Standard and Poor's 1994). This rather complex assessment process does not only theoretically reflect macroeconomic fundamentals and the riskiness of the trading environment, but in practice stock markets also broadly share, or even are influenced by, the relative ratings of sovereign credit risk made by the agencies, as gauged by sovereign debt yields (see *e.g.*, Bulow and Rogoff, 1989; Ferri, Liu and Stiglitz, 1999; Reisen and Von Maltzan, 1999). Second, credit rating agencies rarely, if ever, assign a rating to, among others, provincial governments, local municipality administrations or private companies that is higher than that of the issuer's home country (Cantor and Packer, 1996), which circumstances apply to the majority of debtors in most economies.

Each of the 14 sets of sovereign credit rating presented in Table 11 can be classified into one of ten general classes (or tiers), which can be arranged in descending order of credit worthiness as follows: (1) 'highest grade'; (2) 'high grade'; (3) 'upper medium grade'; (4) 'lower medium grade'; (5) 'speculative grade'; (6) 'highly

[43] Originally, governments only had foreign currency denominated bonds rated by credit rating agencies as this type of debt was more likely to be placed with international investors. Nowadays, due to growing demand from international investors for domestic bonds, governments obtain ratings for bonds denominated in domestic currency as well. Nevertheless, the former type of ratings (simply known as a 'foreign currency ratings') remains to be the more prevalent and influential in the international bond markets and, consequently, it is the one used for the purposes of this study.

[44] *N.B.* The risk associated with the investment environment is not synonymous with country risk, which is usually taken to mean "the risk of sovereign interference in the business conduct of subsovereign entities within the national jurisdiction" (Bhatia, 2002: 4).

speculative grade'; (7) 'substantial risks'; (8) 'extremely speculative'; (9) 'in default with little prospect for recovery'; (10) and 'in default'.[45] The first four classes designate 'investment grade' debt and are considered to be obligations that are likely to be met, with a low probability of default. Differently, the remaining four tiers are collectively referred to as 'non-investment grade' debt and tend to exhibit speculative characteristics.

Out of the 14 countries presented in Table 11 only the UK meets the criteria of the credit rating agencies for the 'highest grade' debtor as S&P downgraded the US in August 2011 to AA+ from AAA, thereby raising the debt burden for that country. However, the US still qualifies as the 'highest grade' debtor by the Fitch Ratings and Moody's standards. In the case of the EU12 countries, exactly six countries meet the criteria for the 'upper medium grade' obligor, *i.e.* Czech Republic, Estonia, Malta, Poland, Slovakia and Slovenia, while the remaining six countries meet the criteria for the 'lower medium grade' obligor, *i.e.* Bulgaria, Cyprus, Latvia, Lithuania, Romania. Only in the case of Latvia and Romania the S&P rating can be described as 'speculative', but similarly to the case of the US, Fitch Ratings' and Moody's evaluations remain one class up. There are, therefore, clear differences between the class of credit worthiness of the developed countries of the US and the UK, and the class of credit worthiness of the developing countries comprising the EU12. Within the EU12 also two distinct groups of debtors emerge, with half of the countries classified as strong 'upper medium grade' obligors and half of the countries classified as a weaker group of 'lower medium grade' obligors, which might be more susceptible to adverse economic conditions or changing circumstances. Nonetheless, in conclusion, all the 14 countries are 'investment grade' debtors, which means that the level of risk associated with those investing environments may be considered to be appropriate even for conservative investors.

The remaining four categories in Table 11 provide complete information on each country's currency and the largest national stock exchange.

[45] See Appendix G for a more detailed credit rating class description.

In terms of national currency, there are two data items that deserve the reader's attention: (1) a country's currency; (2) a country's currency changes since 01/2000. The reason why this information is important links directly to the 'Methodology' chapter, in particular the two 'Currency Conversion' subsubsections. As noted therein, the data for all variables, including the return variable (*i.e.*, R), needed to be converted to a common currency of euro (represented by 'EUR' or, more simply, by '€'). One of the main factors that necessitated this operation was that the data for a number of EU12 countries were not consistent in terms of the units of measurement. Table 11 clearly shows that in the time period under analysis as many as five out of 12 countries changed the national currencies to euro. Therefore, in order to maintain a consistent dataset for each stock market, account for the exchange rate risk, enable direct comparisons of all stock markets as well as construct the EU12 index of stocks all variables for all stock markets needed to be converted to a single currency.

On the other hand, the two categories of data in Table 11 that relate to the largest national stock exchange, *i.e.* 'Largest national stock exchange by market capitalisation' and 'Foundation date of the largest national stock exchange (first trading session)', provide the basic, yet essential information on the main institutions facilitating stock trading in the countries of interest as well as the corresponding foundation and first trading session dates which, as can be seen from the table, may be very different. It is worth noting at this point that, in the case of the EU12 countries and the UK[46], the official main stock exchange is the only stock exchange in the country. This is not the case with the US. There are currently 16 securities exchanges registered with the US Securities and Exchange Commission (SEC) under Section 6(a) of the Exchange Act as national securities exchanges, although not all of them trade stocks, *e.g.* The Chicago Mercantile Exchange (CME) specialises in American financial and commodity derivatives.

[46] Prior to 05/2012, there has also been the PLUS Markets Group stock exchange in the UK which, in addition to the largest national stock exchange (*i.e.*, The London Stock Exchange or, more simply, LSE), allowed stock trading as well as derivatives trading. However, following an unsuccessful attempt to find a buyer in 2012, the exchange started to wind down its operations and, effectively, delist all of its 156 traded companies (Stafford, 2012).

Furthermore, the foundation date as well as the first trading session date quoted for the EU10 countries (*i.e.*, the EU12 excluding Cyprus and Malta) is for the post-communist era, during which period of time all of the ten stock exchanges were re-established[47]. Stock trading essentially ceased under the communist regime as the concept, deeply rooted in the idea of a free market, is not compatible with a planned economy system (also known as a command economy system). However, many of the EU10 stock exchanges existed before the communist era and so, for example, the first state-organised exchange in Poland was established in 1817 and first securities trading minutes had been recorded as early as in the 17th century (Warsaw Stock Exchange, 2012; Surmacz, 2013). It is also informative to learn that, unlike the developed stock markets of the US and the UK, the EU12 stock markets needed much more time to start trading after being re-established. This underscores the troublesome beginnings of those stock markets, which might help to explain their present relative immaturity, and provides further justification for a time lag in commencing data analysis, as mentioned in the 'Methodology' chapter.

As one moves from Table 11 to Table 12, the informational emphasis shifts from the general, country-level trading environment characteristics to the more specific, stock market-level trading environment characteristics. It was mentioned earlier in this section that although in the case of the EU12 countries the official main stock exchange is the only stock exchange in the country, this is not the case with the US and the UK. When one considers stock markets instead of stock exchanges, matters may become even more complicated. Unlike a stock exchange, which usually requires a type of a physical facility, a stock market is essentially a non-physical network of economic transactions conducted by buyers and sellers of company stocks[48] [49]. Stock

[47] It should be noted that Cyprus and Malta were never communist. However, those countries gained their independence from the UK only in the second half of the 20th century, many years after which event the Cyprus Stock Exchange and the Malta Stock Exchange were established for the first time.

[48] 'Stock market' is also a more flexible term as compared to 'stock exchange'. For example, the term 'EU12 stock market' frequently used in this study is a collective name referring to all the stocks traded in the regulated stock markets of the 12 countries comprising the EU12. Considering the fact that in the 12 countries, as well as in the UK, the only regulated stock markets are those available on the official stock exchange, the regulated stock market of the official stock exchange is synonymous with the regulated stock market of a country.

[49] As an interesting point to note, the National Association of Securities Dealers Automated Quotations (NASDAQ) which was created over 40 years ago and is currently the second largest stock market by

markets can be unregulated or regulated and if it is the latter type, then the regulator(-s) are usually a governmental body[50], such as the SEC in the US or the Financial Services Authority (FSA) in the UK. Nevertheless, this study is only concerned with regulated stock markets and, more specifically, with the main regulated secondary stock markets of each country, as described in detail in Table 12. In the case of the EU12 and the UK economies, this specification embraces virtually all of the existing regulated stock markets, but, as was the case with stock exchanges, it does not apply to the US. The two US stock markets investigated are the NYSE Euronext US, mainly consisting of all stocks traded on the New York Stock Exchange (commonly known as NYSE) and the American Stock Exchange (currently known as NYSE MKT LLC), and The NASDAQ Stock Market (or simply NASDAQ), the first and the second largest stock markets in the world, respectively. It is important to note that the fully-electronic, NYSE Euronext US constituent called NYSE Archipelago (commonly known as NYSE Arca) is not a part of this study's database and analysis, because the number of stocks listed exclusively on the NYSE Arca stock exchange is essentially negligible, *e.g.* during the entire time period under analysis only 20 stocks have been exclusively listed on that exchange (as reported by the CRSP/Compustat database) and, thus, only 20 stocks constitute the entire, exclusive NYSE Arca stock market. The word 'exclusive' is critical here as the exchange additionally trades all NYSE, AMEX and over-the-counter (OTC) stocks as well as a number of NASDAQ stocks, which adds up to more than 8,000 exchange-listed equity securities.

The final three categories of qualitative data, as presented in Table 12, provide basic investment information on the largest shareholder of the main regulated secondary stock markets, the leading stock index and the main stock trading platform. Perhaps the most important observation to be made insofar as the three categories are

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market capitalization in the world, after the New York Stock Exchange (NYSE), became a registered national stock exchange only in 2007.

[50] It should be noted, however, that a number of government-independent, domestic as well as international security commissions and regulatory agencies also exist. Those institutions usually operate under a voluntary membership arrangement and include legal entities, such as the Financial Industry Regulatory Authority (FINRA) and the North American Securities Administrators Association (NASSA) in the US or, the international global standard setters for the securities sector, The International Organization of Securities Commissions (IOSCO) and the International Securities Services Association (ISSA).

concerned is, on the one hand, the diversity of the legal and technical structures associated with the stock trading environments across the countries studied and, on the other hand, slow, yet noticeable effect of globalisation and integration. In particular, although five out of the 12 EU stock markets are still largely owned by the respective governments, in six cases the stock markets have merged with two major stock market operators: the NASDAQ OMX Group and the CEE Stock Exchange Group. Following legal integration, index integration, stock trading platform integration or, even more broadly, the entire network integration is already underway. Three examples from the NASDAQ OMX corporate timeline make this very clear. In 2004, the NASDAQ OMX Group consolidated the Baltic Market by creating a common trading system, common listing standards and the Baltic Index (The NASDAQ OMX Group, 2012). Since the year 2007, Estonian, Latvian and Lithuanian securities can clear and settle cross-border transactions in their national currencies across the Baltic markets (*ibid.*). In 2010, the NASDAQ OMX Group converted all Nordic and Baltic equity markets to the INET trading system (*ibid.*). The network integration of the CEE Stock Exchange Group and the government-owned EU12 stock markets progresses markedly more slowly, however, at the same time, fewer changes seem to be needed. A pan-European stock market alliance, also potentially including stocks traded on the exchanges in Frankfurt, London, Paris, Milan, Madrid, Brussels, Amsterdam and Zurich, could in the near future create a single trading platform "possibly via the connection of the European stock exchanges to the German XETRA trading system – or [through a] link [to] the exchanges' existing trading structures." (Schröder, 2000: 495). More recently, in 2009, the CEESEG Composite Index (CEESEG) was launched, which is a capitalization-weighted price index composed of the constituents of the leading share indices of the members of the CEE Stock Exchange Group, *i.e.* Wiener Börse AG (also known as the Vienna Stock Exchange or VSE), BSE, LJSE and PSE. With such consolidation in progress, investors worldwide may soon have effortless and immediate access to all the US, UK and EU12 stock markets. This process is likely to have a particularly significant impact on the 12 less-developed stock markets, which, it is crucial to point out, are still substantially under-researched and, consequently, this is one of the primary reasons why the EU12 stock markets are central to this study.

In conclusion, although there is some variability between the developed countries and the developing countries as well as within the developing countries in terms of sovereign credit rating tiers, which may be considered to proxy for the macroeconomic risk of investing in a given country, all the 14 countries are 'investment grade' debtors and, thus, the level of risk associated with those investment environments may be considered to be appropriate even for conservative investors. Furthermore, five out of 12 countries changed the national currency during this study's time period under analysis. This fact, among others, justifies the need for the conversion of all domestic currencies to a single, common currency for the purposes of valid and systematic analysis. It is also important to mention that, in the case of the EU12 countries as well as the UK, the official, national stock exchange in the country is the only stock exchange in the country as well as the only stock market in the country. While this is not the case in the US, there is substantial evidence of both American and European stock market operators' merger activity, which tends towards complete network integration. Therefore, it may soon be possible to invest effortlessly across all the 14 countries. The impact of such an integration would undoubtedly be the greatest on the developing, EU12 stock markets, which are, however, still considerably under-researched.

4.2.2. QUANTITATIVE INFORMATION

The quantitative part of this section comprises data in Table 13(p. 210), Table 14 (p. 211) and Table 15 (p. 212) as well as the corresponding analysis and discussion that follows. Exactly as per the qualitative part, the information presented in the three tables on the following pages, with the exception of data on GDP, was sourced from the official website of each stock exchange considered on 10/01/2012. In the case of GDP, the source is Eurostat (2013b). Most importantly, though, all information in this part is for the calendar year ended 31/12/2009. To calculate the numerical figures, both domestic as well as foreign companies traded on the main regulated stock markets have been used, which corresponds to the scope of companies found in the dataset used for this research. The conversion of local currencies into euro (€), if not officially provided at source, has been computed using the average annual exchange rate in 2009.

TABLE 13. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. QUANTITATIVE DATA (AS AT 31/12/2009). PART 1.

Secondary stock market	GDP (GDP PPS)	Stock market capitalisation	Stock market capitalisation/ GDP ratio		No. of trading sessions	No. of trading members
US (NYSE-AMEX)	€10,018,425.6m (10,578,122.6m)	€13,401.02bn	162.41%	133.76%	252	498
US (NASDAQ)		€2,869.53bn		28.64%	252	163
UK (LSE)	€1,590,858.0m (1,626,745.6m)	€4,026.53bn	253.10%		253	943
Bulgaria (BSE-Sofia)	€34,932.8m (78,188.2m)	€6.03bn	17.26%		243	86
Cyprus (CSE)	€16,853.5m (18,974.2m)	€7.16bn	42.48%		245	23
Czech Republic (PSE)	€142,197.0m (203,591.9m)	€49bn	34.46%		250	20
Estonia (TSE)	€13,761.7m (19,754.2m)	€1.85bn	13.44%		249	40
Hungary (BSE)	€91,415.4m (153,650.7m)	€21.9bn	23.96%		251	35
Latvia (RSE)	€18,521.3m (27,161.5m)	€1.32bn	7.13%		247	30
Lithuania (VSE)	€26,654.4m (43,080.3m)	€3.22bn	12.08%		248	19
Malta (MSE)	€5,956.0m (8,195.5m)	€2.8bn	47.01%		247	13
Poland (WSE)	€310,681.4m (542,857.1m)	€165.91bn	53.40%		252	46
Romania (BVB)	€118,196.0m (238,103.8m)	€21.99bn	18.60%		250	71
Slovakia (BSSE)	€62,794.4m (92,481.0m)	€3.55bn	5.65%		249	17
Slovenia (LJSE)	€35,556.1m (41,534.9m)	€8.46bn	23.79%		251	25
EU12	€877,520m (1,467,573.3m)	€293.19bn	33.41%		-	-

TABLE 14. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. QUANTITATIVE DATA (AS AT 31/12/2009). PART 2.

<table>
<tr><th>Secondary stock market</th><th>No. of listed companies</th><th>No. of new company listings</th><th>No. of delisted companies</th><th>Total turnover</th><th>Average daily turnover</th><th colspan="2">Turnover/ market capitalisation ratio</th></tr>
<tr><td>US (NYSE-AMEX)</td><td>2,315</td><td>94</td><td>212</td><td>€12,758,370m</td><td>€50,628.45m</td><td rowspan="2">206.06%</td><td>95.20%</td></tr>
<tr><td>US (NASDAQ)</td><td>2,852</td><td>131</td><td>302</td><td>€20,769,228m</td><td>€82,417.57m</td><td>723.79%</td></tr>
<tr><td>UK (LSE)</td><td>2,792</td><td>73</td><td>385</td><td>€2,584,500m</td><td>€10,215.42m</td><td colspan="2">64.19%</td></tr>
<tr><td>Bulgaria (BSE-Sofia)</td><td>287</td><td>0</td><td>18</td><td>€290.21m</td><td>€1.19m</td><td colspan="2">4.81%</td></tr>
<tr><td>Cyprus (CSE)</td><td>128</td><td>0</td><td>7</td><td>€1,335 m</td><td>€5.45m</td><td colspan="2">18.65%</td></tr>
<tr><td>Czech Republic (PSE)</td><td>25</td><td>0</td><td>1</td><td>€17,573m</td><td>€70.29m</td><td colspan="2">35.86%</td></tr>
<tr><td>Estonia (TSE)</td><td>16</td><td>1</td><td>3</td><td>€266.60m</td><td>€1.07m</td><td colspan="2">14.41%</td></tr>
<tr><td>Hungary (BSE)</td><td>47</td><td>4</td><td>2</td><td>€18,464m</td><td>€73.56m</td><td colspan="2">84.31%</td></tr>
<tr><td>Latvia (RSE)</td><td>35</td><td>0</td><td>1</td><td>€13.96m</td><td>€0.06m</td><td colspan="2">1.06%</td></tr>
<tr><td>Lithuania (VSE)</td><td>40</td><td>0</td><td>0</td><td>€214.46m</td><td>€0.86m</td><td colspan="2">6.66%</td></tr>
<tr><td>Malta (MSE)</td><td>20</td><td>1</td><td>0</td><td>€25.27m</td><td>€0.10m</td><td colspan="2">0.90%</td></tr>
<tr><td>Poland (WSE)</td><td>486</td><td>39</td><td>11</td><td>€40,770m</td><td>€161.79m</td><td colspan="2">49.15%</td></tr>
<tr><td>Romania (BVB)</td><td>1,630</td><td>7</td><td>198</td><td>€1,340m</td><td>€5.36m</td><td colspan="2">6.09%</td></tr>
<tr><td>Slovakia (BSSE)</td><td>59</td><td>31</td><td>19</td><td>€121.70m</td><td>€0.49m</td><td colspan="2">3.43%</td></tr>
<tr><td>Slovenia (LJSE)</td><td>74</td><td>0</td><td>8</td><td>€720m</td><td>€2.87m</td><td colspan="2">8.51%</td></tr>
<tr><td>EU12</td><td>2,847</td><td>83</td><td>268</td><td>€121,904m</td><td>-</td><td colspan="2">41.58%</td></tr>
</table>

TABLE 15. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. QUANTITATIVE DATA (AS AT 31/12/2009). PART 3.

Secondary stock market	Total volume	No. of transactions	Average no. of transactions per day	Average value of a transaction
US (NYSE-AMEX)	738,047.3m	2,744,354,800	10,890,297	€4,648.95
US (NASDAQ)	524,855m	3,996,425,500	15,858,831	€5,196.95
UK (LSE)	827,864.6m	166,428,982	657,822	€15,529.15
Bulgaria (BSE-Sofia)	160.45m	182,585	751	€1,589.45
Cyprus (CSE)	2,475m	372,683	1,521	€3,582.13
Czech Republic (PSE)	967.8m	1,571,767	6,287	€11,180.41
Estonia (TSE)	333.47m	84,757	340	€3,145.46
Hungary (BSE)	2,492.9m	3,349,885	13,346	€5,511.83
Latvia (RSE)	13m	21,676	88	€644.03
Lithuania (VSE)	619.89m	222,843	899	€962.38
Malta (MSE)	13.57m	6,790	27.49	€3,721.65
Poland (WSE)	30,265m	13,278,132	52,691	€3,070.46
Romania (BVB)	15,982m	1,501,551	6,006	€892.41
Slovakia (BSSE)	8.88m	1,837	7	€66,249.32
Slovenia (LJSE)	20.75m	135,853	541	€5,299.85
EU12	53,352.71m	20,730,359	-	€5,880.46

There are in total 15 categories of quantitative information presented in Table 13, Table 14 and Table 15.

The first category, 'GDP (GDP PPS)', refers to Gross Domestic Product, which is probably the single most important economic indicator. GDP measures the total market value of all finished goods and services produced within a country less the value of any goods or services used in their creation, *i.e.* a country's total domestic output, during a specific period of time and, therefore, it can be considered to proxy for the size of a country's economy[51]. To allow international comparisons, GDP can be converted to a common currency on the basis of market exchange rates or on the basis of purchasing power parities (PPPs), which are indicators of price level differences across countries. Although the former method is the most straightforward and, as a result, still quite common, it can provide a misleading representation of the relative size of economies, due to the fact that it is based on the implicit assumption that price levels are identical in all countries. In reality, price levels in countries with higher incomes, *i.e.* in developed countries, tend to be consistently higher than in countries with lower incomes, *i.e.* in developing countries, which is known in economics as the Penn effect and results in the real income of the developed countries being overstated if converted at market exchange rates (see *e.g.*, Samuelson, 1994). In other words, international comparisons of GDP based on market exchange rates will tend to understate the size of lower-income economies, *i.e.* the EU12 countries in the present case, because price levels, systemically related to the level of per capita income, are lower in those economies. According to the Balassa-Samuelson theorem, which is typically invoked to explain the Penn effect, productivity gains in the domestic tradable sector[52], typically experienced by developed countries, raise

[51] It is more prudent to assume that GDP is a proxy for the size of a country's economy, rather than an absolute measure, as it does not take into account a number of factors, such as the size of a hidden economy (*e.g.*, the transactions that are unrecorded and excluded from official statistics, in order to avoid tax) or the assessment of the true value of goods (*e.g.*, is an economy with a bigger spending on defence considered larger than an economy with a comparable spending on merit goods, such as vaccination or education?).

[52] The tradable sector is the sector of a country's economy that represents the industries whose goods and services can be supplied and sold internationally, such as automobiles, canned food or consumer electronics. The non-tradable sector, on the other hand, is the sector of a country's economy that represents the industries whose goods and services cannot be traded in a location distant from the production site. Examples of non-tradable goods and services include housing, prepared food, local transportation or educational services to mention only a few.

the relative price of domestic non-tradable sector, causing an increase in real exchange rates and the over-adjustment of real income in the conversion process from domestic currencies to a common, international currency (Balassa, 1964; Samuelson, 1964). However, when PPPs are used to convert GDPs into an artificial common currency, the purchasing power standard (PPS), the effect of price level differences across countries created by fluctuations in currency exchange rates is eliminated. Therefore, it might be argued that converting GDPs on the basis of PPPs represents a more accurate estimate of the size of a country's economy and the real purchasing power within a country.

The theoretically predicted relative disparity between GDPs converted to a common monetary currency and GDPs converted to a common, PPP-based currency is clearly supported by the empirical data for the US, UK and EU12 economies as presented in Table 13. While the difference between GDPs (€) and GDPs (PPS) for the US and the UK is less than 6% in both cases, in the case of the EU12 economies it can be as large as 124% (for Bulgaria) and in three-quarters of cases it is greater than 43%. These results show that the size of the individual EU12 economies and the corresponding real purchasing power is, indeed, significantly understated by all crude, non-price-level-adjusted reports and, in fact, the actual, collective size of the EU12 economy is comparable to that of the UK.

Furthermore, the next two categories in Table 13, that is 'Stock market capitalisation' and 'Stock market capitalisation/GDP ratio', reveal that the EU12 stock markets are still at the early stages of development and that they are significantly undervalued as compared to the UK and the US stock markets. The market capitalisation figures show that the EU12 stock market as a whole is over 55 times smaller than the main US stock markets together and over 13 times smaller than the UK stock market. This data in conjunction with the fact that, as discussed in detailed above, the EU12 economy is comparable to the UK economy and it is only seven times smaller than the US economy suggest that the EU12 stock market is significantly undersized and undervalued, which finds its reflection in the market capitalisation to GDP (henceforth, MC/GDP) ratios. Whereas the US (NASDAQ) is a relatively smaller stock market than the US (NYSE-AMEX), the overall MC/GDP ratio for the main US stock markets is roughly 162%. Even more strikingly, the UK stock market has a MC/GDP ratio of approximately 253%, which is by far the highest result for all the considered stock markets. Although it needs to be stressed that accurately determining the percentage level showing undervaluation and overvaluation is a matter of intense debate, it should not be controversial to conclude that a MC/GDP result of 33% for the EU12 stock market, with the ratio not exceeding 54% in the extreme, individual case of Poland (WSE), indicates underdevelopment and undervaluation of that stock market, especially considering the size of the corresponding economy. It is important to add that the presented MC/GDP figures would be significantly lower for the EU12 still if the ratios were calculated on the basis of GDP (PPS).

Therefore, from the first three categories of data in Table 13 alone it can be concluded that the EU12 stock markets are still largely unrecognised and underappreciated by investors worldwide and constitute a promising investment destination with yet mostly untapped potential.

The two remaining categories in Table 13 are: 'No. of trading sessions' and 'No. of trading members'.

The penultimate column provides the number of days in a year that investors can trade stocks on a stock market. These numbers do not vary greatly throughout the stock markets considered as the maximum difference is only ten days. In the case of the EU12 as a whole, the figure for the number of trading sessions is undetermined as it varies across the individual stock markets, which is a limitation that applies to the next category as well.

The last column in Table 13 demonstrates the number of trading members for each stock market and, hence, quantifies organizations, such as investment firms, proprietary traders, brokerage firms or market makers that act as investors' intermediaries in the process of trading stocks. Individuals are usually not allowed to become a member of a stock market and, thus, trading members constitute the only point of contact, be it personal or electronic, for investors with the stock market[53]. The discussed statistics are the highest for the largest of stock markets, *i.e.* US (NYSE-AMEX), US (NASDAQ) and UK (LSE), with the UK stock market, as in the case of the MC/GDP ratio, again showing by far the highest result. While this information seemingly suggests that UK (LSE) has the lowest transaction costs associated with stock trading out of all the stock markets considered as a result of the competition for investors among trading members, recent empirical research shows that, in fact, the total transaction costs, *i.e.* both explicit costs (*e.g.*, commissions, stock market fees or taxes) and implicit costs (that is, mainly the bid-ask spread), are consistently higher in the UK stock market as compared to the US rates, roughly by the value of the UK's 50-basis-point tax (Pollin and Heintz, 2011). Information in Appendix F confirms that differences in taxation across the 14 countries studied are likely to have a profound impact on the net profit from investment. For example, the short-term capital gains tax on the disposal of shares for the year 2012 ranged from 0% in Bulgaria and Cyprus to over 35% in the US. The important issue of stock-trading-related, implicit transaction costs, on the other hand, is an integral part of the present research and it is discussed in the context of contrarian and momentum investment strategies for each of the 13 stock markets in the 'Market microstructure characteristics' subsections of this chapter.

Table 14 and Table 15 represent, the reader will be relieved to learn, the more self-explanatory part of the above-presented qualitative and quantitative information.

[53] The role of the aforementioned institutions is, however, generally reduced in an order-driven trading system, which, as opposed to a quote-driven trading system (also known as a dealer- or price-driven trading system), does not only rely on the bid prices and the ask prices of market makers and other designated parties, but displays the bid prices and the ask prices of all buyers and sellers. In such a system, once arrived at the trading floor, buy orders and sell orders can be matched by brokers or fully automatically, *e.g.* via the Computer Assisted Trading System (CATS) used on the Toronto Stock Exchange or its later, French versions used on Paris Bourse, the Cotation Assistée en Continu (CAC) and the Nouveau Système de Cotation (NSC). However, quote-driven trading systems, unlike order-driven trading systems, guarantee order execution and, therefore, are much more popular, especially for thinly traded stock markets. Examples of quote-driven trading systems include the UK stock market's SETSqx and SEAQ trading services. There are also hybrid trading systems, which are a more recent development and represent a blend of an order-driven trading system and a quote-driven trading system. Hybrid trading systems are used on, among others, US (NYSE-AMEX), US (NASDAQ) and UK (LSE).

The first of the two tables provides information on the companies of each stock market, including the total number of companies, the number of new company listings and the number of delisted companies, as well as information on turnover for each stock market. Importantly, the number of new company listings is not equivalent to the number of initial public offerings (IPOs) as the former figure includes the latter figure as well as the listings of companies which have already had an IPO, such as cross-listed companies (*i.e.*, companies that are listed on multiples stock exchanges).

In terms of the company data in Table 14, having the previously-discussed figures for stock market capitalisation in mind, it comes as little surprise that US (NYSE-AMEX), US (NASDAQ) and UK (LSE) have the largest number of companies in each of the three categories. What is interesting, however, is that the relatively small stock market of Romania (BVB), as judged by the market capitalisation of €21.99bn, has as many as 1,630 companies. This can be explained by the fact that in 2005 the electronic, Romanian stock market called RASDAQ, characterised by a large number of small market capitalisation companies, was absorbed by the official Romanian stock market. By comparison, in 2009, the RASDAQ segment of Romania (BVB) had 1,561 companies with market capitalisation of approximately €3bn, whereas the main BVB segment had 69 companies with market capitalisation of over €19bn. The EU12 stock market as a whole is, again, comparable to the UK stock market insofar as the company data categories in Table 14 are concerned, however, as mentioned earlier in this subsection, the EU12 companies are extremely undervalued as compared to the UK companies. Finally, the relatively larger number of company delistings as compared to new company listings, especially in Europe, is likely to be a direct result of the Global Financial Crisis as well as the Eurozone Crisis, discussed in the introduction, however, a more thorough analysis of yearly, business cyclical and event-based data on worldwide company listings dynamics would be necessary to reach any more definite conclusions.

As far as the turnover data in Table 14 are concerned, those show the total yearly turnover, the average daily turnover as well as the turnover to market capitalisation ratio. All figures are based on turnover values for one side of the transaction, *i.e.*

turnover is single-counted. The average daily turnover is calculated by dividing the total value of share trading by the number of trading days during 2009.

Turnover, together with volume and the number of transactions discussed next, are all essentially **absolute** measures of liquidity as well as trading activity (see *e.g.*, Lo and Wang, 2009 for a summary of related academic studies). Only the turnover to market capitalisation ratio accounts for the relative size of a stock market, which is particularly important when stock markets of radically different sizes are analysed.

Overall, not surprisingly, there is a moderate-to-high positive correlation between the turnover figures and the number of listed companies ($r \approx 0.6302$)[54] as well as stock market capitalisation ($r \approx 0.63939$), which means that the number and the market value of companies is moderately-to-strongly related to the value of share trading on each stock market. In terms of the correlation between turnover and market capitalisation, US (NASDAQ) constitutes the largest exception from the general pattern (or, simply, the largest outlier) and once it is removed from the sample, the correlation for the remaining 15 stock markets rises to $r \approx 0.9955$. In terms of the correlation between turnover and the number of companies, there are no outliers as extreme as in the preceding case, yet the correlation of the 15 most highly correlated groups of variables, *i.e.* exclusive of the EU12 stock market, is equal to $r \approx 0.7595$. Therefore, turnover appears to be most highly correlated with market capitalisation and, in consequence, is the highest for the developed stock markets of the US and the UK. Lastly, the turnover to market capitalisation ratio, being an aggregate measure of a stock market's relative liquidity, is overall, again, the highest for the developed countries as compared to the developing countries. The US stock markets are the most liquid, with a 206% average and a staggering result of 724% for US (NASDAQ), followed by the Hungary (BSE) ratio of 84% and the UK (LSE) ratio of 64%. Most importantly, however, although the total turnover for the EU12 as a whole is approximately 2100% smaller than that of UK (LSE), once market capitalisation is considered, the UK (LSE) overall liquidity, *i.e.* the turnover to market capitalisation ratio, is only 54% greater than that of the EU12 stock market. This result clearly

[54] Where r is the sample Pearson correlation coefficient.

signifies the difference between absolute and relative measures of liquidity and trading activity.

The last table in this section, *i.e*. Table 15, contains information on stock market volume and transactions. Stock trading volume is, simply, the number of stocks exchanged between buyers and sellers for a security or, as in the present case, for an entire market within a given period of time. It is almost always reported as a single-counted figure, *i.e.* it includes only one side of the transaction. As mentioned before, volume is closely related to turnover and the number of transactions in that all these variables are essentially absolute measures of liquidity as well as trading activity, especially when relating to an entire market[55]. In fact, volume and turnover are often grouped together and called 'turnover by volume' and 'turnover by value', respectively. The number of transactions (or trades) represents, quite straightforwardly, the actual number of stock buy-sell transactions which have occurred during the considered period on the relevant stock market. This number should always be lower than the corresponding figure for volume as each transaction typically involves trading more than one stock. Similarly to volume, the number of transactions is almost always reported as a single-counted figure.

When the total volume measure is used, it is UK (LSE), and not the individual main US stock markets, that is the most liquid stock market, followed by US (NYSE-AMEX) and US (NASDAQ), respectively. The EU12 stock market is not 54% less liquid than UK (LSE), as determined by the relative total turnover to market capitalisation ratio, but as much as 1500% less liquid, which is a figure of comparable order of magnitude to the total turnover figure. This is not surprising, because, as mentioned before, total volume is an absolute measure, which does not account for the size of the market. A similar pattern can be observed for the number of transactions as well as the average number of transactions per day, which is the total number of transactions divided by the number of trading sessions provided in Table 13, variables, except that UK (LSE) is, again, positioned on the third place in descending order of value, right after the

[55] When relating to a single security, volume, turnover and the number of transactions are usually employed to measure 'commitment' or 'support' behind a stock price movement and are commonly used in technical analysis, especially volume.

two US stock markets. In terms of the average value of a transaction, however, which is the total value of share trading divided by the total number of trades, Slovakia (BSSE) is the stock market with the highest value. The reason for this is that even though Slovakia (BSSE) has the smallest turnover out of all the considered stock markets, it still has relatively few trades during the year, which results in a small number of very high-value trades. The Slovak stock market is followed by UK (LSE) and the EU12 stock market, whose trades are, on average, worth only three times less. Interestingly, US (NYSE-AMEX) finds itself roughly with the median value for the average value of a transaction, which can be explained by high trading activity in that stock market as well as low transaction costs as compared to the UK, for example.

In conclusion, the quantitative data presented in this subsection, in particular data in Table 13, suggest that the EU12 stock markets are still largely unrecognised and underappreciated by investors worldwide. Hence, those stock markets may represent an attractive investment destination with substantial growth potential. Furthermore, it was found that although the number of trading members may be a proxy for the level of transaction costs, once factors such as taxation are accounted for, the conclusions may be very different, as was the case with the US and the UK investment environments. The data on transaction costs associated with stock trading in the EU12 countries are substantially scarcer, however, the issue of stock-trading-related transaction costs is, among others, an integral part of the present research and it is discussed in the context of contrarian and momentum investment strategies in the 'Market microstructure characteristics' subsections of this chapter. Lastly, in addition to the information on each stock market's companies, Table 14 as well as Table 15 introduced a number of liquidity and trading activity metrics. The most important finding thereof is that when comparing stock markets at different stages of development, it is vital, in addition to absolute measures that are of highest relevance to institutional investors, to also consider relative measures, such as the turnover to market capitalisation ratio. This is clearly seen on the comparison of the EU12 stock market with the UK stock market, where using relative measures lowered the relative liquidity and trading activity difference by as much as 39 times. A similar result can observed for the GDP (€) and GDP (PPS) economic indicators, for which data were presented in Table 13.

4.3. TESTING HYPOTHESIS ONE: IS EITHER THE CONTRARIAN OR THE MOMENTUM EFFECT PRESENT IN THE US, UK OR EU12 STOCK MARKETS?

This section of the 'Empirical results and analysis' chapter formally addresses the first and foremost hypothesis of the present research, which has been defined in the 'Methodology' chapter. Therefore, the primary objective of the ensuing data presentation, analysis and discussion is to verify whether the contrarian or the momentum effect is present in the stock markets of the US, the UK and the EU12 countries.

There are 13 subsections to follow, each corresponding to one of the 13 stock markets studied, *i.e.* US (NYSE-AMEX), US (NASDAQ), UK (LSE), Bulgaria (BSE-Sofia), Cyprus (CSE), Czech Republic (PSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania (BVB), Slovakia (BSSE), Slovenia (LJSE) and the EU12 stock market. For every stock market, there are in total three past-return-based stock portfolios (*i.e.*, the highest past-return portfolio, the lowest past-return portfolio and the arbitrage portfolio) that, according to the theories underlying this research, have the potential to individually exhibit either the contrarian effect or the momentum effect. The portfolios can be based on two types of long-short investment positions, *i.e.* a long position or a short position. For brevity and clarity, only the results relating to the long-short positions that generate positive test-period returns are presented and examined in this chapter.

It is crucial to reiterate at this point that the concept of economic significance, which, as discussed in the 'Methodology' chapter, is becoming increasingly important, has not hitherto been applied in the contrarian and momentum literature. In consequence, strategies classified as successful by this research, *i.e.* strategies for which $H_{0(1)}$ can be rejected, have to meet the more stringent criteria of exhibiting, among others, both statistical as well as economic significance of returns, rather than just statistical significance of returns as it was the case in previous studies. While, as will be shown in all respective subsections, there are, on average, approximately one-third as many strategies of the 'economic and statistical significance' standard as compared to the number of 'statistical significance' standard strategies, with the former standard the reader can have, indeed, considerably greater confidence that the presented, analysed and discussed investment strategies are not a mere statistical fluke and that these can be reliably used in practice. The issue of data mining and statistical misuse is a legitimate concern, particularly in finance research, on account of the fact that computing power is relatively cheap, while public attention as well as potential reputational and financial gain associated with finding a new, exploitable stock market anomaly is extremely high. In the present case, this concern seems to be most pertinent to the studies on the momentum effect, where the documented profits may be viewed as small in absolute terms, the timeframes as relatively prolonged and the methodologies as over-elaborate for what is essentially portrayed to be an investment strategy exclusively based on one of the most very basic financial variables, *i.e.* stock returns.

4.3.1. US (NYSE-AMEX)

The first stock market to be evaluated in terms of hypothesis number one (*i.e.*, $H_{(1)}$) and, therefore, examined for the presence of a practically exploitable contrarian or momentum effect is US (NYSE-AMEX). US (NYSE-AMEX) is likely to be by far the most researched stock market in the world, as can be clearly seen on the example of the contrarian and momentum investing literature presented in the 'Literature review' chapter. However, the existing studies on the contrarian effect may be considered to be outdated, predominantly focused on one sample period and not comparable across countries as well as with the momentum studies, on account of considering an absolute, rather than a relative, number of extreme performers. Research in the area of the momentum effect, on the other hand, is almost exclusively based on only one methodological approach, which was introduced by JT (1993). It is, therefore, highly informative to investigate the effectiveness of investment strategies based on the two effects by using a consistent and unconventional methodology.

Table 16 on the next page presents all $H_{(1)}$-relevant empirical data for US (NYSE-AMEX).

TABLE 16. US (NYSE-AMEX): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns that are calculated over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six consecutive months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	217	0.88	0.07	0.1518	0.3096	-0.01	0.6373
P10L	217	-0.42	0.05	0.5054	0.1412	-0.06	0.0811
P1L /P10S	-	1.30	0.03	0.5896	0.1141	0.04	0.4644
PmL	2166	0.10	0.08	-	-	0.00	-

As can be seen from Table 16, none of the portfolios of interest demonstrates either statistically or economically significant returns. Of note is the fact that while the highest past-return portfolio (*i.e.*, P1L) appears to be associated with the return continuation effect, the lowest past-return portfolio (*i.e.*, P10L) seems to exhibit return reversal of comparable magnitude. Specifically, the difference between the two portfolios is only about 2% after six months (*i.e.*, 0.07 – 0.05) or 0.33% per month. Consequently, the net result for the arbitrage portfolio (*i.e.*, P1L/P10S) can be characterised by the lowest statistical and economic significance of returns of the three investment portfolios, with $p > 0.58$ and $\Delta < 0.11$. More importantly still, P1L, P10L and P1L/P10S generate returns below the return on the market portfolio (*i.e.*, PmL) and thus, risk and market microstructure considerations aside, PmL appears to promise the largest profit. Although the alpha of the Capital Asset Pricing Model (or CAPM, for short) is positive for the arbitrage portfolio, thereby suggesting that P1L/P10S is a superior investment to PmL once relative return volatility and the 'risk-free' rate are considered in addition to average returns, it should be pointed out that the corresponding p-value is substantially above the $p = 0.05$ threshold. Therefore, it would seem that in the stock market under consideration past returns are not predictive of future returns at either a statistically or an economically significant level, at least by the adopted specifications and standards.

Overall, the US (NYSE-AMEX) results are largely inconsistent with the results presented in the contrarian and momentum literature. In particular, a number of authors have reported momentum patterns in the intermediate-term (see *e.g.*, Ball and Kothari, 1989; Chopra *et al.*, 1992; JT, 1993). Even though most contrarian-effect researchers used fixed-in-size extreme past-performance portfolios that are four to six times smaller than those in the present study, the effect was also observed on decile portfolios (see *e.g.*, JT, 2001; Moskowitz and Grinblatt, 1999). Furthermore, the semi-overlapping methodological approach applied on a recent time period produced no strategies with, at least, statistically significant returns. This does not substantiate the evidence presented in the momentum studies based on overlapping portfolio calculation periods, which documented intermediate-term abnormal momentum profits for numerous strategies, in specific the here ineffective six-month/six-month strategy (see *e.g.*, Chordia and Shivakumar, 2002; Grundy and Martin, 2001; JT, 1993).

In conclusion, there are no equal-weighted, decile portfolio-size group, past-return-based strategies for US (NYSE-AMEX) that generate statistically and economically significant returns, at least by this study's specifications and standards. The alternative hypothesis number one is, therefore, rejected for US (NYSE-AMEX). Furthermore, the overall results are largely inconsistent with the contrarian and momentum literature, showing statistically significant profitability across multiple portfolio-size groups and timeframes. While in the case of contrarian investing this is most likely due to the fact that, in contrast to the overwhelming majority of contrarian studies, this research examines an intermediate-term, rather than a long-term, timeframe and/or the fact that the existing contrarian studies are outdated, in the case of momentum investing the primary cause probably lies in the difference in methodological approaches.

4.3.2. US (NASDAQ)

US (NASDAQ) has received appreciably less attention from the academic community as compared to US (NYSE-AMEX), discussed in the preceding subsection, especially in the context of contrarian and momentum investing. Although a few notable exceptions exist (see *e.g.*, Chordia and Shivakumar, 2002; Fuertes *et al.*, 2009; JT, 2001; Liu and Zhang, 2008), excluding US (NASDAQ) firms from the studied sample is a commonly used size filter in the literature in lieu of excluding 'penny stocks'. However, not only does this practice inadequately account for the breadth of potential problems associated with the inclusion of 'penny stocks' in the sample, as pointed out by, *inter alios*, Bhootra (2011), but also it might be argued that US (NASDAQ), being the second largest individual stock market by market capitalisation in the world, is of great importance to the investment community. Therefore, in order to investigate the effectiveness of contrarian and momentum strategies on The NASDAQ Stock Market as well as to account for its unique characteristics, US (NASDAQ) is examined separately from US (NYSE-AMEX).

Table 17 on the next page presents all $H_{(1)}$-relevant empirical data for US (NASDAQ).

TABLE 17. US (NASDAQ): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	313	1.11	0.04	0.4482	0.1610	-0.02	0.4905
P10L	313	-0.53	0.03	0.7169	0.0766	-0.05	0.2377
P1L /P10S	-	1.64	0.01	0.9131	0.0230	0.02	0.7369
PmL	3129	0.08	0.06	-	-	0.00	-

Table 17 clearly demonstrates that there are no past-return-based portfolios that show either statistical or economic significance of returns, with all the p-values and Δ-values being firmly above the p = 0.4 level and below the Δ = 0.17 level, respectively. In fact, the highest past-return portfolio, the lowest past-return portfolio and the arbitrage portfolio are all associated with profits that are both close to zero and substantially below the average market return. Therefore, contrarian and momentum strategies appear to perform even worse in this stock market than in US (NYSE-AMEX), discussed in the preceding section. These findings are clearly corroborated by CAPM alphas, most of which are below zero for the three investment portfolios.

However, what is particularly noteworthy about the results in Table 17 is that, in perfect agreement with the evidence for US (NYSE-AMEX), one of the two extreme past-return portfolios, *i.e.* the highest past-return portfolio, is associated with the momentum effect, whereas the other extreme past-return portfolio, *i.e.* the lowest past-return portfolio, exhibits the contrarian effect. As it transpires, this is not an uncommon occurrence, confined only to US (NYSE-AMEX) and US (NASDAQ), but it can also be observed for all other stock markets examined with the exception of Cyprus (CSE) and Slovenia (LJSE). In the former case the pattern of returns on the extreme past-performance portfolios shows a moderate contrarian effect for the highest past-return portfolio and a weak momentum effect for the lowest past-return portfolio, whereas in the latter case there is a weak contrarian effect for the highest past-return portfolio and a strong contrarian effect for the lowest past-return portfolio. Therefore, for the two stock markets discussed there are in total three cases of the contrarian effect (in terms of magnitude ranging from weak through moderate to strong) and only one case of a weak momentum effect. The significance of this observation will become apparent shortly, when it is shown that the two seeming exceptions do, in fact, fit in the overall pattern.

In addition to the aforementioned relationship between extreme past-performance portfolios and past-return-based effects, it is always the case that the momentum effect accompanying the highest-past return portfolio is less pronounced (or extreme) in the test period than it is in the formation period. Differently, the contrarian effect associated with the lowest past-return portfolio is by definition a more pronounced result in the test period as compared to the formation period, since not only does the extremely negative formation-period return decrease to zero, but it also necessarily turns positive in the test period.

These two crucial findings suggest, at the very least, that the observed, test-period behaviour of past-return-stratified portfolios can be generally characterised by a relatively weak return continuation (or momentum) effect in the highest past-return portfolios and a relatively strong return reversal (or contrarian) effect in the lowest past-return portfolios. However, the discussed results are more likely to be indicative of asymmetric mean reversion patterns in the stock markets of America and Europe. In particular, it is proposed here that both high past-return portfolios and low past-return portfolios are effectively subject to the contrarian effect, yet this affects the former group to a noticeably lesser extent as it does affect the latter group. Such conclusion would be consistent with the extensive body of **economic** literature showing mean reversion in stock market prices, which results in negative autocorrelation in stock returns (see *e.g.*, DBT, 1989; Fama and French, 1988; Kim, Nelson and Startz, 1991; Lo and Mackinlay, 1990; Richardson, 1993; Spierdijk, Bikker, Van Den Hoek, 2012). Specifically, in line with the observations documented in this research, Nam, Pyun and Arize (2002) found, using asymmetric nonlinear smooth-transition (ANST)GARCH(M) models, that for monthly US data negative returns, on average, revert more quickly and with a greater reverting magnitude to positive returns than positive returns revert to negative returns. It should also be noted that while the finance literature focuses on the highest and the lowest past-return portfolios and the economics literature concentrates on the market portfolio, *i.e.* the entire sample of stocks, the underlying reasoning and the trading implications derived from these two parallel strands of research are identical (Chen and Sauer, 1997).

To conclude, there are no equal-weighted, decile portfolio-size group, past-return-based strategies that produce either statistically or economically significant returns on US (NASDAQ), at least by the adopted specifications and standards. For this reason, $H_{1(1)}$ is rejected for the discussed stock market. This finding is in line with the earlier-analysed evidence for the much more researched US (NYSE-AMEX).

In addition to allowing the evaluation of Hypothesis One, the results for US (NASDAQ) also demonstrate a very interesting and important pattern which, as it emerges, is also observable for most of the other 12 stock markets covered by this study. Namely, it would seem that, in general, high past-return portfolios are associated with a relatively weak momentum effect, whereas low past-return portfolios are associated with a relatively strong contrarian effect. This information, among others, is suggestive of broad-spectrum, asymmetric mean reversion patterns, which have been widely documented in the parallel, economics-orientated literature on mean reversion and negative autocorrelation.

4.3.3. UK (LSE)

The third developed stock market to be examined in terms of the first and foremost hypothesis of this study is also currently the world's third largest stock market by market capitalisation of its listed companies, after US (NYSE-AMEX) and US (NASDAQ), although its position is continually challenged by the Tokyo Stock Exchange (TSE) segment of Japan's stock market[56]. It is, therefore, not surprising that UK (LSE), Europe's leading centre for stock trading, has been the object of intensive academic research and publications. However, studies on the contrarian effect are few and to a large extent concerned with large capitalisation stocks only (*e.g.*, Dissanaike, 1994; 1997), whereas research into the momentum effect has left many issues unresolved, such as the impact of economy-level risk factors and transaction costs on the strategies' profitability. Consequently, it is one of this thesis's aims to meaningfully add to the contrarian and momentum literature by investigating investment returns as well as investment characteristics of contrarian and momentum strategies based on a comprehensive sample of all Datastream's UK stocks for a period of time that involves both up- and down-market states.

Table 18 on the next page presents all $H_{(1)}$-relevant empirical data for UK (LSE).

[56] It is worth pointing out that, unlike the case of UK (LSE), Japan (TSE) is not the only stock market in Japan. Once the stock market capitalisation of companies traded on Osaka Securities Exchange, Nagoya Stock Exchange, Fukuoka Stock Exchange and Sapporo Stock Exchange is included in the calculation, the UK stock market is reliably smaller than Japan's stock market.

TABLE 18. UK (LSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	691	0.86	0.06	0.0606	0.4124	0.03	0.2595
P10L	691	-0.36	0.01	0.8219	0.0475	-0.01	0.8066
P1L/ P10S	-	1.22	0.04	0.4070	0.1763	0.03	0.6084
PmL	6909	0.04	0.03	-		0.00	-

As can be seen from Table 18, none of the three past-return-based portfolios generates returns that are either of statistical or economic significance. Although the highest past-return portfolio earns a gross profit of about 1% per month during the time period under analysis, it should be noted that the portfolio's statistical and economic significance figures do not meet this study's criteria for a successful strategy. In particular, the p-value of 0.06 for test-period returns is above the $p = 0.05$ threshold, while the corresponding Δ-value of 0.41 is below the $\Delta = 0.5$ threshold. Furthermore, CAPM alphas, despite being positive in two out of the three cases, are on average even more statistically insignificant than the test-period returns themselves.

The above-presented results are inconsistent with the majority of UK-stock-market-based evidence on the contrarian and momentum effects as most of the studies documented sizeable intermediate-term returns, typically in excess of 1% per month (see *e.g.*, Chelley-Steeley and Siganos, 2004; Hon and Tonks, 2003; Li *et al.*, 2008; Siganos and Chelley-Steeley, 2006; Weimin *et al.*, 1999). For example, in one of the more recent studies Li *et al.* (2008), investigating monthly LSPD data between 1975 and 2001, reported that a six-month/six-month strategy yields the highest return out of all momentum strategies, with profits estimated at 1.93% per month.

Furthermore, in line with the results for the two US stock markets discussed in the previous sections, in UK (LSE) the positive formation-period average return on the highest past-return portfolio seems to revert to a negative average return in the test period, albeit more slowly than the negative formation-period average return on the lowest past-return portfolio reverts to a positive average return in the test period.

In conclusion, equal-weighted, decile portfolio-size group, contrarian and momentum strategies are not profitable in UK (LSE), at least by the adopted specifications and standards. Therefore, the first alternative hypothesis is rejected for this stock market. These results are in contrast to the earlier findings for UK (LSE) in the area of contrarian and momentum investing. In addition, there appears to be strong evidence of negative autocorrelation in returns on the extreme past-return portfolios.

4.3.4. BULGARIA (BSE-SOFIA)

Bulgaria (BSE-Sofia) is the first EU12 stock market to be evaluated in terms of hypothesis number one of the present research. As can be verified by an examination of Table 13 and Table 14 in the 'Background information on the US, UK and EU12 investment environments' section of this chapter, the Bulgarian stock market positions itself at the 45th percentile of the EU12 stock markets by market capitalisation and at the 82nd percentile of the EU12 stock markets by the number of companies which, among other statistics, suggests that it is of medium-to-high importance as compared to the remaining 11 individual European populations that comprise the EU12.

Similarly to the rest of the EU12 stock markets, there are virtually no studies of the contrarian effect or the momentum effect for Bulgaria (BSE-Sofia). To be more accurate, in the case of Bulgaria and seven other EU12 stock markets only one academic publication on the momentum effect could be identified, *i.e.* by De Groot *et al.* (2012), and none on the contrarian effect. This very recent study by De Groot *et al.* (2012), as it was published and included in the 'Literature review' chapter after over two-thirds of the present research had been completed, is however, it might be argued, subject to a number of consequential shortcomings. Although a more thorough analysis of those limitations is available in the 'Literature review' chapter, it should be noted that the authors based their study on, *inter alia*, one aggregate stock market (*i.e.*, results for individual stock markets were not published) and an unconventional portfolio-size group, *i.e.* quintiles. However, since it is the only publication with, at least, some direct relevance for six out of the nine individual EU12 stock markets studied, it shall be referred to on a number of occasions. The present study constitutes, therefore, the only consistent and comprehensive research into both the contrarian effect and the momentum effect for the EU12 economies.

Table 19 on the next page presents all $H_{(1)}$-relevant empirical data for Bulgaria (BSE-Sofia).

TABLE 19. BULGARIA (BSE-SOFIA): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	30	4.66	0.22	$0.01 <= p <= 0.05$	0.3043	0.07	0.6381
P10L	29	-0.48	1.18	$p < 0.01$	0.7391	-0.12	0.7564
P1S/P10L	-	-5.14	0.95	$p < 0.01$	0.3913	-0.21	0.6648
PmL	291	0.43	0.27	-	-	0.00	-

The investment strategies based on P1L, P10L and P1S/P10L all demonstrate statistical significance of returns (at $p < 0.05$), but only in the case of P10L are the returns also economically significant (at $\delta > 0.5$). Specifically, P10L produces an astounding average, market-adjusted return of about 15.2% per month during the time period studied, which explains the low p-value of below 0.01 and the high δ-value of approximately 0.74. This result is the more impressive given that the Bulgarian stock market as a whole appears to have performed extraordinarily well between 2000 and 2011, with monthly returns ranging from 4.5% in the test period to 7.2% in the formation period, on average. The presence of a strong 'bull market', to some extent, also helps to rationalise the very high returns in absolute terms to all of the investment portfolios discussed. However, P10L's CAPM alpha is decidedly negative and statistically insignificant (at $p_{OLS} \approx 0.76$ and $p_{NW} \approx 0.68$), which means that the portfolio's systematic risk can account for all of its profitability (and more). Still, as for US (NYSE-AMEX), US (NASDAQ) and UK (LSE), there is evidence here strongly indicative of asymmetric return reversion for both P1 and P10.

As far as the magnitude of contrarian and momentum returns is concerned, the above results by far exceed the profits documented in the related literature. Specifically, De Groot *et al.* (2012), who have been the only researchers to formally consider Bulgaria (BSE-Sofia) in the context of momentum investing up until now, albeit exclusively as a part of an aggregate universe of stocks from 24 developing markets, documented returns ranging from 0.87% to 1.69% per month. This profit is comparable to the momentum return for the Latin American markets of 1.17% per month reported by Muga and Santamaria (2007a) as well as the contrarian return for Brazil (Sao Paulo Stock Exchange) of between 1.58% to 2.14% per month reported by Da Costa (1994). However, both Rouwenhorst (1999) and Griffin *et al.* (2003) showed that the overall momentum profitability in international emerging markets is reliably below 1%.

To conclude, Bulgaria (BSE-Sofia) positions itself as one of the more important EU12 stock markets, as measured by the number of listed companies, but it is not associated with any successful contrarian and momentum strategies, at least by this study's specification and standards. Consequently, $H_{1(1)}$ is rejected for Bulgaria (BSE-Sofia). There is, however, evidence of asymmetric negative autocorrelation in returns.

4.3.5. CYPRUS (CSE)

The Cypriot stock market is perhaps of lesser importance if compared to Bulgaria (BSE-Sofia) by the number of listed companies, *i.e.* 128 ($P_{\text{EU12}} \approx 0.72$)[57] *versus* 287 ($P_{\text{EU12}} \approx 0.82$) companies, respectively, however in terms of stock market capitalisation it actually surpasses the Bulgarian stock market by 18.74%, with the respective figures of €7.16bn ($P_{\text{EU12}} \approx 0.55$) *versus* €6.03bn ($P_{\text{EU12}} \approx 0.45$), as presented in Table 13 and Table 14. Therefore, contrary to what might be suggested by its relatively small GDP ($P_{\text{EU12}} \approx 0.18$), Cyprus (CSE) in fact positions itself in the more important half of the EU12 stock markets, as determined by the first two measures.

As mentioned in the second paragraph of the previous subsection, this study constitutes the only consistent and comprehensive research into both the contrarian effect and the momentum effect for the EU12 economies. What is more, unlike the case of Bulgaria (BSE-Sofia), there are no studies on either of the two effects to date that even consider Cyprus (CSE) and, thus, no direct comparisons will be possible.

Table 20 on the next page presents all $H_{(1)}$-relevant empirical data for Cyprus (CSE).

[57] 'P_{EU12}' stands for the percentile of the EU12 stock markets, excluding the aggregate EU12 stock market.

TABLE 20. CYPRUS (CSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10S is the lowest past-return portfolio (based on a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1S	12	-1.11	0.08	$p > 0.05$	0.3913	0.06	0.0952
P10S	12	0.52	0.03	$p > 0.05$	0.2174	0.00	0.9825
P1S/ P10L	-	-1.63	0.05	$p < 0.01$	0.1304	0.04	0.2700
PmL	122	0.00	-0.01	-	-	0.00	-

It can be immediately seen from Table 20 that only the arbitrage portfolio, based on a short position in P1 and a long position in P10, generates returns that are statistically different from zero at $p < 0.01$. However, the economic significance accompanying this result is unacceptably low at $\delta \approx 0.13$, which falls substantially below the $\delta = 0.5$ threshold. In addition, even though the arbitrage portfolio's CAPM alpha is positive, it lacks statistical significance at $p_{OLS} \approx 0.27$ and $p_{NW} \approx 0.28$. Of note is also the fact that while the return pattern for both P1 and P10 does show signs of reversal in the test period, in the case of this stock market positive returns associated with **P1L** appear to revert more quickly to negative returns than negative returns associated with **P10L** appear to revert to positive returns.

In terms of magnitude, the observed returns to Cyprus's (CSE) contrarian and momentum strategies, seem to match the less than 1% per month documented by some earlier studies of international emerging markets (*e.g.*, Griffin *et al.*, 2003; Rouwenhorst, 1999), but in most cases are appreciably below the 1% to 2% per month found by Muga and Santamaria (2007a) for the Latin America markets, Naughton *et al.* (2008) for China or Sehgal and Balakrishnan (2004) for India.

In conclusion, despite the relatively small size of the Cypriot economy, Cyprus (CSE) may be regarded as one of the most important stock markets studied, as determined by the number of listed companies and stock market capitalisation. There have, nevertheless, been no studies directly testing either the contrarian or the momentum hypothesis for the Cypriot stock market or even indirectly, as a part of an aggregate universe of stocks, until now. Overall, Cyprus (CSE) can be characterised as a stock market with little past-return-based effect inclination, at least by the adopted specifications and standards. Although the average return on the arbitrage portfolio is statistically significant, it does not even approach the economic significance threshold set by this study. Importantly, for the majority of the past-return-based portfolios considered, these findings are in contrast to the results reported for most international developing markets, both in terms of the magnitude of returns as well as the statistical significance of returns. Hypothesis One can, therefore, be rejected for Cyprus (CSE). It should be added, however, that there seems to be evidence of negative autocorrelation in returns for both extreme past-performance portfolios.

4.3.6. CZECH REPUBLIC (PSE)

Out of all EU12 stock markets, Czech Republic (PSE) has by far the highest average stock market capitalisation per listed company. With the stocks of each of the 25 listed companies being worth, on average, as much as €1.96bn (see Table 13 and Table 14), the relative importance of the Czech stock market is, not surprisingly, very high as compared to the other EU12 stock markets by the market value of equity ($P_{\text{EU12}} \approx 0.91$), but at the same time it is very low when importance is measured by the number of companies ($P_{\text{EU12}} \approx 0.18$). This means that although Czech Republic (PSE) is a stock market which can be characterised by relatively stable and secure equity-issuing companies (also known as blue-chip companies), on its own, the stock market offers little diversification to investors.

Identically to the case of Cyprus (CSE), the Czech stock market has not been examined in terms of either the contrarian or the momentum effect by any study to date, even as a part of an aggregate universe of stocks, as was the case with Bulgaria (BSE-Sofia) and the publication by De Groot *et al.* (2012) mentioned earlier. Therefore, the present research constitutes the only existing inquiry into the profitability of the two past-return-based effects for Czech Republic (PSE).

Table 21 on the next page presents all $H_{(1)}$-relevant empirical data for Czech Republic (PSE).

TABLE 21. CZECH REPUBLIC (PSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	30	0.33	0.09	$p < 0.01$	0.5652	0.04	0.0980
P10L	30	-0.11	0.06	$p < 0.01$	0.6522	0.01	0.5767
P1L/P10S	-	0.44	0.03	$p < 0.01$	0.0435	0.02	0.5617
PmL	295	0.04	0.04	-	-	0.00	-

Alongside Bulgaria (BSE-Sofia) and the aggregate EU12 stock market, Czech Republic (PSE) is one of the few stock universes examined in the course of this research for which, at least, one of the past-return-based portfolios studied demonstrates statistical and economic significance of returns. In particular, as shown in Table 21, both extreme past-performance portfolios generate test-period returns that are associated with $p < 0.01$ and $\delta > 0.5$. However, the corresponding CAPM alphas, despite being positive, are not statistically significant for either P1L (with $p_{OLS} \approx 0.10$ and $p_{NW} \approx 0.16$) or P10L (with $p_{OLS} \approx 0.58$ and $p_{NW} \approx 0.53$).

With the documented past-return-based effects not persisting after CAPM adjustment, the above-presented results may be argued to be inconsistent with the observations of Griffin *et al.* (2003) and Rouwenhorst (1999) for a number of international emerging markets, who reported average momentum payoffs above 0.5 % per month.

Notwithstanding the aforementioned lack of evidence in support of the contrarian and momentum effects, there appears to be a pattern in the results indicative of negative autocorrelation in returns for both extreme past-performance portfolios. Specifically, the return on the highest past-return portfolio seems to revert to negative returns, albeit not fully, while the return on the lowest past-return portfolio reverts to positive returns. This phenomenon can also be observed for the vast majority of the examined stock markets.

Overall, Czech Republic (PSE) may be considered to be one of the most important EU12 stock markets on account of its very high stock market capitalisation, both in total as well as per company. However, in light of the fact that none of the past-return-based portfolios investigated in this subsection survives CAPM adjustment for market risk, at least by the adopted specifications and standards, the alternative hypothesis number one is rejected for Czech Republic (PSE). Lastly, it should be noted that the returns on the extreme past-performance portfolios appear to exhibit asymmetric mean reversion, which affects the lowest past-return portfolio to a relatively greater degree than the highest past-return portfolio.

4.3.7. HUNGARY (BSE)

Similarly to the Czech stock market discussed earlier, Hungary (BSE) can be characterised by one of the highest figures for the average market value of equity per company out of all EU12 stock markets. Specifically, the stock market capitalisation of a typical BSE company amounts to approximately €466m (see Table 13 and Table 14), which places the Hungarian stock market at $P_{\text{EU12}} \approx 0.73$ by stock market capitalisation, right after Czech Republic (PSE), and at $P_{\text{EU12}} \approx 0.45$ by the number of listed companies. Therefore, as in the case of Bulgaria (BSE-Sofia), Hungary (BSE) may be considered to be of medium-to-high importance as compared to the other 11 individual EU12 stock markets.

However, not unlike Cyprus (CSE), the Hungarian stock market has not been the object, be it primary or secondary, of any inquiry into the effectiveness of contrarian or momentum strategies to date. This study may, consequently, be considered to be the first of its kind.

Table 22 on the next page presents all $H_{(1)}$-relevant empirical data for Hungary (BSE).

TABLE 22. HUNGARY (BSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	9	0.72	0.05	$p > 0.05$	0.0435	0.01	0.7259
P10L	9	-0.31	0.09	$p > 0.05$	0.1304	0.04	0.4782
P1S/P10L	-	-1.04	0.04	$p < 0.01$	0.1304	0.01	0.8546
PmL	88	0.05	0.03	-	-	0.00	-

The main findings of this subsection are as follows. There are no past-return-based strategies that are associated with both statistical and economic significance of returns for Hungary (BSE). This is consistent with the results for all individual EU12 stock markets. Although the arbitrage portfolio produces a statistically significant average return, this figure is not reliably different from zero at $\delta \approx 0.13$. Moreover, the probability accompanying CAPM alphas is dependably statistically insignificant for P1L, P10L as well as P1S/10L, with the *p*-values on all occasions being above 0.45.

In comparison with previous studies researching either the contrarian effect or the momentum effect in international developing markets, the findings for Hungary (BSE) would fall short of expectations even if all of the present portfolio returns were statistically and economically significant, considering that in the case of the least unsuccessful portfolio here (*i.e.*, P10L) the average monthly return amounts to only about 0.67% in market-risk-adjusted terms. While this return is in line with the results of Griffin *et al.* (2003) and Rouwenhorst (1999), it is substantially below the results of Da Costa (1994), Hameed and Kusnadi (2002) or Sehgal and Balakrishnan (2004).

It should be noted, however, that both the highest past-return portfolio and the lowest past-return portfolio appears to be subject to return reversal, whereby test-period returns move in the opposite direction to formation-period returns, yet in a manner that affects the former portfolio to a lesser extent than the latter portfolio.

To conclude, the Hungarian stock market is, similarly to Bulgaria (BSE-Sofia), one of the medium-to-high-importance EU12 stock markets, as determined by its percentile position in terms of stock market capitalisation and the number of listed companies. Alike its Bulgarian counterpart, Hungary (BSE) does not demonstrate any contrarian or momentum profitability on a statistically and economically significant level, at least by the adopted specifications and standards. Therefore, $H_{1(1)}$ is rejected for the Hungarian stock market. Still, of note is the fact that both extreme past-performance portfolios appear to be associated with asymmetric negative autocorrelation in returns, which is consistent with the evidence for the other stock markets examined.

4.3.8. LITHUANIA (VSE)

Together with Estonia (TSE) and Latvia (RSE), Lithuania (VSE) is a part of the NASDAQ OMX three-member group of Baltic stock markets (see Table 12). Not unlike its NASDAQ OMX co-members, the Lithuanian stock market is one of the smallest, individual EU12 stock universes, with a relative percentile position of $P_{\text{EU12}} \approx 0.27$ as determined by the total market value of equity and of $P_{\text{EU12}} \approx 0.36$ as determined by the total number of listed companies. The only study to consider this stock market in the context of contrarian and momentum investment strategies is, again, De Groot *et al.* (2012), who in their recent paper measured momentum returns in a single, aggregate stock market comprising the S&P Frontier BMI constituents. The findings of the present study are however, among other aspects, far more specific on account of considering Lithuania (VSE) separately from other stock markets.

Table 23 on the next page presents all $H_{(1)}$-relevant empirical data for Lithuania (VSE).

TABLE 23. LITHUANIA (VSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	6	0.90	0.20	$p > 0.05$	0.2174	0.07	0.1344
P10L	6	-0.36	0.11	$p > 0.05$	0.2174	0.01	0.8512
P1L/P10S	-	1.26	0.10	$p > 0.05$	0.3043	0.04	0.6255
PmL	58	0.10	0.09	-	-	0.00	-

As can be seen from Table 23, the results for Lithuania (VSE) are comparable in most aspects to the results for Latvia (RSE), discussed in the preceding subsection.

To being with, decile portfolios are of almost identical absolute size across the two stock markets, ranging between four and six stocks per an extreme past-return portfolio in the formation period. Another similar feature is the formation-period average return, with the highest past-return portfolio's (the lowest past-return portfolio's) absolute six-monthly return of 90% (-36%) and 96% (-29%) for Lithuania (VSE) and Latvia (RSE), respectively. The primary difference between the two sets of results lies in test-period average returns, whereby in the case of the Lithuanian stock market the highest past-return portfolio exhibits a stronger return continuation effect, while the lowest past-return portfolio shows a weaker return reversal effect. Still, both extreme past-performance portfolios seem to clearly exhibit asymmetric negative autocorrelation in returns. However, of greatest importance is the fact that neither one of the two stock markets is associated with a statistically and economically significant past-return-based effect. This finding may be surprising given many accounts of high contrarian and momentum profitability in international developing markets (see *e.g.*, Da Costa, 1994; De Groot *et al.*, 2012; Hameed and Kusnadi, 2002; Naughton *et al.*, 2008).

In conclusion, the Lithuanian stock market is one of the smaller and, consequently, less important EU12 stock markets, which offers no past-return-based strategies with both statistically and economically significant returns, at least by the adopted specifications and standards. For this reason, the first alternative hypothesis is rejected for the discussed stock universe. The present result is unexpected, given returns in excess of 1% per month to contrarian and momentum strategies documented in the pertinent literature on international developing markets. Nevertheless, a pattern of asymmetric return reversal can be observed for both extreme past-performance portfolios, which is in line with the evidence for the other stock markets examined in this study.

4.3.9. POLAND (WSE)

Poland (WSE) is the largest stock market in the EU12 by stock market capitalisation and the second largest by the number of listed companies. The total market value of equity of WSE's 486 companies is over 7.5 times the corresponding figures for BVB and PSE, the second and the third largest stock exchanges by the total market value of equity in the EU12, respectively (see Table 13). Although the Romania (BVB) boasts over three times the number of companies listed on Poland (WSE), the average stock market capitalisation of a Romanian company is more than 25 times lower than that of a typical Polish company. The Polish stock market is, therefore, one of the very most important individual universes of stocks studied in this thesis. Notwithstanding, there have been no publications on either the contrarian or the momentum effect for Poland (WSE), which underscores the uniqueness of this research.

Table 24 on the next page presents all $H_{(1)}$-relevant empirical data for Poland (WSE).

TABLE 24. POLAND (WSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	37	1.04	0.17	$p > 0.05$	0.0435	0.07	0.0275
P10L	36	-0.43	0.08	$p > 0.05$	0.1304	-0.01	0.7834
P1L/ P10S	-	1.47	0.09	$0.01 <= p <= 0.05$	0.4783	0.07	0.2134
PmL	361	0.09	0.07	-	-	0.00	-

Consistent with the evidence from all of the earlier-examined stock markets, there are no contrarian or momentum strategies for Poland (WSE) that can produce both statistically and economically significant profits. However, three aspects of the results in Table 24 should be noted.

Firstly, alike the case of four other EU12 stock markets[58], the returns on the arbitrage portfolio for Poland (WSE) can be characterised by statistical significance at $p \leq 0.05$, but not by economic significance equal to or above the $\delta = 0.5$ threshold. In addition, while the CAPM alpha of P1L/P10S is reasonably large and positive, the accompanying statistical significance of $p_{OLS} \approx 0.21$ and $p_{NW} \approx 0.17$ does not meet the standard of proof set by the first alternative hypothesis of this research.

Secondly, the highest past-return portfolio reliably outperforms the market portfolio even after risk-adjustment, as indicated by a CAPM alpha of 0.07 and the corresponding statistical significance of $p_{OLS} \approx 0.03$ and $p_{NW} \approx 0.03$. The fact that the portfolio's returns are associated with a low p-value of above 0.05 and an extremely low δ-value of approximately 0.04 suggests very high overall variability of returns. Indeed, a closer inspection of P1L's monthly returns reveals considerable variation, whereby returns range from a low of -6.39% per month to a high of 16.94% per month. Consequently, the portfolio has high overall average return, high overall variation of returns and low, marginally positive skewness of returns, as a result of the asymmetries on both sides of the standardised distribution balancing out. This observation finds its reflection in P1L's standard deviations and betas, which will be discussed in the next section of this chapter.

Thirdly, the results in Table 24 do appear to show the typical signs of asymmetric negative autocorrelation in returns. In particular, the highest past-return portfolio lost about 84% of its formation-period **upside** momentum in the test period, whereas the lowest past-return portfolio not only lost all of its formation-period **downside** momentum in the test period, but its average return also reversed to the upside by approximately 19%.

[58] These stock markets are Bulgaria (BSE-Sofia), Cyprus (CSE), Czech Republic (PSE) and Hungary (BSE).

In conclusion, Poland (WSE) is one of the very largest EU12 stock markets as determined by both the total stock market capitalisation and the total number of listed companies. Despite its regional importance, it has not been studied to date in the context of either the contrarian effect or the momentum effect. This research has found that the Polish stock market is not associated with either contrarian or momentum profitability of a statistically and economically significant magnitude, at least by the adopted specifications and standards. Therefore, the first alternative hypothesis is rejected for Poland (WSE). The analysed results do, however, indicate that both extreme past-return portfolios may be subject to return reversal, albeit to a varying degree.

4.3.10. ROMANIA (BVB)

Similarly to Poland (WSE), discussed in the previous subsection, Romania (BVB) is one of the very most important stock markets examined in this study. Relative to the remaining 11 constituents of the EU12 investment universe, the Romanian stock market is the largest stock market as measured by the number of listed companies and the third largest stock market as measured by the total market value of equity. However, like all of its EU12 counterparts, Romania (BVB) has not received much attention from the researchers investigating the contrarian and momentum effects in international developing markets. In fact, it has only been considered by De Groot *et al*. (2012), yet exclusively as a part of a substantially larger, collective pool of stocks. Therefore, this study constitutes the only research into the effectiveness of contrarian and momentum investment strategies in Romania (BVB) to date.

Table 25 on the next page presents all $H_{(1)}$-relevant empirical data for Romania (BVB).

TABLE 25. ROMANIA (BVB): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	32	2.23	0.18	$p > 0.05$	0.1304	-0.19	0.0108
P10L	32	-0.43	0.61	$p > 0.05$	0.8261	0.32	0.1128
P1S/ P10L	-	-2.66	0.43	$p > 0.05$	0.3913	0.49	0.0463
PmL	316	0.22	0.22	-	-	0.00	-

As can be seen from Table 25, all three past-return-based portfolios for Romania (BVB) fail to generate statistically and economically significant returns, despite the fact that test-period profitability reaches as high as 10.17% per month in absolute terms for P10L. Although the lowest past-return portfolio's result is economically significant with $\delta \approx 0.83$, the corresponding statistical significance is still above the $p = 0.05$ threshold. It is also interesting to note that while P10L's CAPM alpha is large and positive, the associated p-value is above $p_{OLS} = 0.11$ (but $p_{NW} \approx 0.05$). This suggests high variability of returns, which is confirmed by standard deviations and betas in Table 82 and Table 83, respectively. On the other hand, the arbitrage portfolio, based on a short position in P1 and a long position in P10, also has high variability of returns, but not relative to the market. Consequently, the portfolio's test-period average return is not statistically different from zero at $p \leq 0.05$, but it has a large, positive and statistically significant CAPM alpha of 0.49 at $p_{OLS} \approx 0.05$ and $p_{NW} \approx 0.02$. As the last point concerning the discussed empirical data it should be highlighted that, in line with the evidence from the previous subsections, the returns on the two extreme past-performance portfolios appear to demonstrate asymmetric negative autocorrelation.

Not unlike the case of its EU12 counterparts, the results for the Romanian stock market may disappoint in the light of many accounts documented in the relevant literature. Specifically, De Groot *et al*. (2012) reported statistically significant momentum profits ranging from 0.87% to 1.69% per month in absolute terms for a large, artificially-created stock universe consisting of 24 frontier markets. Although Rouwenhorst (1999) showed that the overall momentum profitability across 20 international emerging markets is reliably below 1% for an arbitrage portfolio, the estimate was still statistically significant.

To conclude, the Romanian stock market is one of the most important individual universes of stocks examined in this study. However, none of the three past-return-based portfolios examined for Romania (BVB) can be characterised by both statistical and economic significance of returns in the test period, at least by the adopted specifications and standards. Therefore, $H_{1(1)}$ is rejected for this stock market. There is, however, evidence of asymmetric negative autocorrelation in returns.

4.3.11. SLOVAKIA (BSSE)

Slovakia (BSSE) positions itself at the 0.36 percentile of the EU12 stock markets by the total market value of equity and at the 0.55 percentile of the EU12 stock markets by the total number of listed companies. Therefore, it is one of the low-to-medium importance individual EU12 stock universes. Slovakia (BSSE), similarly to Slovenia (LJSE) discussed next and five other EU12 stock markets, has only been considered in the context of contrarian and momentum investing in one study of return momentum by De Groot *et al*. (2012). The study, however, suffers from a number of consequential limitations, including not investigating stock markets of individual countries, but an aggregate sample comprising 24 such stock universes. In consequence, the present research is the only examination of the Slovak stock market for the presence of a viable past-return-based investment strategy to date.

Table 26 on the next page presents all $H_{(1)}$-relevant empirical data for Slovakia (BSSE).

TABLE 26. SLOVAKIA (BSSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	18	4.83	0.49	$p > 0.05$	0.3913	0.36	0.4531
P10L	18	-0.29	1.03	$p > 0.05$	0.5652	0.58	0.5263
P1S/ P10L	-	-5.12	0.54	$p > 0.05$	0.1304	0.21	0.8406
PmL	177	0.49	0.50	-	-	0.00	-

It can be seen from Table 26 that all three past-return-based portfolios are associated with statistically, and in most cases economically, insignificant returns. As with Romania (BVB), the lowest past-return portfolio for Slovakia (BSSE) does demonstrate an economically significant return of as much as 17.17% per month in absolute terms, but as per the other two investment portfolios the corresponding *p*-value is statistically insignificant at $p > 0.05$. It is worth noting that the Slovak stock market as a whole performed extraordinary well between 2000 and 2011, showing an absolute average monthly return of about 8.33%. A similar phenomenon has been observed for Bulgaria (BSE-Sofia), where average monthly returns ranged from 4.5% in the test period to 7.2% in the formation period. Additionally, neither one of the three past-return-based portfolios can be seen to reliably outperform the market, as indicated by the CAPM figures, despite boasting large CAPM alphas. It is interesting to note, however, that both extreme past-return portfolios appear to demonstrate asymmetric negative autocorrelation in returns, which is in line with the evidence presented for the other 12 stock universes covered by this study.

Even though the magnitude of the observed, test-period returns on P1L, P10L and P1S/P10L for Slovakia (BSSE) is substantially greater than the corresponding values for even the most contrarian-effect- and momentum-effect-conducive international developing stock markets (see *e.g.*, Muga and Santamaria, 2007a; Naughton *et al.*, 2008; Sehgal and Balakrishnan, 2004), it is never accompanied by statistical significance. The profitability of a similar strategy in De Groot *et al*. (2012) is 1.19% per month in absolute terms, except that the authors used: (1) an aggregate universe of stocks comprising 24 stock markets, including Slovakia (BSSE); (2) quintile, rather than decile, portfolio-size groups; and (3) a 12-month formation period.

In conclusion, Slovakia (BSSE) might be regarded as one of the low-to-medium importance EU12 stock markets, as indicated by the total market value of equity and the total number of listed companies measures. The results presented in this subsection indicate that no statistically and economically significant past-return-based strategies exist for the discussed stock market, at least by the adopted specifications and standards. $H_{1(1)}$ can, therefore, be rejected. There is, however, evidence of asymmetric negative autocorrelation in returns.

4.3.12. SLOVENIA (LJSE)

The last individual stock market to be discussed in the context of the first and foremost hypothesis of this research is Slovenia (LJSE). Its relative percentile position to the remaining 11 stock markets of the EU12 is $P_{\text{EU12}} \approx 0.64$ by both stock market capitalisation as well as the number of listed companies. Thus, the Slovenian stock market is reliably one of the most important individual EU12 stock universes examined. To date, Slovenia (LJSE), similarly to Bulgaria (BSE-Sofia), Lithuania (VSE), Romania (BVB) and Slovakia (BSSE), has only been considered in the context of either contrarian or momentum investing by De Groot *et al*. (2012) in a study of the momentum effect in international stock markets based on an aggregate universe of S&P Frontier BMI stocks.

Table 27 on the next page presents all $H_{(1)}$-relevant empirical data for Slovenia (LJSE).

TABLE 27. SLOVENIA (LJSE): INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1S	15	-1.14	0.01	$p > 0.05$	0.2174	0.01	0.6792
P10L	15	-0.36	0.51	$p > 0.05$	0.3043	-0.10	0.4555
P1S/ P10L	-	-1.50	0.53	$p > 0.05$	0.4783	-0.07	0.6112
PmL	147	0.09	0.09	-	-	0.00	-

The main finding of this subsection is that there are no strategies associated with statistically and economically significant returns for Slovenia (LJSE). This result is consistent with the earlier observations for all individual EU12 stock markets. The arbitrage portfolio, based on a short position in P1 and a long position in P10, generates the largest average monthly return of 8.83% in absolute terms. Although this figure is not statistically significant, it does approach the economic significance threshold, with δ-value equal to about 0.48. It is also worth noting that none of the three past-return-based portfolios performs reliably better than the market portfolio. The lowest p-value of roughly 0.46 for a CAPM alpha can be observed for the highest past-return portfolio, albeit the alpha itself is negative.

In addition to the above it should be added that both P1S and P10L appear to exhibit pronounced return reversal. While this is rather evident in the case of P10L, whose return, on average, reverses from -6% per month in the formation period to 8.5% per month in the test period, it might not be as clear in the case of P1S, whose test-period average return is only about 0.17% per month. However, it needs to be stressed that P1 is associated with over three times larger formation-period momentum in terms of absolute value than P10.

As far as the magnitude of returns is concerned, the contrarian profits documented for Slovenia (LJSE) are, in the case of P10L and P1S/P10L, nearly four times greater than those documented by earlier studies for the most promising international developing markets (see *e.g.*, De Groot *et al.*, 2012; Muga and Santamaria, 2007a; Naughton *et al.*, 2008; Sehgal and Balakrishnan, 2004). Nonetheless, due to the lack of statistical (and economic) significance, this result should be seen as unreliable.

Taking the above into consideration, $H_{1(1)}$ can be rejected for Slovenia (LJSE). Therefore, it would appear that in the present case past performance is not predictive of future performance, at least by the adopted specifications and standards. While the magnitude of returns to the Slovenian past-return-based strategies is sometimes substantially greater than that reported in other relevant studies, this result cannot be regarded as reliable. There is, however, evidence of negative autocorrelation in returns.

4.3.13. THE EU12 STOCK MARKET

The EU12 stock market is an artificial stock universe created for the purposes of this study, which comprises stocks traded in all developing EU countries (also known as the EU12). It should be reiterated at this point that the level of each country's development has been determined not only on the basis of a country's ability to meet the strict economic EU accession requirements[59], but also on the basis of a demanding, global-investor-orientated Standard and Poor's Dow Jones Indexes Country Classification System (2011), as discussed in the introduction to this thesis. To understand the importance of the EU12 as an investment destination, for both EU investors as well as non-EU, international investors, it is necessary to be aware of the fact that, through a standardised system of laws that apply in all member states, the EU has developed a single market (also known as the European Economic Area or, simply, EEA), which, among many other privileges, allows for the free movement of people, goods, services and capital within the EEA as well as is characterised by common policies on trade and most important legislation in justice (European Commission, 2013). The main idea behind this integration is to create an internal market free of national borders and barriers, which enables businesses and individuals to operate as seamlessly across the EU member states as within each EU member state (*ibid.*). Therefore, the EEA may be portrayed as an economic environment that is, indeed, very secure, transparent and conducive to financial investment. This evaluation is clearly corroborated by the analysis in the 'Background information on the US, UK and EU12 investment environments' section, especially by the provided recent example of unswerving support of EU institutions for those of the member states that have been most severely affected by the Eurozone Crisis.

However, what is significant, while there are a number of studies investigating the functioning of stock markets for the developed EU economies (*i.e.*, the EU15[60]), this is

[59] *N.B.* The EU15 countries have been full EU members on/before the 1st of January 1995, whereas the EU12 candidate countries gained accession to the EU between the 1st of May 2004 and 31st of June 2013 inclusive. It is important to note that Croatia, which joined the EU on the 1st of July 2013, as well as any potential, future EU members are not studied in this thesis.

[60] The EU15 comprises the following 15 EU member countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom.

not the case for the newer, less-developed EU members (*i.e.*, the EU12[61]), as was clearly indicated by, among others, each foregoing EU12-related subsection. From the practical perspective of investors, this research gap may constitute a significant investing deterrent, deepening the already substantial home bias of the investment community (see *e.g.*, French and Poterba, 1991; Karlsson and Norden, 2007), despite the fact that the EU12 stock markets, similarly to their US and UK counterparts, are suitable even for conservative investors, as shown in Section 4.2., and the fact that less-developed stock markets have been documented to allow much greater return on investment (see *e.g.*, Cajueiro and Tabak, 2005; Claessens *et al.*, 1995; Harvey, 1995). From the theoretical perspective of policymakers and academics, it is absolutely crucial for the prosperous future of the EU12 stock markets, and by implication the EU12 economies, to promote the publication of investor-orientated research, so as to attract foreign capital and facilitate wealth equalisation within the EEA.

Currently, this study represents the only EU12-focused research into stock market efficiency founded on the performance examination of the most rudimentary, historical-data-based investment strategies, *i.e.* the contrarian and momentum investment strategies. As presented in the earlier subsections, there are virtually no studies on either the contrarian or the momentum effect for the individual countries comprising the EU12. This is also the case for the EU12 market as a whole. One of the main reasons behind the creation of the aggregate, EU12 stock universe was to construct an index of those EU stocks that are traded in countries which, on the one hand, share similar economic characteristics and growth potential and, on the other hand, can successfully compete with the larger, more-developed, individual stock universes, such as US (NYSE-AMEX), US (NASDAQ) and UK (LSE), both in terms of investment opportunities as well as in terms of liquidity and diversification. This objective, as shown in the present chapter, has been successfully accomplished.

Table 28 on the next page presents all $H_{(1)}$-relevant results for the EU12 stock market.

[61] Just as a reminder, the EU12 consists of the following 12 EU member countries: Bulgaria, Czech Republic, Cyprus, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia.

TABLE 28. EU12 STOCK MARKET: INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter. In addition to CAPM alphas (and the associated statistical significance), Appendix H also considers the Fama and French's (1996) three-factor model alphas (and the associated statistical significance) as well as the Carhart's (1997) four-factor model alphas (and the associated statistical significance). However, unlike the CAPM-related statistics presented here, those additional models are based on (1) factors discounted from an annual to a semi-annual form to match the six-monthly portfolio return data; and (2) the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors for both the UK and the EU12 regressions. Therefore, all data and analysis in Appendix H should only be treated as complementary to the main data and analysis that is presented in this section.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	193	2.05	0.22	0.0017	0.7461	-0.02	0.8261
P10L	193	-0.43	0.32	0.0000	1.1879	0.21	0.0221
P1S/P10L	-	-2.48	0.11	0.1874	0.2837	0.20	0.0953
PmL	1924	0.17	0.14	-	-	0.00	-

The observed returns on P1L and P10L are the only results in Table 28 that demonstrate statistical significance below the p = 0.05 threshold and economic significance above the Δ = 0.5 threshold. In particular, the highest past-return portfolio generates about 22% after six months or 3.67% per month (with p < 0.01 and $\Delta \approx 0.75$), whereas the lowest past-return portfolio produces an even more astounding profit of approximately 32% after six months or 5.33% per month (with p < 0.01 and $\Delta \approx 1.19$). Even after adjusting for the market return, P1L and P10L still yield a respectable return of roughly 1.33% and 3% per month, respectively. The arbitrage portfolio, on the other hand, appears to perform worse than the market as a whole, risk considerations aside, and a positive return only arises under the condition that the more favourable long-short positions are adopted. However, it needs to be stressed that this underperformance is neither statistically nor economically significant, with $p \approx 0.19$ and $\Delta \approx 0.28$.

Although both P1L and P10L yield profits that are statistically and economically different from zero, it seems that only the return on P10L would survive a risk adjustment using CAPM. The reason for this is that the CAPM alpha of the highest past-return portfolio is both negative and statistically insignificant, whereas the lowest past-return portfolio has a large and positive CAPM alpha of 0.21, which also happens to be statistically significant at $p_{OLS} \approx 0.02$ and $p_{NW} \approx 0.05$. Therefore, the CAPM-adjusted return on P10L would be equal to 3.5% per month.

Incidentally, the contrarian effect associated with P10L is also robust to a more severe risk adjustment using a model based on two factors: the market factor (defined, identically to the case of CAPM, as the return on the market portfolio less the 'risk-free' rate) and the size factor (defined as the return on the portfolio of stocks issued by the 10% of the smallest companies less the return on the portfolio of stocks issued by the 10% of the largest companies[62]). The inclusion of the second factor can be justified by the fact that a number of studies have viewed company size as a proxy for risk (see *e.g.*, Chan and Chen, 1988; Chen and Zhang, 1998; Fama and French, 1995) or the size effect (see *e.g.*, Banz, 1981; Brown, Kleidon and Marsh, 1983;

[62] This specification of the size (or 'small-minus-big') factor is consistent with several studies (for a review see *e.g.*, van Dijk, 2011).

Jegadeesh, 1992; Keim, 1983; Reinganum, 1981). While the size effect (also known as the small-firm effect) is a separate stock market phenomenon to the momentum effect and, by itself, is not linked to any adverse investment consequences, the same cannot be said about excess risk exposure. However, it is important to stress that seeing company size as a proxy for risk is controversial, among others, due to the lack of a consistent underlying theory, such as the Modern Portfolio Theory for CAPM. Still, the alpha of the aforementioned multivariate regression with two explanatory variables is large, positive and statistically significant, with $\alpha \approx 0.17$, $p_{OLS} \approx 0.04$ and $p_{NW} \approx 0.04$. Therefore, the two-factor-model-adjusted return on P10L would be equal to about 2.83% per month, which is less than 20% below the CAPM-adjusted figure.

From a practical perspective, by adopting a long position in P10 alone investors may expect an absolute return of 5.33% per month. Thus, an investment of €1m should earn, on average, approximately €53,300 each month gross of transaction costs. This profit is not only substantial when considered in the broad financial markets' investment context, but it is also well in excess of the corresponding figures reported in the related literature for aggregate developing-country stock universes to date.

By comparison, Rouwenhorst (1999) documented an average monthly return on the lowest past-return portfolio for the six-month/six-month timeframe of 1.74% in absolute terms for 20 international emerging markets. An identical strategy yielded only 0.32% per month for the 20 emerging markets studied in Griffin *et al.* (2003). Similarly to Rouwenhorst (1999), the best performing strategy in De Groot *et al.* (2012) based on all of the 24 S&P Frontier BMI markets returned 1.69% per month. Therefore, it can be clearly seen that the test-period profitability of the lowest past-return portfolio for the EU12 stock market yields over three times the return of other developing-country stock universes. It is also important to remember that unlike the case of the vast majority of other developing countries, the EU12 offers a secure, transparent and supportive investment environment, as discussed in, among others, the introduction to this subsection.

To conclude, the EU12 stock market is a universe of stocks constructed for the purposes of this study that comprises stocks traded in the less-developed economies of the EU. The primary reason behind creating this index was to combine the otherwise small stock markets operating in the investment-conducive EEA, which have received very little attention from the academic community, despite the virtually untapped stock market potential thereof, and form a collective stock pool that can successfully compete with the more developed stock markets not only in terms of investment returns, but also in terms of investment liquidity, stability and diversification. This subsection, together with the information in the 'Background information on the US, UK and EU12 investment environments' section, suggests that the aforementioned objective has been achieved.

While the EU12 investment environment is, indeed, comparable to that of the US and the UK, as pointed out in Section 4.2., the EU12 stock market is the only stock universe in this study with any past-return-based portfolios demonstrating both statistical and economic significance of returns as well as positive and statistically significant CAPM alpha. In specific, the lowest past-return portfolio yields, on average, 5.33% per month in absolute terms, 3.5% per month in CAPM-adjusted terms or 2.83% per month in the two-factor-model-adjusted terms. This return is over three times that documented in the relevant earlier studies, which is especially impressive considering the substantially greater relative transparency and supportiveness of the EEA investment environment. Therefore, the first alternative hypothesis of this research is accepted for this stock universe.

4.4. TESTING HYPOTHESIS TWO: ARE CONTRARIAN OR MOMENTUM STRATEGIES ASSOCIATED WITH UNFAVOURABLE INVESTMENT CHARACTERISTICS?

The primary objective of this part of the chapter is to establish whether stocks comprising extreme past-performance and, where applicable, arbitrage portfolios can be considered to possess unfavourable investment characteristics as compared to the typical stock from the same stock market. In particular, if contrarian and momentum strategies are associated with excess risk exposure, low-priced stocks, illiquid trading positions or high transaction costs, then those investment strategies may effectively be impracticable regardless of the level of profitability prior to risk or market microstructure adjustment. It is, therefore, important to view the following analysis and evaluation of Hypothesis Two, *i.e.* $H_{(2)}$, as complementary to the earlier discussion pertaining to the first and foremost hypothesis of the present research.

There are two broad groups of investment characteristics that are considered for each of the 13 stock markets. The first group, labelled 'risk characteristics', comprises a comprehensive selection of seven different measures of risk found in finance and financial economics literature, those are: (1) standard deviation; (2) downside standard deviation; (3) beta; (4) downside beta; (5) the standard error of the CAPM regression; (6) the R-squared of the CAPM regression; and (7) the market value of equity. In addition, it should be noted that exchange rate risk as well as macroeconomic risk have already been factored in the return calculations analysed in Section 4.3., as discussed in 'Methodology' chapter and the 'Background information on the US, UK and EU12 investment environments' subsection of this chapter. The second group of investment characteristics considered, named 'market microstructure characteristics', consists of three measures, *i.e.* average price, average volume and average bid-ask spread, which estimate the actual average price of a stock per portfolio, the actual average volume of stocks traded per portfolio (serving as a proxy for the level of liquidity) and the average bid-ask spread per portfolio (serving as a proxy for the level of transaction costs), respectively. For more information about the aforementioned measures and the associated calculation procedures the reader should refer to the 'Methodology' chapter.

4.4.1. US (NYSE-AMEX)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for US (NYSE-AMEX). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.1.1. RISK CHARACTERISTICS

The risk assessment of past-return-based portfolios for US (NYSE-AMEX) can be divided into two main parts. In the first, more involved part the analysis is focused on the standard deviation statistics (see Table 29, p. 271) and the CAPM-related statistics (see Table 30, p. 272). The complexity thereof entails a special need for good judgement and perspicuity. Meanwhile, the second part is limited to the ME statistics only (see Table 31, p. 275), which can be relatively easily evaluated on the basis of the statistical and economic significance test results. It is also important to note that unlike the measures discussed in the first part, the appropriateness of employing average ME as a proxy for risk is much more controversial, among others, due to the lack of a consistent underlying theory, such as the Modern Portfolio Theory for volatility-based measures.[63]

[63] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 29. US (NYSE-AMEX): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	0.44	N/A	0.23	0.25
P10	0.19	0.47	0.32	0.26
P1/P10	0.36	N/A	0.22	0.12
Pm	0.20	0.19	0.21	0.20

TABLE 30. US (NYSE-AMEX): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (*p*) associated with an *F*-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	1.82	-1.07	1.04	1.20	0.2263	0.0850	0.7337	0.8634	0.0000	0.0000
P10L	0.85	2.64	1.40	1.43	0.0946	0.1438	0.7730	0.8004	0.0000	0.0000
P1L/P10S	1.00	-3.66	-0.35	-0.19	0.2982	0.2149	0.3032	0.0656	0.0038	0.1256
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

The standard deviation figures in Table 29 indicate that past-return-based strategies may be subject to a certain degree of excess total risk, depending on which investment portfolio is selected. In particular, test-period figures suggest that while the extreme past-performance portfolios are associated with above market-average volatility, the arbitrage portfolio is equally or less volatile than the market as a whole. Furthermore, the conventional standard deviation indicates that the test-period difference between P10 and Pm is as high as 52.38% relative to the benchmark. However, the corresponding figure for the downside measure[64] is equal to 30% and in the case of P1/P10 it is -40%, which means that the arbitrage portfolio is substantially less volatile than the market as a whole. Arguably, the latter gauge of total risk is more relevant to investors, considering that the focus thereof is solely on the possibility of an unexpected financial loss and not on the possibility of an unexpected financial gain.

The above results are in line with the CAPM-related statistics, which can be seen in Table 30. Although the conventional and downside test-period betas are higher for the extreme past-return portfolios as compared to the market portfolio, especially in the case of downside beta, the figures for the arbitrage portfolio are below one. In fact, the conventional as well as the downside beta of P1L/P10S is negative in the test period, which is a result of going long in the less volatile P1 and going short in the more volatile P10. This finding is in line with the observations made in the existing literature (*e.g.*, JT, 1993; 2001) and has two important implications. First, it suggests that P1L/P10S is associated with no positive systematic risk. Second, it indicates that the return volatility detected by the corresponding standard deviations is either mostly unsystematic in nature or CAPM itself is incorrectly specified. This interpretation is strongly supported by the standard error, adjusted R-squared and p-value of the CAPM regression (see Table 31), all of which show that the market factor

[64] *N.B.* The unavailability of the downside standard deviation statistic for P1/P10 in the formation period is due to the fact that there are no negative returns for P1 in that period. This is not unusual for a portfolio that comprises stocks with the highest past return and is also clearly supported by the corresponding downside beta statistic, which is negative. However, it is important to stress that the unavailability of a downside statistic in any time period is not synonymous with the absence of downside risk. It only signifies that during the time period considered there is insufficient data to evaluate the behaviour of a portfolio below zero (standard deviation) or on the falling market (beta).

alone offers little help in the process of rationalising the observed pattern of returns on the arbitrage portfolio, especially in the test period.

As far as the risk change hypothesis is concerned (see *e.g.*, Ball and Kothari, 1989; Chan, 1988; Vermaelen and Verstringe, 1986), both standard deviations and betas show that the risk premium associated with the arbitrage portfolio is typically lower in the test period than in the formation period. In the case of the extreme past-return portfolios, there is no conclusive evidence in that respect, with roughly half of the results suggesting increasing risk and the other half decreasing risk.

The results for the last factor to be discussed in this part of the subsection, *i.e.* the market value of equity (ME), are presented in Table 31 on the next page.

TABLE 31. US (NYSE-AMEX): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***Δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***Δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	3206.61	0.0000	1.6477	3741.31	0.0001	1.5007	0.0246
P10	1992.75	0.0000	2.2122	1707.34	0.0000	2.4408	0.0450
Pm	6749.60	-	-	6988.36	-	-	-

Unlike the previous six measures, which are based on return volatility, average ME may be considered to be a less reliable proxy for risk as it is based on the controversial premise that smaller companies are inherently more risky than larger companies (see *e.g.*, Fama and French, 1996). If this is assumed to be the case, then individually the extreme past-return portfolios are, indeed, more risky than the market portfolio, both in the formation period as well as in the test period (see Table 31). However, it is important to point out that the test-period average ME for P1 is over twice the corresponding figure for P10 and, therefore, any small-firm-in-distress risk premium for which ME may proxy (see *e.g.*, Chan and Chen, 1988; Chen and Zhang, 1998; Fama and French, 1995) will highly depend on the investment portfolio selected. Furthermore, in the case of the arbitrage portfolio based on a long position in P1 and a short position in P10, the counterbalancing effect of shorting a still lower-than-average-ME portfolio also needs to be taken into account. In reality, if ME is correlated with risk positively and uniformly across the cross-section of stocks, then the positive risk premium associated with holding P1 should be more than offset by the negative risk premium earned by short-selling P10. Therefore, there should be no additional (positive) risk premium resulting from differences in ME associated with P1L/P10S. The above findings are equally applicable to a scenario where ME does not proxy for risk, but only for the size effect (see *e.g.*, Banz, 1981; Brown, Kleidon and Marsh, 1983; Jegadeesh, 1992; Keim, 1983; Reinganum, 1981).

Another important consideration is that if the small-firm-in-distress risk premium were to be adjusted for in addition to the earlier-discussed excess return volatility premium, then this operation would no doubt lead to a substantial over-adjustment. The reason for this is that it is more than likely that the returns on shares of marginal firms in distress are characterised by abnormal volatility, assuming only the lowest levels of investor rationality and market efficiency in response to, among others, drastic dividend cuts and high financial leverage associated with such firms (see *e.g.*, Chan and Chen, 1988).

4.4.1.2. MARKET MICROSTRUCTURE CHARACTERISTICS

In addition to the risk characteristics discussed earlier, there are three fundamental market microstructure characteristics that will be considered, *i.e.* price (see Table 32, p. 278), volume (see Table 33, p. 279) and the bid-ask spread (see Table 34, p. 280).[65]

[65] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 32. US (NYSE-AMEX): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***Δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***Δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	66.37	0.5859	0.6874	77.14	0.7497	0.4788	0.1392
P10	12.54	0.0000	2.3522	10.62	0.0000	2.5762	0.0041
Pm	88.59	-	-	92.33	-	-	-

TABLE 33. US (NYSE-AMEX): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***Δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***Δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	226.55	0.4284	0.2365	249.01	0.5223	0.1939	0.0622
P10	231.93	0.5117	0.1971	250.47	0.6000	0.1834	0.3042
Pm	258.86	-	-	276.13	-	-	-

TABLE 34. US (NYSE-AMEX): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***Δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***Δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	1.68%	0.5412	0.1901	1.27%	0.9709	0.0103	0.0034
P10	3.10%	0.0205	1.2105	3.50%	0.0091	1.7933	0.0941
Pm	1.41%	-	-	1.28%	-	-	-

In line with Conrad and Kaul (1993) as well as Ball *et al*. (1995), the information in Table 32 suggests that P10, *i.e.* the lowest past-return portfolio, is composed of relatively low-priced stocks, which may suffer from increased price-related microstructure-induced effects. However, this problem is perhaps not as serious as the price statistics would indicate, with the average price of a P10 stock being seven to nine times lower than the market average, considering the fact that a stock valued at €10 cannot be accurately described as a low-priced (or 'penny') stock. The US Securities and Exchange Commission (2013) generally defines a 'penny stock' as a security issued by a very small company that trades at less than $5 per share. This price is substantially below €10 per share considering that the highest USD/EUR exchange rate during the time period under analysis was 1.17 (*N.B.,* $5 x 1.17 = €5.85), while the average exchange rate was a mere 0.85 (*N.B.,* $5 x 0.85 = €4.25). Furthermore, the more informative bid-ask spread statistics (see Table 34) also suggest that the impact of market microstructure frictions may be substantially less pronounced than previously indicated, given that the P10 figures here are only up to 2.73 times higher than the market average. The observed divergence of the price-based and the bid-ask-spread-based indicators can be explained by the fact that the average liquidity of stocks in both extreme past-return portfolios is, in fact, comparable to the liquidity of the market portfolio (see Table 33), thereby reducing the effect of market frictions initially implied by price estimates. This also means that a liquidity risk premium, as proposed by Sadka (2003), does not help to rationalise the momentum anomaly within the efficient market hypothesis framework. On a closing note, it is crucial to highlight that the above-mentioned adverse market microstructure effects do not relate to the highest past-return portfolio.

In conclusion, the extreme past-performance portfolios formed from US (NYSE-AMEX) stocks appear to be associated with excess risk and excess market microstructure frictions, at least by the adopted specifications and standards. It should be noted, however, that the arbitrage portfolio is likely to benefit from a netting effect, whereby the net exposure to risk and market microstructure frictions is below the market-average level. Taking the above into consideration, the second alternative hypothesis is rejected for US (NYSE-AMEX).

4.4.2. US (NASDAQ)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for US (NASDAQ). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.2.1. RISK CHARACTERISTICS

This part of the subsection focuses on the evaluation of past-return-based portfolios' risk characteristics, which process is facilitated by empirical data provided in Table 35 (p. 283), Table 36 (p. 284) and Table 37 (p. 285).[66]

[66] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 35. US (NASDAQ): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	0.63	N/A	0.24	0.24
P10	0.19	0.58	0.41	0.32
P1/P10	0.56	N/A	0.33	0.15
Pm	0.24	0.21	0.23	0.21

TABLE 36. US (NASDAQ): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (*p*) associated with an *F*-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	2.26	-1.80	0.91	1.09	0.3245	0.1132	0.7354	0.7810	0.0000	0.0000
P10L	0.67	2.92	1.51	1.54	0.1102	0.2021	0.6760	0.7542	0.0000	0.0000
P1L/P10S	1.61	-4.66	-0.59	-0.39	0.4193	0.3005	0.4485	0.1442	0.0003	0.0417
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 37. US (NASDAQ): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, and Δ-values are the Glass's Effect Sizes. The probability (p) associated with the Student's Paired t-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***Δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***Δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	861.09	0.0284	0.9107	1070.21	0.2255	0.5031	0.0002
P10	378.16	0.0000	1.9406	281.56	0.0000	2.0580	0.0023
Pm	1288.09	-	-	1325.35	-	-	-

The standard deviation statistics in Table 35 suggest that the lowest past-return portfolio is much more volatile than either the highest past-return portfolio or the market portfolio in the test period. Differently, the highest past-return portfolio has similar risk characteristics to the market portfolio, while the arbitrage portfolio is substantially more advantageous as compared to the market portfolio in terms of total downside risk. The same pattern can be observed for betas in Table 36. In particular, two observations should be noted. First, the lowest past-return portfolio consistently demonstrates a large and positive test-period beta of about 1.5, as indicated by both the conventional as well as the downside measure. Second, the arbitrage portfolio is associated with a negative beta, which is quite rare and implies that the portfolio's returns move in the opposite direction to most stocks and, thus, could be used as a hedge against the market. However, what is more significant still is that the absolute value of the negative beta does not exceed $|\beta| = 1$ and, thus, under no market conditions is past-return-based arbitrage expected to be more risky than the market-average level. As far as the standard error, adjusted R-squared and p-value of the CAPM regression are concerned, both the formation-period and the test-period statistics indicate that P1L/P10S has the lowest systematic component out of all portfolios. Overall, these results are closely in line with the evidence for US (NYSE-AMEX) discussed in the preceding subsection, perhaps with the small difference being that here the highest (lowest) past-return portfolio is more (less) similar to the market portfolio.

Furthermore, it would appear that both P1 and P10 comprise companies that are, on average, smaller than the typical US (NASDAQ) company. However, while the difference in the test-period average ME between P10 and Pm is statistically and economically significant at $p < 0.01$, this is not the case with P1, for which the test-period p-value equals $p \approx 0.23$. It should also be noted that the change in the average ME between the formation period and the test period is statistically significant for both P1 and P10, with the associated p-values being below the $p = 0.01$ threshold, albeit only the lowest past-return portfolio can be characterised by decreasing ME over time.

4.4.2.2. MARKET MICROSTRUCTURE CHARACTERISTICS

Alike the case of the other stock markets that are under analysis in this study, there are three groups of market microstructure statistics that will be considered for US (NASDAQ): price, volume and the bid-ask spread. All the essential information is presented in Table 38 (p. 288), Table 39 (p. 289) and Table 40 (p. 290).[67]

[67] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 38. US (NASDAQ): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***Δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***Δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	18.48	0.8664	0.0754	21.06	0.2057	0.5354	0.0039
P10	8.06	0.0000	2.0204	6.12	0.0000	2.3338	0.0006
Pm	18.11	-	-	18.28	-	-	-

TABLE 39. US (NASDAQ): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, and Δ-values are the Glass's Effect Sizes. The probability (p) associated with the Student's Paired t-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***Δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***Δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	128.49	0.5613	0.2566	142.32	0.1325	0.6544	0.0045
P10	100.80	0.0413	0.9217	96.91	0.0040	1.2800	0.3769
Pm	122.46	-	-	126.96	-	-	-

TABLE 40. US (NASDAQ): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, and Δ-values are the Glass's Effect Sizes. The probability (p) associated with the Student's Paired t-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***Δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***Δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	1.66%	0.4025	0.2579	1.28%	0.0223	0.5878	0.0185
P10	2.63%	0.0847	0.6429	3.14%	0.0149	1.0555	0.0613
Pm	1.94%	-	-	1.94%	-	-	-

It can be immediately noticed from Table 38, Table 39 and Table 40 that as far as the price, volume and bid-ask spread estimates are concerned only the lowest past-return portfolio can be described as statistically and economically different from the market portfolio at the 5% significance level. In particular, the test-period average price for a P10 stock of €6.12, which is 2.99 times below the market average and might be regarded as borderline consistent with the basic definition of a 'penny stock' provided by the US Securities and Exchange Commission (2013), also referred to as SEC. However, the corresponding ME figure for P10 is €281.56m (see Table 37), which is substantially above the market value of $5m normally expected by SEC for a company issuing 'penny stocks', as detailed in the Securities Exchange Act of 1934. In addition, it is important to point out that the volume statistics and the bid-ask spread statistics are much less unfavourable for P10, both statistically as well as in terms of relative value. Specifically, P10 is 'only' 1.31 times less liquid and 1.61 times more transaction-cost intensive than Pm in the test period. The highest past-return portfolio, on the other hand, is in most cases statistically indistinguishable from the market portfolio, albeit the average price and volume for P1 are consistently higher in both the formation period and the test period as compared with the corresponding Pm figures. More importantly still, the highest past-return portfolio's stocks typically have lower bid-ask spreads than the market average, which difference is both statistically and economically significant in the test period.

In conclusion, although US (NASDAQ) can, indeed, be characterised by substantially smaller equity-issuing companies than US (NYSE-AMEX), the risk and market microstructure profile of past-return-based strategies is similar across the two stock markets. In particular, while the highest past-return portfolio appears to have comparable, albeit somewhat less favourable, investment characteristics in relation to the market portfolio, the returns on the lowest past-return portfolio tend to be much more volatile and potentially prone to excess market microstructural frictions. This is interesting, considering the fact that it is the highest past-return portfolio that earns the greatest return on both US (NYSE-AMEX) as well as US (NASDAQ) during the time period under analysis, although the return itself is neither statistically nor economically different from zero. Still, $H_{1(2)}$ is rejected for this stock market.

4.4.3. UK (LSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for UK (LSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.3.1. RISK CHARACTERISTICS

As in all previous subsections of this section, the first stage of the past-return-based strategies' investment characteristics appraisal is risk assessment. This can be divided into two parts: (1) return-volatility-based statistics and analysis (see Table 41 and Table 42, pp. 293-294); and (2) ME statistics and analysis (see Table 43, p. 297).[68]

[68] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 41. UK (LSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	1.38	N/A	0.13	0.14
P10	0.15	0.39	0.29	0.23
P1/P10	1.37	N/A	0.23	0.16
Pm	0.17	0.10	0.16	0.10

TABLE 42. UK (LSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (*p*) associated with an *F*-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	7.68	-1.23	0.32	0.98	0.5396	0.1283	0.8472	0.1108	0.0000	0.0679
P10L	0.43	4.18	0.66	2.31	0.1414	0.2755	0.1677	0.1035	0.0281	0.0810
P1L/P10S	7.25	-5.24	-0.33	-1.15	0.6588	0.2328	0.7670	0.0171	0.0000	0.2805
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

The standard deviation and beta statistics shown in Table 41 and Table 42 indicate that, in most cases, the lowest past-return portfolio may be regarded as more risky than the market portfolio. Although the formation-period downside return variability is not a reliable measure of relative riskiness, considering that P10 is by design composed of the most extreme stock returns on the low side, the test-period figures for the downside standard deviation and beta suggest that the lowest past-return portfolio's returns might be approximately 2.3 times more volatile than the market portfolio's returns, on average. The highest past-return portfolio, on the other hand, is typically accompanied by less risk than the market portfolio, both in terms of total exposure as well as relative to the market portfolio. Only the downside standard deviation is higher for P1 as compared to Pm by 40%, which in conjunction with the fact that the conventional and downside betas are below one suggests either a reasonably large unsystematic component of risk or misspecification of CAPM. The former explanation seems to be corroborated by, among others, the very low test-period adjusted *R*-squared of the CAPM regression ($R^2 < 12\%$) as well as the unacceptably high corresponding *p*-values ($p > 0.06$) for **all** past-return-based portfolios.

The arbitrage portfolio appears to position itself somewhere between the lowest past-return portfolio and the highest past-return portfolio in terms of riskiness. In the case of P1/P10 (or, more precisely, P1L/P10S) the total risk, as indicated by standard deviations, is substantially above the market figures, while market risk, as indicated by betas, is in three out of four instances markedly below the market-average level. Importantly, as far as the market risk calculations for P1L/P10S are concerned, the arbitrage portfolio benefits from what might be called a 'bilateral netting effect', whereby the systematic risk exposure is lowered by assuming a long position in the portfolio with the lower beta (*i.e.*, P1L) and a short position in the portfolio with the higher beta (*i.e.*, P10L). It should be mentioned, however, that this effect can also be observed for the reverse long-short arrangement (*i.e.*, with a long position in the more volatile portfolio and a short position in the less volatile portfolio), but it becomes less beneficial as the divergence between the betas increases (see *e.g.*, Table 60).

Furthermore, as Table 43 on page 297 clearly demonstrates, the companies whose stocks comprise the lowest past-return portfolio are smaller in the test period than the market average at a statistically and economically significant level. Therefore, if ME were to proxy for risk, then, *ceteris paribus*, investing in P10 would be reliably more risky than investing in Pm. The highest past-return portfolio can, however, be characterised by companies that are, on average, larger than a typical UK (LSE) company, which observation is supported by statistical significance at $p \approx 0.08$ and economic significance at $\Delta \approx 1.86$.

TABLE 43. UK (LSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, and Δ-values are the Glass's Effect Sizes. The probability (p) associated with the Student's Paired t-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***Δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***Δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	3492.02	0.2085	1.1683	3797.40	0.0753	1.8590	0.0306
P10	2113.43	0.0658	1.4115	1671.26	0.0016	2.1903	0.0945
Pm	2867.70	-	-	2821.31	-	-	-

4.4.3.2. MARKET MICROSTRUCTURE CHARACTERISTICS

All empirical information necessary to determine whether UK's (LSE) past-return-based strategies are associated with above-average market frictions has been organised into three tables found on pages 299, 300 and 301.[69]

[69] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 44. UK (LSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***Δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***Δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	19.99	0.5846	0.6446	18.89	0.3438	0.8874	0.7015
P10	17.00	0.9158	0.0918	11.08	0.0107	1.8515	0.0066
Pm	17.37	-	-	16.36	-	-	-

TABLE 45. UK (LSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***Δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***Δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	24771.39	0.9288	0.0642	24092.06	0.4486	0.5882	0.3216
P10	18870.99	0.0009	2.5633	19803.01	0.0020	2.5081	0.0228
Pm	24627.18	-	-	25406.06	-	-	-

TABLE 46. UK (LSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***Δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***Δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	7.12%	0.0039	0.8429	6.69%	0.0006	1.0424	0.1794
P10	13.63%	0.0000	1.6348	14.64%	0.0000	2.0001	0.1016
Pm	9.34%	-	-	9.41%	-	-	-

The price statistics in Table 44 suggest that the test-period average price of a P10 stock is both statistically and economically different from a typical UK (LSE) stock, which implies price-related microstructure-induced biases for that portfolio. Furthermore, the corresponding volume and bid-ask spread data, presented in Table 45 and Table 46, respectively, clearly indicate the possibility of excess market frictions in both the formation period as well as the test period. Specifically, the lowest past-return portfolio is about 22.05% less liquid and 55.58% more transaction-cost intensive than the market portfolio, which is confirmed by both statistical significance at $p < 0.01$ and economic significance at $\Delta > 2$. It should be noted, however, that allowing for all differences in investment characteristics simultaneously would result in over-adjustment, on account of the fact that price-related biases, liquidity premia and bid-ask spread premia are related. Buying or selling the highest past-return portfolio, on the other hand, would be associated with market microstructural factors that are more favourable than it would be the case with buying or selling the market portfolio. In particular, the bid-ask spread is 28.91% lower for P1 relative to Pm, which figure is both statistically and economically significant.

Importantly, the above results are in line with Ellis and Thomas (2003), who found that transaction costs associated with momentum investing in UK (LSE) are substantially higher than it has been previously assumed in the literature (see *e.g.*, JT, 1993; Rouwenhorst, 1998; Weimin *et al.*, 1999). In addition, as reported by Agyei-Ampomah (2007), Badreddine *et al.* (2012) and Li *et al.* (2009), here the overall cost of implementing momentum strategies also dominates the return.

In conclusion, it would seem that the lowest past-return portfolio for UK (LSE) can, indeed, be reliably characterised as an investment with above-average risk and market microstructure frictions, at least by the adopted specifications and standards. This, however, does not appear to be the case with the highest past-return portfolio, which is typically associated with a more favourable investment profile than the portfolio of all UK (LSE) stocks. Still, the second alternative hypothesis is rejected for the discussed stock market.

4.4.4. BULGARIA (BSE-SOFIA)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Bulgaria (BSE-Sofia). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.4.1. RISK CHARACTERISTICS

In line with the methodology employed in the preceding subsections, two categories of risk characteristics are considered, these are: (1) return-volatility-based characteristics (see Table 47 and Table 48, pp. 304-305); and (2) the market-value-of-equity characteristics (see Table 49, p. 307).[70]

[70] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 47. BULGARIA (BSE-SOFIA): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	5.11	N/A	0.54	0.19
P10	0.21	0.53	1.85	0.07
P1/P10	5.12	N/A	1.98	N/A
Pm	0.57	N/A	0.26	N/A

TABLE 48. BULGARIA (BSE-SOFIA): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	8.94	N/A	0.53	N/A	0.7211	0.5297	0.9801	0.0215	0.0000	0.2366
P10L	0.04	N/A	5.08	N/A	0.2142	1.3251	-0.0369	0.4841	0.6455	0.0001
P1S/P10L	-8.90	N/A	4.53	N/A	0.8985	1.6293	0.9692	0.3219	0.0000	0.0028
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

Both the conventional standard deviation and the conventional beta statistics indicate that the variability of P1's (or, more precisely, P1L's) returns decreases substantially from the formation period to the test period both in absolute terms as well as relative to Pm (or, more precisely, PmL). However, while in the case of the latter risk measure the decline in return volatility is drastic and a negative risk premium is observed in the test period, in the case of the former risk measure it is only moderate and the risk premium remains high in the test period at about twice the benchmark figure. This can be contrasted with the results for P10L, for which there is approximately a ninefold increase in total risk and a 127-fold increase in market risk between the two periods. It should be noted, however, that while in terms of the conventional standard deviation the results for both P1 and P10 are substantially above the market average, as far as the conventional beta is concerned only P10L appears to be excessively risky. Similarly to P10L, the arbitrage portfolio is associated with over 7.5 times the total risk and over 4.5 times the market risk of the portfolio composed of all Bulgaria (BSE-Sofia) stocks in the test period.

The high standard error and the low *R*-squared of the CAPM regression in the test period for all past-return-based portfolios seem to suggest that CAPM could be misspecified, although it is also possible that most of the return volatility detected by the test-period standard deviations and betas is unsystematic in nature.

Furthermore, the ME statistics presented in Table 49 on the next page indicate that only the lowest past-return portfolio can be subject to excess size-related risk or the size effect. The two statistically significant results thereof, at $p < 0.05$, signal that: (1) P10 is comprised of companies with predominantly below-average market capitalisation; and (2) the average size of a P10's company decreases from the formation period to the test period. Both these effects may be considered to be undesirable on account of the fact that a number of studies show an inverse relationship between ME and risk (see *e.g.*, Chan and Chen, 1991; Chen and Zhang, 1998). At this point it should be reiterated, though, that small-firm-in-distress risk and return volatility are likely to be correlated and adjusting for the two risk premia separately is likely to lead to an over-adjustment.

TABLE 49. BULGARIA (BSE-SOFIA): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	22.96	$p > 0.05$	0.1718	26.60	$p > 0.05$	0.2961	$p > 0.05$
P10	10.58	$0.01 <= p <= 0.05$	0.3775	7.33	$p < 0.01$	0.5474	$0.01 <= p <= 0.05$
Pm	18.37	-	-	19.45	-	-	-

4.4.4.2. MARKET MICROSTRUCTURE CHARACTERISTICS

Following risk assessment, it would now be informative to consider the impact of market microstructure on past-return-based strategies for Bulgaria (BSE-Sofia). Table 50 (p. 309), Table 51 (p. 310) and Table 52 (p. 311) provide all the necessary empirical data for this purpose.[71]

[71] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 50. BULGARIA (BSE-SOFIA): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	**δ-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	**δ-value** (test period price)	***p*-value** (formation-test period price)
P1	4.67	$p > 0.05$	0.0586	5.83	$p > 0.05$	0.1531	$0.01 <= p <= 0.05$
P10	2.70	$p > 0.05$	0.1342	1.86	$p > 0.05$	0.2779	$p < 0.01$
Pm	2.80	-	-	2.74	-	-	-

TABLE 51. BULGARIA (BSE-SOFIA): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	120.31	$p > 0.05$	0.0624	125.88	$p > 0.05$	0.0208	$p > 0.05$
P10	398.55	$p < 0.01$	0.5614	86.61	$p < 0.01$	0.5803	$p > 0.05$
Pm	158.83	-	-	170.10	-	-	-

TABLE 52. BULGARIA (BSE-SOFIA): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	**δ-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	**δ-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	0.45	$p > 0.05$	0.1976	0.41	$p > 0.05$	0.0167	$p > 0.05$
P10	0.43	$p > 0.05$	0.1071	0.53	$p > 0.05$	0.2782	$p > 0.05$
Pm	0.39	-	-	0.42	-	-	-

As can be clearly seen from Table 50 and Table 52, the price and the bid-ask spread associated with stocks creating both P1 as well as P10 are not reliably different, by either the statistical or the economic significance standards adopted by this study, from Pm. It is informative to learn, nonetheless, that while the average price of P1's stocks increases in a statistically significant manner from the formation period to the test period, the opposite can be observed for P10. This would strongly suggest that P10 is associated with excess time-varying risk if, at least, the portfolio's test-period average price were itself statistically and economically different from the test-period average stock price for Bulgaria (BSE-Sofia).

However, the only $H_{(2)}$-relevant results indicating both statistical and economic significance are volume statistics (see Table 51), which show that stocks in P10 are, on average, traded more often in the formation period and less often in the test period relative to stocks in Pm. Specifically, test-period volume figures suggest that the typical P10 stock is about half as liquid as the typical Bulgaria (BSE-Sofia) stock. This means that trading P10's stocks might be associated with a liquidity premium.

In conclusion, Bulgarian past-return-based portfolios appear to be affected by excess risk exposure, due to above market-average volatility of test-period returns. In addition, the ME statistics indicate that buying or selling the lowest past-return portfolio's stocks is associated with unfavourable investment characteristics in the form of holding stocks issued by companies with below-average market capitalisation. Such investment positions have been linked in the finance literature to abnormal risk and/or the size effect, which is a separate stock market anomaly from the contrarian or momentum effects. It should be noted, nevertheless, that the Sharpe-Lintner CAPM has relatively low explanatory power in Bulgaria (BSE-Sofia) in general, which suggests either stock market inefficiency or the inadequacy of the model to account for the cross-sectional dispersion of expected stock returns. The gathered evidence points towards the latter explanation, especially considering the return statistics and the exceptionally high total risk of all past-return-based portfolios. Moreover, the market microstructure analysis revealed that the lowest past-return portfolio may be associated with a liquidity premium. In the light of all of the above evidence, $H_{1(2)}$ is rejected for this stock market.

4.4.5. CYPRUS (CSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Cyprus (CSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.5.1. RISK CHARACTERISTICS

The risk assessment of past-return-based strategies for Cyprus (CSE) entails the analysis of (1) return-volatility-related statistics, which process is based on empirical data in Table 53 (p. 314) and Table 54 (p. 315); as well as (2) the market-value-of-equity statistics, for which the relevant empirical information can be found in Table 55 (p. 316).[72]

[72] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 53. CYPRUS (CSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	1.74	N/A	0.21	0.24
P10	0.15	0.55	0.28	0.25
P1/P10	1.67	N/A	0.18	0.13
Pm	0.30	0.19	0.30	0.20

TABLE 54. CYPRUS (CSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10S is the lowest past-return portfolio (based on a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1S	-5.02	1.26	-0.45	-0.87	0.9143	0.1583	0.7245	0.4213	0.0000	0.0006
P10S	-0.41	-2.48	-0.69	-0.90	0.0917	0.1965	0.6372	0.5152	0.0000	0.0001
P1S/P10L	-4.60	3.82	0.24	0.10	0.9807	0.1766	0.6562	0.1091	0.0000	0.0683
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 55. CYPRUS (CSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	79.42	$p < 0.01$	0.3535	84.82	$p < 0.01$	0.3384	$p > 0.05$
P10	73.58	$p < 0.01$	0.6030	37.64	$p < 0.01$	0.7240	$p < 0.01$
Pm	84.37	-	-	72.73	-	-	-

As can be seen from Table 53 and Table 54, past-return-based portfolios are unlikely to be associated with abnormal risk, at least insofar as return volatility measures are concerned. With the exception of the downside standard deviation, all test-period statistics relating to P1S, P10S and P1S/P10L suggest a level of riskiness that is well below the market average. Although the downside standard deviation for P1 and P10 is greater as compared to Pm by 20% and 25%, respectively, the remaining results do not support the view that either one of the two groups of stocks is riskier than Pm. Interestingly, the standard error and the adjusted R-squared of the CAPM regression seem to indicate that, out of all portfolios, P1S/P10L has the largest firm-specific component in the test period, assuming that CAPM itself is correctly specified. However, the associated p-value is above the $p = 0.05$ threshold, which suggests that this assumption may not be valid and that the market factor, at least on its own, lacks explanatory power insofar as the returns on the two portfolios are concerned.

The last group of the investment characteristics discussed in this part of the subsection are the market-value-of-equity statistics, which may be seen as a proxy for either risk or the size effect (see Table 55).

Chen and Zhang (1998) as well as Chan and Chen (1991), among others, suggested that profits to past-return-based strategies are linked to differences in ME, whereby smaller equity-issuing companies outperform larger equity-issuing companies (a phenomenon also known as the size effect or the small-firm effect). If marginal firms in distress indeed drive contrarian and momentum profitability, then a strategy based on a long position in larger companies and a short position in smaller companies should earn a negative risk premium. This could be the case in the investment context of Cyprus (CSE). It can be seen from Table 55, that a long position in P1 is associated with firms of above market-average ME in the test period, which result is statistically significant at $p < 0.01$. The ME statistics for the lowest past-return portfolio, on the other hand, demonstrate statistically and economically significant below-average ME per the typical P10 company in both periods, which value is additionally reliably decreasing in time with the corresponding p-value equal to $p < 0.01$. However, a strategy solely based on P10 or, alternatively, on a short position in P1 and a long position in P10 (*i.e.*, P1S/P10L) would earn a positive risk premium.

4.4.5.2. MARKET MICROSTRUCTURE CHARACTERISTICS

Although contrarian and momentum strategies for Cyprus (CSE) do not appear to be associated with excess risk in the case of most measures employed, it is also critical to address another group of practical considerations, *i.e.* market microstructure characteristics (see Table 56, Table 57 and Table 58, pp. 319-321).[73]

[73] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 56. CYPRUS (CSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	**δ-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	**δ-value** (test period price)	***p*-value** (formation-test period price)
P1	536.64	$p < 0.01$	0.6597	534.82	$p < 0.01$	0.6597	$p > 0.05$
P10	1.07	$p < 0.01$	0.9471	0.43	$p < 0.01$	1.0000	$p < 0.01$
Pm	245.13	-	-	244.78	-	-	-

TABLE 57. CYPRUS (CSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	1664.18	$p > 0.05$	0.1115	1206.52	$p > 0.05$	0.2817	$p < 0.01$
P10	1541.03	$p > 0.05$	0.1758	1255.68	$p > 0.05$	0.1493	$p > 0.05$
Pm	1347.67	-	-	1169.27	-	-	-

TABLE 58. CYPRUS (CSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	**δ-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	**δ-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	18.02%	$p > 0.05$	0.0769	19.50%	$p > 0.05$	0.0510	$p > 0.05$
P10	29.40%	$0.01 <= p <= 0.05$	0.5621	27.53%	$p > 0.05$	0.4694	$p > 0.05$
Pm	14.63%	-	-	16.01%	-	-	-

The empirical data in both Table 57 and Table 58 indicate that the extreme past-performance portfolios are unlikely to suffer from above-average market microstructure frictions. Most notably, while the test-period expected bid-ask spread for P10 is borderline economically significant with $\delta \approx 0.47$, the statistic remains statistically insignificant with $p > 0.05$. Additionally, it should be pointed out that the expected formation-period and test-period volume for both P1 and P10 is above-average, which means that, during the time period studied, stocks comprising the two past-return-based portfolios were more liquid than the market portfolio of all stocks. Therefore, on the basis of data presented thus far, there is no reason to think that either contrarian or momentum strategies might be abnormally illiquid or costly.

However, the price statistics in Table 56 worryingly suggest that P10 might be composed of extremely low-priced stocks, which would normally be indicative of price-related microstructure-induced biases. A closer inspection reveals that both the highest past-return portfolio and the market portfolio results are mainly driven by one outlier, *i.e.* a share priced at around €40,000, which according to Datastream is a major Cypriot security issued by a company named Ucyprus (DS code: 143911; DS mnemonic: HLTST), with a listing history of over 19 years and comprehensive data type availability, including variables such as the return index (RI), the price index (PI), the dividend yield (DY) or the P/E ratio (PE). Importantly, the extraordinarily high price of the security alone is insufficient to render it an erroneous data entry. It is, indeed, possible for a stock to be priced that high and the NYSE-listed Berkshire Hathaway Inc. provides a prominent example of this. On the last trading day of the studied time period, *i.e.* on the 30th of December 2011, one share of that American company traded at over €150,000 and upon its exclusion from the sample of over 4350 stocks the average market price for NYSE-AMEX on that day dropped from €116.91 to €38.44. While it is relatively easy to authenticate such fundamental financial information for a still active and well-known American company, this is not the case for an inactive company from Cyprus. Importantly, the Cypriot security does not appear to be an outlier in the case of other variables. Most importantly, in terms of RI it is neither in the top 10th nor in the bottom 10th percentile of the data.

It is of course tempting to simply remove the 'inconvenient' data. After excluding the problematic share from the sample, the test-period price for P1 drops dramatically from its current level of €534.82 to just €3.72 or in the case of Pm from €244.78 to €3.37. However, this incident underscores the fact that even after comprehensive data screening, it is still necessary to critically evaluate research outcomes. It is also important to remember that stocks in the highest past-return portfolio as well as stocks in the lowest past-return portfolio are, strictly speaking, return outliers from a statistical point of view, which is clearly not very helpful insofar as data screening and data analysis are concerned. While some might suggest to use the median as an indicator of central tendency in this situation, not only would that be inconsistent with most results presented in the existing literature (see *e.g.*, Conrad and Kaul, 1993; Ball *et al*., 1995; Loughran and Ritter, 1996), but more importantly it would require a different type of statistical test as the present tests are based on the difference between means. As regards statistical tests for the difference in medians, those are not very popular due to, among others, the fact that the standard error of the median is about 25% larger than that of the mean for large samples and, hence, the tests are not very powerful (Yule, 1917).

The foregoing discussion raises the question of market microstructure implications. It is clear that even after excluding the outlier, the price of a typical P10 stock is still well below the market average and it matches most price-based definitions of a penny stock. However, while P10 stocks may be considered to be penny stocks on the basis of price alone, the volume and the bid-ask spread statistics indicate that these stocks are neither less liquid nor more transaction-cost intensive than Pm stocks, which mitigates many of the problems mentioned by SEC (2013). The bid-ask spread is also a more reliable statistic than price as it is based on data that is (1) very detailed (which is unlikely to be available for a fictitious stock); (2) standardised (*i.e.*, it is expressed in relative terms and so price outliers are less likely to affect its value); and (3) available for two variables (hence, it requires more information to be calculated). Another potential issue is that low-priced stocks might be associated with greater return volatility, since a practically small price change will lead to a large return change in absolute terms. However, the notion that the return of P10 is more volatile than the return of Pm is generally not supported by the evidence presented in the preceding part of this subsection. When discussing the price-related microstructure-induced biases in the context of contrarian and momentum strategies for Cyprus (CSE) it is important to remember that P1 is not composed of low-priced stocks, be it before or after the problematic outlier has been removed. Therefore, it would seem that although P10 can be characterised by below-average-price stocks, the return volatility, volume and bid-ask spread statistics indicate that this is unlikely to impact negatively on the performance of a strategy based on that portfolio.

In conclusion, while there is little evidence to suggest that past-return-based strategies are associated with excess return volatility on Cyprus (CSE), the lowest past-return portfolio appears to be predominantly composed of stocks issued by relatively small companies. If the market value of equity is assumed to proxy for risk, such as small-firm-in-distress risk (see *e.g.*, Chan and Chen, 1988; Chen and Zhang, 1998; Fama and French, 1995), then the portfolio should be seen as reliably riskier than the benchmark of all Cypriot stocks. Furthermore, having considered all aspects of market microstructure in the context of the extreme past-performance portfolios, it might be argued that although the lowest past-return portfolio is composed of below-average-price stocks, this is unlikely to have negative investment consequences. It is important to note, however, that price statistics have been significantly affected by an outlier, whose authenticity is difficult to determine. This incident underscores the need for critical analysis, even after rigorous data screening, and highlights the real-life challenges associated with research in applied quantitative finance and financial economics. Overall, on account of unfavourable ME statistics for the lowest past-return portfolio, the alternative hypothesis number two is rejected for the discussed stock market.

4.4.6. CZECH REPUBLIC (PSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Czech Republic (PSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.6.1. RISK CHARACTERISTICS

The data relating to the risk characteristics of past-return-based strategies for the Czech stock market has been organised into three categories: standard-deviation-related statistics (see Table 59, p. 326); CAPM-related statistics (see Table 60, p. 327); and ME-related statistics (see Table 61, p. 328).[74]

[74] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 59. CZECH REPUBLIC (PSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	0.24	N/A	0.13	0.08
P10	0.13	0.17	0.10	0.13
P1/P10	0.29	N/A	0.11	0.07
Pm	0.05	0.07	0.05	0.06

TABLE 60. CZECH REPUBLIC (PSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	3.04	0.10	1.76	1.17	0.1857	0.0981	0.3721	0.4466	0.0012	0.0003
P10L	1.11	2.84	1.64	1.65	0.1216	0.0564	0.1314	0.6867	0.0499	0.0000
P1L/P10S	1.96	-2.49	0.13	-0.25	0.2799	0.1181	0.0666	-0.0443	0.1239	0.7997
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 61. CZECH REPUBLIC (PSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	718.61	$p < 0.01$	0.5085	805.68	$p < 0.01$	0.5047	$p < 0.01$
P10	360.37	$p > 0.05$	0.1078	309.15	$p > 0.05$	0.0964	$p > 0.05$
Pm	172.79	-	-	178.04	-	-	-

The standard deviation statistics presented in Table 59 suggest that although past-return-based portfolios are noticeably more volatile than the market portfolio in the test period, most of that volatility comes from unexpected above-average returns, rather than from unexpected below-average returns. This is evident from the fact that the relevant differences in downside standard deviations are typically much lower than the relevant differences in conventional standard deviations. Specifically, the former figures range from 100% to 160%, while the latter figures start at only 16% and end at 117% in the most extreme case.

The CAPM-related statistics presented in Table 60 clearly support the above observation for standard deviations by showing that, in the test period, the extreme past-performance portfolios are more volatile as compared to the market portfolio by 64% to 76% when the conventional CAPM beta is used as a metric and only by 17% to 65% when the downside CAPM beta is used as a metric. On the other hand, both test-period betas of the arbitrage portfolio are substantially below one, which is a result of the highest past-return portfolio's and the lowest past-return portfolio's betas being almost identical. The standard errors (adjusted R-squared) of the CAPM regression is exceptionally high (low) for past-return-based portfolios, both in the formation period and in the test period, which suggests that CAPM does not rationalise contrarian and momentum returns very well. This notion is confirmed by the very low probability associated with the F-test for the overall significance of the CAPM regression line for the arbitrage portfolio.

Lastly, according to the ME data available in Table 61, neither the highest past-return portfolio nor the lowest past-return portfolio is composed of stocks issued by smaller-than-average companies. In fact, the average size of a P1 and P10 company is higher than the average size of a Pm company, both in the formation period as well as in the test period. In the case of P1, the difference is statistically significant at $p < 0.01$ and economically significant at $\delta \geq 0.5$.

4.4.6.2. MARKET MICROSTRUCTURE CHARACTERISTICS

The price and volume data describing the market microstructure characteristics of contrarian and momentum strategies for Czech Republic (PSE) is shown in Table 62 (p. 331) and Table 63 (p. 332), respectively. The bid-ask spreads are unavailable for this stock market in the Thomson Reuters Datastream Database.[75]

[75] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 62. CZECH REPUBLIC (PSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	**δ-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	**δ-value** (test period price)	***p*-value** (formation-test period price)
P1	42.26	$0.01 <= p <= 0.05$	0.4178	48.05	$p < 0.01$	0.4669	$p < 0.01$
P10	16.36	$p < 0.01$	0.6295	15.12	$p < 0.01$	0.7051	$p > 0.05$
Pm	27.75	-	-	28.70	-	-	-

TABLE 63. CZECH REPUBLIC (PSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	**δ-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	**δ-value** (test period volume)	***p*-value** (formation-test period volume)
P1	2978.63	$p > 0.05$	0.0359	2927.26	$p > 0.05$	0.0057	$p > 0.05$
P10	1735.49	$0.01 <= p <= 0.05$	0.3497	2538.36	$p > 0.05$	0.2174	$p > 0.05$
Pm	2582.12	-	-	2622.14	-	-	-

As can be seen from Table 62, the highest past-return portfolio can be characterised by stocks with above-average price in the formation period as well as in the test period. The price estimates for that portfolio are statistically significant in both periods, but are never economically significant at $\delta \geq 0.5$. By contrast, the typical lowest-past-return-portfolio stock has a statistically and economically lower price than the average Czech Republic (PSE) stock. However, considering that the test-period average price for P10 is as high as €15.12, it seems unlikely that price-related microstructure-induced biases would be a problem. Additionally, stocks priced that high do not meet SEC's (2013) criteria for a 'penny stock', especially once the corresponding, above market-average ME figures are taken into account.

The volume statistics in Table 63 clearly support the foregoing conclusion that neither P1 nor P10 appears to be prone to excess market microstructure frictions. In particular, the test-period data indicates that the extreme past-performance portfolios' stocks are associated with trading volumes that are not only statistically and economically indistinguishable from the corresponding figures for the market portfolio of all Czech stocks, but are also comparable in absolute terms.

Overall, past-return-based portfolios for Czech Republic (PSE) seem to be associated with a meaningful degree of excess risk and no excess market microstructure frictions as compared to the market-average level, at least by the adopted specifications and standards. Specifically, the risk characteristics analysis revealed that contrarian and momentum strategies do demonstrate high volatility of returns, albeit most of the risk thereof comes from unexpected gains, rather than unexpected loses. As downside betas are unavailable for the portfolios of interest, it is difficult to assess the market risk that is, arguably, most important to investors. In terms of market microstructure, the only important abnormalities can be found in price statistics, whereby the average price of the highest past-return portfolio's stocks is above the market average and the average price of the lowest past-return portfolio's stocks is below the market average. However, taking all available information into consideration, it seems very unlikely that the extreme past-performance portfolios are affected by any type of market microstructure frictions or biases. Still, $H_{1(2)}$ is rejected for the Czech stock market, due to excess risk exposure.

4.4.7. HUNGARY (BSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Hungary (BSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.7.1. RISK CHARACTERISTICS

Two categories of risk characteristics will be examined in this part of the subsection, these are: return-volatility-based statistics (see Table 64 and Table 65, pp. 335-336); and the market-value-of-equity statistics (see Table 66, p. 337).[76]

[76] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 64. HUNGARY (BSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	0.53	N/A	0.23	0.15
P10	0.17	0.37	0.36	0.23
P1/P10	0.49	N/A	0.35	0.15
Pm	0.10	0.10	0.11	0.12

TABLE 65. HUNGARY (BSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (*p*) associated with an *F*-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	4.23	-1.14	1.60	1.23	0.3259	0.1540	0.6182	0.5458	0.0000	0.0000
P10L	1.21	4.21	2.39	1.77	0.1236	0.2649	0.4744	0.4713	0.0002	0.0002
P1S/P10L	-3.00	5.52	0.80	0.66	0.3997	0.3420	0.3385	0.0169	0.0021	0.2537
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 66. HUNGARY (BSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	342.12	$p < 0.01$	0.0926	416.75	$p < 0.01$	0.0851	$p < 0.01$
P10	322.61	$p < 0.01$	0.4707	252.59	$p < 0.01$	0.4858	$p < 0.01$
Pm	251.69	-	-	252.47	-	-	-

The standard deviation statistics in Table 64 clearly show that past-return-based portfolios are riskier than the market portfolio of all Hungary (BSE) stocks. Nevertheless, the test-period figures suggest that most of the observed abnormal return volatility comes from unexpected gains, rather than unexpected losses. This becomes evident once the results for the conventional standard deviation and the downside standard deviation are compared. When unexpected above-average returns are treated on a par with unexpected below-average returns, through the use of the former measure, then the excess risk associated with P1, P10 and P1/P10 relative to Pm ranges from 109% to 227%. However, in the case of employing the latter measure, the range is narrowly restricted between 25% and 92%.

As presented in Table 65, the results for both conventional and downside beta are in line with the earlier-discussed findings for standard deviation. Namely, all past-return-based portfolios can be characterised by abnormal test-period return volatility that is greater with the former measure than it is with the latter measure. Additionally, in the case of standard deviations as well as in the case of betas, the lowest past-return portfolio is consistently the most risky past-return-based portfolio in the test period. It is also worth noting that the test-period CAPM beta of the arbitrage portfolio is below one, which, given the corresponding conventional standard deviation, standard error, adjusted R-squared and CAPM regression p-value, suggests that the risk associated with investing in this portfolio has a large firm-specific component and/or CAPM does not capture all of its systematic risk.

The ME figures in Table 66, on the other hand, indicate that both P1 and P10 are composed of stocks which have been issued by companies that are, on average, statistically larger than the typical Hungarian company. Despite always being favourable for the extreme past-return portfolios, the differences in ME are, nonetheless, never economically significant at $\delta \geq 0.5$.

4.4.7.2. MARKET MICROSTRUCTURE CHARACTERISTICS

The three market microstructure characteristics to be considered for contrarian and momentum strategies in the context of Hungary (BSE) are price (see Table 67, p. 340), volume (see Table 68, p. 341) and the bid-ask spread (see Table 69, p. 342).[77]

[77] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 67. HUNGARY (BSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	18.09	$p < 0.01$	0.3081	19.16	$p > 0.05$	0.0473	$0.01 <= p <= 0.05$
P10	12.95	$p < 0.01$	0.5879	9.74	$p < 0.01$	0.6975	$p < 0.01$
Pm	18.45	-	-	18.07	-	-	-

TABLE 68. HUNGARY (BSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	2401.37	$p < 0.01$	0.3043	1914.03	$p < 0.01$	0.5198	$p > 0.05$
P10	1760.24	$p < 0.01$	0.5161	2093.07	$p < 0.01$	0.4896	$0.01 <= p <= 0.05$
Pm	2341.86	-	-	2386.58	-	-	-

TABLE 69. HUNGARY (BSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	**δ-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	**δ-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	22.53%	$p > 0.05$	0.0839	19.37%	$p > 0.05$	0.1860	$p < 0.01$
P10	25.20%	$0.01 <= p <= 0.05$	0.2744	22.53%	$p > 0.05$	0.0455	$p > 0.05$
Pm	17.32%	-	-	17.09%	-	-	-

As can be seen from Table 67, only the lowest past-return portfolio is associated with statistically and economically significant below market-average stock price in the formation period as well as in the test period. While the formation-period figure for P10 is about 30% lower than the corresponding Pm statistic, it decreases across the two periods in a statistically significant manner and widens the difference to roughly 46% in the test period. It should be noted, though, that a portfolio whose stocks are priced, on average, at €9.47 and whose average ME is statistically and borderline economically larger than the market-average figure is unlikely to be adversely affected by excess market microstructure frictions. The average price of a P1 stock, on the other hand, is only statistically different from a Pm stock in the formation period and it never reaches the economic significance threshold of δ = 0.5.

A different situation is portrayed by the volume statistics in Table 68, where it is only the highest past-return portfolio that appears to differ statistically and economically from the market portfolio in the test period. However, the difference thereof is less than -20% relative to the market. The lowest past-return portfolio's average volume is also statistically lower than the average volume of the market portfolio, but this difference is not associated with economic significance in the test period.

Unlike the case of the price and volume statistics discussed above, the bid-ask spreads (see Table 69) for both the highest past-return portfolio and the lowest past-return portfolio are indistinguishable from the bid-ask spreads of the market portfolio in the formation period as well as in the test period. Therefore, there is no compelling evidence to suggest that the contrarian and momentum strategies based on those portfolios would be more transaction-cost intensive than a strategy based on a portfolio of typical Hungary (BSE) stocks.

To conclude, past-return-based portfolios' returns appear to be almost always more volatile than returns on the market portfolio of all Hungarian stocks, at least by the adopted specifications and standards. This means that contrarian and momentum strategies are likely to be accompanied by above market-average risk. In addition, some market microstructure concerns have been raised, especially with regard to the liquidity of P1's stocks. Consequently, $H_{1(2)}$ is rejected for Hungary (BSE).

4.4.8. LITHUANIA (VSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Lithuania (VSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.8.1. RISK CHARACTERISTICS

The riskiness of past-return-based strategies will be evaluated on the basis of their standard deviation statistics (see Table 70, p. 345), CAPM-related statistics (see Table 71, p. 346) and ME statistics (see Table 72, p. 347), all of which data is available on the next three pages.[78]

[78] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 70. LITHUANIA (VSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	0.63	N/A	0.35	0.19
P10	0.16	0.40	0.32	0.26
P1/P10	0.57	N/A	0.38	0.16
Pm	0.20	0.23	0.20	0.23

TABLE 71. LITHUANIA (VSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	2.79	-0.28	1.51	0.88	0.3149	0.1954	0.7536	0.6946	0.0000	0.0000
P10L	0.63	2.31	1.02	1.39	0.1033	0.2607	0.5867	0.3526	0.0000	0.0017
P1L/P10S	2.18	-2.51	0.50	-0.44	0.3883	0.3717	0.5447	0.0248	0.0000	0.2256
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 72. LITHUANIA (VSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	**δ-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	**δ-value** (test period ME)	***p*-value** (formation-test period ME)
P1	102.76	$p > 0.05$	0.0662	118.99	$p > 0.05$	0.0208	$0.01 <= p <= 0.05$
P10	36.45	$p < 0.01$	0.6144	30.28	$p < 0.01$	0.7316	$0.01 <= p <= 0.05$
Pm	79.26	-	-	82.31	-	-	-

The conventional test-period standard deviations provided in Table 70 suggest that all past-return-based portfolios are noticeably more volatile than the market portfolio, with the total risk differential ranging between 60% in the case of the lowest past-return portfolio and 90% in the case of the arbitrage portfolio. By contrast, the downside test-period standard deviations indicate that only the lowest past-return portfolio can be characterised by higher risk than the market portfolio and, what is more, the difference thereof appears to be less than 13.5%. Considering that the latter measure does not treat unexpected losses and unexpected gains as equally undesirable, it is likely to be preferred by most investors.

Albeit somewhat more balanced, the CAPM-related statistics shown in Table 71 are consistent with the standard deviation results discussed before. In terms of the conventional beta, the only test-period figure that stands out as disadvantageous and meaningfully different from the market portfolio relates to the highest past-return portfolio. On the other hand, the lowest past-return portfolio's CAPM beta is comparable to the market figure, while the arbitrage portfolio is clearly associated with below-average market risk. The results are, on average, more favourable still when, the arguably more useful for investors, downside betas are considered. Here, it is the lowest past-return portfolio that is associated with higher return volatility than the market portfolio, although not as high as 151% the market figure, but a markedly lower 139%.

As the last point concerning the empirical data in Table 71 it should be noted that, alike the case of the vast majority of the EU12 stock markets, the standard errors, adjusted R-squared and p-values of the CAPM regression suggest low explanatory power of the model and/or high firm-specific risk accompanying contrarian and momentum investing, especially in the test period.

In terms of the ME statistics in Table 72, only the lowest past-return portfolio is reliably different from the market portfolio. However, not only is the average ME for P10 statistically and economically below market-average in both the formation period and the test period, but it also statistically decreases across the two periods. Some finance scholars would link this to excess risk and/or the small-firm effect.

4.4.8.2. MARKET MICROSTRUCTURE CHARACTERISTICS

Having performed risk assessment, it is now important to verify if contrarian and momentum strategies for Lithuania (VSE) are associated with above-average market microstructure frictions. This will be evaluated on the basis of three measures: price; volume; and the bid-ask spread. The relevant statistics are available in Table 73 (p. 350), Table 74 (p. 351) and Table 75 (p. 352).[79]

[79] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 73. LITHUANIA (VSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***δ*-value** (test period price)	***p*-value** (formation -test period price)
P1	6.06	$p < 0.01$	0.2968	7.11	$0.01 <= p <= 0.05$	0.2174	$p < 0.01$
P10	2.33	$p < 0.01$	0.7807	2.35	$p < 0.01$	0.7467	$p > 0.05$
Pm	4.55	-	-	4.63	-	-	-

TABLE 74. LITHUANIA (VSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation -test period volume)
P1	571.08	$p > 0.05$	0.3081	523.18	$0.01 <= p <= 0.05$	0.4064	$p > 0.05$
P10	391.70	$0.01 <= p <= 0.05$	0.4972	559.41	$p < 0.01$	0.4518	$p > 0.05$
Pm	787.32	-	-	801.30	-	-	-

TABLE 75. LITHUANIA (VSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	3.92%	$p > 0.05$	0.3018	5.65%	$p > 0.05$	0.5816	$p > 0.05$
P10	9.25%	$p > 0.05$	0.5266	12.29%	$p > 0.05$	0.2755	$p > 0.05$
Pm	5.22%	-	-	5.78%	-	-	-

The price statistics in Table 73 show that the highest past-return portfolio's average stock price is statistically (but not economically) different from the lower, market portfolio's figure in both the formation period and the test period, and, what is more, it increases across the two periods in a statistically significant manner as well. While the average price associated with the lowest past-return portfolio does not appear to meaningfully change from the formation period to the test period, in both absolute terms and statistical terms, it is below the market-average level in both periods. Importantly, all the differentials thereof are supported by tests of both statistical as well as economic significance. While the average stock prices of over €2 for the lowest past-return portfolio do not appear to be abnormally low in absolute terms, when the ME statistics in Table 72 are taken into account, then the SEC's (2013) definition of 'penny stocks' may be argued to be applicable in this context.

In addition to the above, the volume statistics in Table 74 also suggest that the lowest past-return portfolio might be composed of relatively illiquid stocks. It needs to be stressed, nonetheless, that although this notion is supported by statistical significance in the formation period as well as in the test period, the relevant statistics are only borderline economically significant. As regards the highest past-return portfolio, none of the estimates of trading volume even comes close to being economically significant, as was the case with the price data in Table 73.

On the other hand, the bid-ask spreads in Table 75 are no different for the extreme past-performance portfolios than for the market portfolio, as indicated by all available tests of statistical and economic significance. This suggests that there are no excess transaction costs associated with contrarian and momentum strategies.

In conclusion, the lowest past-return portfolio for Lithuania (VSE) seems to be affected by both excess risk as well as excess market microstructure frictions, at least by the adopted specifications and standards. Although the extent to which P10 suffers from unfavourable investment characteristics tends to vary from measure to measure, all the measures considered by this study suggest some degree of abnormality. While the remaining past-return-based portfolios do not appear to share the same attributes as P10, $H_{1(2)}$ is still rejected for (Lithuania VSE).

4.4.9. POLAND (WSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Poland (WSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.9.1. RISK CHARACTERISTICS

In this part of the subsection, the empirical results for three groups of risk measures will be examined. These groups are standard deviations (see Table 76, p. 355), CAPM-related measures (see Table 77, p. 356) and the market value of equity (see Table 78, p. 357).[80]

[80] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 76. POLAND (WSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	0.75	N/A	0.41	0.20
P10	0.20	0.48	0.39	0.31
P1/P10	0.58	N/A	0.24	0.15
Pm	0.24	0.18	0.25	0.22

TABLE 77. POLAND (WSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	3.03	-1.03	1.51	0.90	0.2072	0.1378	0.9239	0.8859	0.0000	0.0000
P10L	0.81	3.06	1.35	1.40	0.0670	0.1939	0.8927	0.7556	0.0000	0.0000
P1L/P10S	2.23	-4.00	0.17	-0.43	0.2442	0.2391	0.8248	-0.0122	0.0000	0.4007
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 78. POLAND (WSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	244.61	$0.01 <= p <= 0.05$	0.3875	281.83	$p > 0.05$	0.2779	$0.01 <= p <= 0.05$
P10	107.27	$p < 0.01$	0.7580	96.22	$p < 0.01$	0.7883	$0.01 <= p <= 0.05$
Pm	294.17	-	-	297.27	-	-	-

As can be seen from Table 76, test-period statistics corresponding to the two versions of standard deviation are both in agreement with regard to two out of three past-return-based portfolios. Namely, the two measures consistently show that the lowest past-return portfolio's return is abnormally volatile, while the arbitrage portfolio's return volatility is less than the market-average level. Where the results for the conventional version of standard deviation depart from the results for the downside version of standard deviation is with respect to the highest past-return portfolio. Specifically, the former measure suggests that the portfolio's total risk is 164% the market figure, whereas the latter measure estimates it to be 91% the market figure. Since investors are typically less concerned about unexpected gains and more concerned about unexpected losses, it might be argued that the second statistic is of greater relevance to the investment community.

The conventional and downside betas presented in Table 77 show a very similar pattern to the earlier-discussed standard deviations, whereby, in the test period, the lowest past-return portfolio's (the arbitrage portfolio's) returns are more (less) volatile as compared to the returns on the benchmark portfolio of all stocks, while the general classification of the highest past-return portfolio in terms of volatility relative to the market portfolio depends on the type of beta considered. Incidentally, this correspondence between standard deviations and betas is not limited to the test period, but it can also be observed in the formation period. What is particularly interesting about the discussed CAPM-related statistics is that, unlike the case of most of the analysed EU12 stock markets, the Sharpe-Lintner CAPM appears to predict returns on the extreme past-performance portfolios reasonably well in both periods, with the adjusted R-squared being above 75% on all occasions. However, the same cannot be said about the arbitrage portfolio, in which case the test-period adjusted R-squared is negative.

The ME statistics in Table 78 add to the foregoing evidence by revealing that while P1 is not statistically and economically different from Pm as regards the average ME in either the formation period or the test period, the opposite is true for P10. Moreover, the average size of a P1 company increases from the formation period to the test period ($p \leq 0.05$), which greatly contrasts with the decreasing P10 figures ($p \leq 0.05$).

4.4.9.2. MARKET MICROSTRUCTURE CHARACTERISTICS

This part of the subsection investigates three market microstructure characteristics accompanying contrarian and momentum strategies for Poland (WSE), which are the following: price (see Table 79, p. 360); volume (see Table 80, p. 361); and the bid-ask spread (see Table 81, p. 362).[81]

[81] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 79. POLAND (WSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	**p-value** (formation period price)	**δ-value** (formation period price)	**Average price** (test period)	**p-value** (test period price)	**δ-value** (test period price)	**p-value** (formation-test period price)
P1	7.82	$0.01 <= p <= 0.05$	0.2363	9.55	$p > 0.05$	0.1304	$p < 0.01$
P10	4.00	$p < 0.01$	0.7353	3.33	$p < 0.01$	0.7618	$p < 0.01$
Pm	7.57	-	-	7.73	-	-	-

TABLE 80. POLAND (WSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	4783.39	$p > 0.05$	0.0851	4337.83	$p > 0.05$	0.0170	$p > 0.05$
P10	3305.84	$p > 0.05$	0.1418	4584.24	$p > 0.05$	0.0586	$p < 0.01$
Pm	3508.96	-	-	3849.22	-	-	-

TABLE 81. POLAND (WSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	4.52%	$p > 0.05$	0.1000	5.57%	$p > 0.05$	0.0023	$p > 0.05$
P10	10.45%	$p > 0.05$	0.2500	9.26%	$p > 0.05$	0.1746	$p > 0.05$
Pm	5.73%	-	-	5.78%	-	-	-

As the price statistics in Table 79 demonstrate, only the lowest past-return portfolio is associated with below market-average price in either the formation period or the test period. The difference between P10 and Pm in that respect ranges from 47% to 57%, depending on the period under analysis, and it is always statistically and economically significant. However, it should be pointed out that, despite being abnormally low relative to the market, the average price of a P10 stock does not go below €3.33, which does not seem to be abnormally low in absolute terms, especially by SEC's (2013) standards. Therefore, it seems unlikely that investing in P10 will have any adverse price-related consequences.

The remaining two groups of statistics, pertaining to volume (see Table 80) and the bid-ask spread (see Table 81), show no abnormalities at either statistically or economically significant level. In terms of average volume, both the highest past-return portfolio and the lowest past-return portfolio are associated with above market-average results. What is more, in the case of the lowest past-return portfolio a statistically significant increase in stock trading activity can be observed across the two periods, which is a desirable effect as investors would be able to, among others, close their investment positions at the end of the test period with less market impact than could be expected from the formation-period data available at the time of committing funds. As regards the average bid-ask spread, even though the figures for the lowest past-return portfolio appear to be substantially higher than the market figures in both periods, none of the results thereof is either statistically significant or nearly economically significant, with all the δ-values being below 0.25. Consequently, there is no indication of illiquidity or excess transaction costs insofar as extreme past-performance portfolios are concerned.

In conclusion, the lowest past-return portfolio for Poland (WSE) can be characterised by excess risk, as indicated by all available risk measures. The results for the highest past-return and arbitrage portfolios, on the other hand, do not unanimously suggest any abnormalities, especially in the latter case. However, considering that the lowest past-return portfolio is a critical component in contrarian and momentum strategies, both individually and as a part of arbitrage, $H_{1(2)}$ is rejected for the Polish stock market.

4.4.10. ROMANIA (BVB)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Romania (BVB). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.10.1. RISK CHARACTERISTICS

The first group of investment characteristics to be considered for Romania (BVB) is risk characteristics, which encompasses return-volatility-related statistics (see Table 82 and Table 83, pp. 365-366) and the market-value-of-equity statistics (see Table 84, p. 367).[82]

[82] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 82. ROMANIA (BVB): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	1.64	N/A	0.51	0.15
P10	0.16	0.47	0.78	0.55
P1/P10	1.58	N/A	0.85	0.19
Pm	0.27	N/A	0.26	N/A

TABLE 83. ROMANIA (BVB): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	5.49	N/A	1.73	N/A	0.7013	0.2520	0.8163	0.7561	0.0000	0.0000
P10L	0.41	N/A	1.36	N/A	0.1153	0.7146	0.4747	0.1649	0.0002	0.0310
P1S/P10L	-5.07	N/A	-0.36	N/A	0.7966	0.8628	0.7454	-0.0349	0.0000	0.6169
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 84. ROMANIA (BVB): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	**δ-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	**δ-value** (test period ME)	***p*-value** (formation-test period ME)
P1	40.39	$p > 0.05$	0.3043	50.46	$p > 0.05$	0.2325	$p < 0.01$
P10	31.96	$0.01 <= p <= 0.05$	0.4556	27.84	$p < 0.01$	0.5085	$p > 0.05$
Pm	46.31	-	-	47.95	-	-	-

It can be clearly seen from the information on the conventional measure of total risk in Table 82 that all past-return-based portfolios are likely to be associated with much greater return volatility than the market portfolio. The test-period figures for that measure suggest that this difference might be as large as 227%. While, arguably, it is the downside standard deviations that are of most relevance to investors, who are usually less concerned with the possibility of earning more than expected (*i.e.*, upside potential, sometimes misleadingly called 'upside risk') and more concerned with the possibility of a financial loss (*i.e.*, downside risk), the corresponding statistics are unavailable for most of the portfolios in the formation period and, more importantly, for the market portfolio in the test period.

Similarly to the case of standard deviations, the CAPM-related statistics in Table 83 are limited to the conventional measures of systematic risk only. The available data indicate that, at least in the test period, both extreme past-performance portfolios are accompanied by excess market risk. However, despite still being noticeably above the market average, the differences in the test-period conventional betas for P1L and P10L are much smaller than the corresponding differences in standard deviations and range from 36% and 73%. An even more meaningful divergence between the results in Table 82 and Table 83 pertains to the arbitrage portfolio. In specific, the test-period systematic risk associated with that portfolio is well below the benchmark figure. This means that either most of the excess risk detected by the standard deviation thereat is idiosyncratic in nature or CAPM is incorrectly specified and it does not capture all systematic risk. The standard error, adjusted R-squared and p-value of the CAPM regression seem to point towards the latter possibility, due to the fact that CAPM appears to explain little of the test-period return behaviour of the arbitrage portfolio.

The ME statistics presented in Table 84, on the other hand, show that the highest past-return portfolio is not composed of stocks issued by companies whose average size is statistically different at $p \leqslant 0.05$ from the average size of a company listed on Romania (BVB). However, this is not the case with the lowest past-return portfolio, for which the average ME is lower than the corresponding figure for the market portfolio with the p-value below 0.01 and the δ-value of about 0.51.

4.4.10.2. MARKET MICROSTRUCTURE CHARACTERISTICS

The second and last group of investment characteristics to be considered for Romania (BVB) is market microstructure characteristics, which comprise price, volume and the bid-ask spread statistics. All data that is essential for the ensuing analysis has been organised into three tables (see Table 85, Table 86 and Table 87, pp. 370-372).[83]

[83] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 85. ROMANIA (BVB): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	1.72	$p < 0.01$	0.6673	2.27	$p < 0.01$	0.5766	$p < 0.01$
P10	50.37	$p < 0.01$	0.4442	49.60	$p < 0.01$	0.5161	$p > 0.05$
Pm	23.96	-	-	21.42	-	-	-

TABLE 86. ROMANIA (BVB): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation -test period volume)
P1	3409.65	$p > 0.05$	0.2628	3247.32	$p > 0.05$	0.3270	$p > 0.05$
P10	2885.18	$p < 0.01$	0.5123	3754.18	$0.01 <= p <= 0.05$	0.4064	$p > 0.05$
Pm	4101.25	-	-	4201.82	-	-	-

TABLE 87. ROMANIA (BVB): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	**p-value** (formation period bid-ask spread)	**δ-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	**p-value** (test period bid-ask spread)	**δ-value** (test period bid-ask spread)	**p-value** (formation-test period bid-ask spread)
P1	34.27%	$p > 0.05$	0.2661	26.85%	$p > 0.05$	0.0673	N/A
P10	33.36%	$p > 0.05$	0.1257	31.37%	$p > 0.05$	0.1468	N/A
Pm	29.37%	-	-	26.85%	-	-	-

As far as the market microstructure is concerned, there is no consequential difference supported by statistical significance between the two extreme past-performance portfolios and the market portfolio with two important exceptions.

First, price statistics in Table 85 portray a potentially undesirable situation, whereby the average price of the highest past-return portfolio's stock is reliably below the overall average stock price for Romania (BVB). While this result is both statistically and economically significant, it is improbable that stocks priced at €2.27, on average, are affected by price-related microstructure biases as those could only accompany low-priced stocks. Although there is no universal definition of a low-priced stock, for example, Ball *et al*. (1995), who explored the impact of stock price on contrarian performance in depth, mainly warned about stocks priced at $1 or less. On the other hand, the average stock price for the lowest past-return portfolio is well above the market average, especially in the test-period when the difference is both statistically and economically significant.

Second, the statistical significance figures associated with the test-period volume data in Table 86 lead to suggest that the lowest past-return portfolio might be less liquid relative to the market portfolio. However, the observed difference in liquidity is not economically significant, with $\delta \approx 0.41$.

The bid-ask spread statistics in Table 87 do not show any abnormalities both in statistical and economic terms as well as in absolute terms, considering that the observed differences in six-monthly, two-way (or 'round-trip') transaction costs between the extreme past-performance portfolios and the market portfolio are less than 5%.

To conclude, the returns on the past-return-based portfolios appear to be substantially more volatile than the returns on the market portfolio of all Romanian stocks almost by all available measures. However, the analysis of the market microstructure does not reveal any abnormal characteristics associated with the extreme past-performance portfolios, which could meaningfully affect investment returns. Still, the second alternative hypothesis is rejected for Romania (BVB).

4.4.11. SLOVAKIA (BSSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Slovakia (BSSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.11.1. RISK CHARACTERISTICS

There are three groups of measures that are considered herein for the purpose of assessing the riskiness of contrarian and momentum strategies, these are: standard-deviations (see Table 88, p. 375); CAPM-related measures (see Table 89, p. 376); and ME (see Table 90, p. 377).[84]

[84] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 88. SLOVAKIA (BSSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	12.15	N/A	2.05	0.23
P10	0.25	0.39	4.08	0.08
P1/P10	12.21	N/A	4.56	0.23
Pm	1.30	0.04	1.26	0.07

TABLE 89. SLOVAKIA (BSSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	9.32	-3.39	0.24	3.03	0.6075	2.0714	0.9975	-0.0250	0.0000	0.5038
P10L	-0.03	7.15	0.88	0.44	0.2514	4.0204	-0.0151	0.0298	0.4210	0.2096
P1S/P10L	-9.35	10.88	0.64	-2.35	0.8334	4.5970	0.9953	-0.0145	0.0000	0.4172
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 90. SLOVAKIA (BSSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	76.62	$p < 0.01$	0.3875	87.85	$p < 0.01$	0.4102	$p < 0.01$
P10	42.44	$p > 0.05$	0.2470	42.85	$0.01 <= p <= 0.05$	0.2668	$0.01 <= p <= 0.05$
Pm	35.80	-	-	38.04	-	-	-

From the investigation of the standard deviation figures in Table 88 alone, it is clear that the return volatility of past-return-based portfolios is likely to be much higher than the return volatility of the market portfolio. The statistics indicate a difference in the conventional standard deviation as high as 839% in the formation period and 262% in the test period for the arbitrage portfolio. However, it might be argued that the downside standard deviation statistics for the test period are of most relevance to investors, which show a smaller difference of 229% between the arbitrage portfolio and the market portfolio. The higher relevance of the aforementioned results mainly stems from the important distinction between downside risk and upside potential, which the conventional measure simply fuses together, thereby equating a strategy's capacity to generate lower profits than expected with its capacity to generate higher profits than expected. As far as the other investment portfolios are concerned, the highest past-return portfolio can be characterised by an identical total downside risk exposure in the test period as the arbitrage portfolio, whereas the lowest past-return portfolio is associated with virtually no excess total downside risk relative to the market as a whole.

The CAPM-related empirical data in Table 89 largely support the view that, in the test period, the returns on the highest past-return portfolio are likely to be substantially more volatile on the downside than the returns on the market portfolio, but the opposite appears to apply to the arbitrage portfolio's and the lowest past-return portfolio's returns. However, it should be emphasised that CAPM seems to perform exceptionally poorly in the test period in Slovakia (BSSE), as indicated by the extremely large standard errors and *p*-values of the CAPM regression as well as the extremely low adjusted *R*-squared of the CAPM regression.

Lastly, the statistics presented in Table 90 show that both in the formation period and in the test period the companies whose stocks form the two extreme past-performance portfolios are, on average, larger than a typical company listed on the Slovak stock market. This observation is confirmed by statistical significance in three out of four cases, but never by economic significance.

4.4.11.2. MARKET MICROSTRUCTURE CHARACTERISTICS

In this part, the market microstructure analysis of contrarian and momentum strategies for Slovakia (BSSE) will be performed. As before, three types of statistics are considered: price (see Table 91, p. 380); volume (see Table 92, p. 381); and the bid-ask spread (see Table 93, p. 382).[85]

[85] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 91. SLOVAKIA (BSSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	254.44	$p > 0.05$	0.1493	274.10	$p > 0.05$	0.2098	$p < 0.01$
P10	63.49	$p > 0.05$	0.3308	44.10	$0.01 <= p <= 0.05$	0.4253	$p > 0.05$
Pm	70.85	-	-	72.39	-	-	-

TABLE 92. SLOVAKIA (BSSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	68.86	$p > 0.05$	0.1456	37.48	$p > 0.05$	0.1078	$p > 0.05$
P10	52.15	$p > 0.05$	0.1947	179.48	$p > 0.05$	0.2854	$p > 0.05$
Pm	59.38	-	-	58.64	-	-	-

TABLE 93. SLOVAKIA (BSSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	29.74%	$p > 0.05$	0.4104	26.30%	$0.01 <= p <= 0.05$	0.5083	$p > 0.05$
P10	45.14%	$p > 0.05$	0.1880	44.09%	$p > 0.05$	0.1494	N/A
Pm	38.72%	-	-	36.76%	-	-	-

The information in Table 91, Table 92 and Table 93 strongly suggests that neither P1 nor P10 is likely to be linked to excess market microstructure frictions relative to the market portfolio. This conclusion is clearly supported by the tests of statistical and economic significance for all statistics considered.

In the case of the average stock price per portfolio (see Table 91), even though the test-period figure for P10 is below the market average with the corresponding *p*-value of less than 0.05, the result is not economically significant. P1, on the other hand, is associated with a substantially higher average price than Pm, both in the formation period as well as in the test period, but the difference thereof is never statistically or economically significant.

Furthermore, the volume statistics in Table 92 show even more consistently that the extreme past-performance portfolios and the market portfolio are statistically and economically indistinguishable, with all *p*-values being above 0.05 and all δ-values not exceeding 0.3. The same general description applies to the bid-ask spreads in Table 93, with the only exception being that the test-period average bid-ask spread for P1 is statistically and economically below the market-average level.

Therefore, there is no evidence for this stock market to indicate that the extreme past-performance portfolios suffer from price-related microstructure frictions/biases, illiquidity or above-average transaction costs.

Overall, in the six-month/six-month investment timeframe, contrarian and momentum strategies for Slovakia (BSSE) appear to be associated with excess risk premium due to abnormal return volatility. It should be noted, however, that the size of the typical company is statistically larger in the case of the extreme past-performance portfolios than it is in the case of the portfolio of all Slovak stocks. In terms of market microstructure, neither the highest past-return portfolio nor the lowest past-return portfolio is different from the market portfolio at both statistically and economically significant level. Still, taking the result of the risk assessment into consideration, the second alternative hypothesis is rejected for this stock market.

4.4.12. SLOVENIA (LJSE)

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for Slovenia (LJSE). Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.12.1. RISK CHARACTERISTICS

Three categories of risk characteristics will be analysed in this part of the subsection, these are: standard deviation statistics (see Table 94, p. 385); CAPM-related statistics (see Table 95, p. 386); and the market-value-of-equity statistics (see Table 96, p. 387).[86]

[86] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 94. SLOVENIA (LJSE): INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	1.81	N/A	0.13	0.11
P10	0.15	0.40	1.67	0.18
P1/P10	1.79	N/A	1.66	0.12
Pm	0.19	0.05	0.19	0.05

TABLE 95. SLOVENIA (LJSE): INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1S	-9.01	6.37	-0.17	-0.80	0.5188	0.1254	0.9181	0.0182	0.0000	0.2486
P10L	0.29	8.07	8.43	1.84	0.1419	0.5821	0.1017	0.8792	0.0757	0.0000
P1S/P10L	-8.72	14.18	8.26	0.77	0.6184	0.6218	0.8805	0.8594	0.0000	0.0000
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 96. SLOVENIA (LJSE): INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	**δ-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	**δ-value** (test period ME)	***p*-value** (formation-test period ME)
P1	86.80	$0.01 <= p <= 0.05$	0.3308	107.20	$0.01 <= p <= 0.05$	0.2930	$p < 0.01$
P10	84.08	$p < 0.01$	0.6333	62.77	$p < 0.01$	0.6106	$0.01 <= p <= 0.05$
Pm	111.21	-	-	110.85	-	-	-

The standard deviation statistics in Table 94 clearly show that investing in past-return-based portfolios on Slovenia (LJSE) is likely to be associated with excess total risk. When the conventional standard deviation is used as a measure of risk, only the highest past-return portfolio demonstrates below market-average return volatility, while the remaining two investment portfolios show an increase over the market figure. It should also be noted that in the case of P1 the result is only about 32% less than the result for the benchmark, but in the case of P10 and P1/P10 the results are over 770% more than the result for the benchmark. The downside standard deviations, on the other hand, are more consistent and much less extreme than the conventional statistics, with all the relative differences in excess risk between the past-return portfolios and the market portfolio falling within the 120% - 260% range.

The above-discussed results for standard deviations are largely in contrast to the results for betas. In particular, two differences should be highlighted. First, the test-period market risk of P1S is consistently negative, which means that the portfolio's returns, on average, tend to move in the opposite direction to PmL's returns. Better still, the absolute values of the test-period betas for P1S are below one and, therefore, neither in 'bull markets' nor in 'bear markets' are P1S's returns expected to be more volatile than PmL's returns. Second, while, similarly to the conventional standard deviations, the conventional betas for both P10L and P1S/P10L appear to indicate abnormal volatility in excess of 700%, the downside betas, unlike the downside standard deviations, suggest that most of the considered past-return-based portfolios are accompanied by below market-average risk. The only portfolio that carries more market risk than PmL is P10L, yet the premium thereof is below 85%. It is also worth noting that, in general, CAPM can be characterised by mixed performance, either showing very high (R^2 > 85%) or very low (R^2 < 11%) effectiveness at explaining portfolio returns.

Lastly, the ME statistics in Table 96 indicate that although both P1 and P10 are composed of stocks whose issuing companies are statistically smaller than the typical Slovenian company in the formation period as well as in the test period, only in the case of P10 are the differences also economically significant and decreasing across the two periods in a statistically significant manner.

4.4.12.2. MARKET MICROSTRUCTURE CHARACTERISTICS

Following risk assessment, three market microstructure characteristics of contrarian and momentum strategies for Slovenia (LJSE) will be examined, these are: price (see Table 97, p. 390); volume (see Table 98, p. 391); and the bid-ask spread (see Table 99, p. 392).[87]

[87] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 97. SLOVENIA (LJSE): INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	59.29	$p > 0.05$	0.2212	68.84	$p > 0.05$	0.2968	$p < 0.01$
P10	42.63	$p > 0.05$	0.4216	35.11	$p < 0.01$	0.4518	$0.01 <= p <= 0.05$
Pm	46.36	-	-	46.70	-	-	-

TABLE 98. SLOVENIA (LJSE): INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	**δ-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	**δ-value** (test period volume)	***p*-value** (formation-test period volume)
P1	223.68	$p > 0.05$	0.0019	54.95	$0.01 <= p <= 0.05$	0.3573	$p < 0.01$
P10	53.58	$p < 0.01$	0.5879	87.78	$p < 0.01$	0.5841	$p > 0.05$
Pm	129.65	-	-	142.17	-	-	-

TABLE 99. SLOVENIA (LJSE): INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test and δ-values are the Cliff's Effect Sizes. The probability (p) associated with the two-tailed Wilcoxon Matched-Pairs Signed-Ranks Test for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	19.87%	$p > 0.05$	0.7913	19.92%	$p > 0.05$	0.8087	$p > 0.05$
P10	27.79%	$0.01 <= p <= 0.05$	1.4682	28.61%	$p > 0.05$	1.3199	$p > 0.05$
Pm	10.69%	-	-	12.23%	-	-	-

It can be seen from the price information in Table 97 that neither the highest past-return portfolio nor the lowest past-return portfolio is statistically and economically different from the market portfolio. While the average price of past 'losers' decreases from the formation period to the test period in a statistically significant manner and it becomes statistically different from the average price of the typical Slovenian stock in the test period, the test-period figure is not associated with economic significance by this study's standards.

The volume statistics in Table 98, on the other hand, clearly indicate that the lowest past-return portfolio's stocks are traded less frequently as compared to the market-average level, which observation is supported by both statistical and economic significance. In the formation period this difference amounts to approximately 142%, but it diminishes in the test period to just below 62%. Unlike the case of the lowest past-return portfolio, the highest past-return portfolio is not associated with either statistically or economically different stock trading volume than it would be expected on that stock market.

As far as the bid-ask spread statistics in Table 99 are concerned, no statistically and economically significant abnormalities with respect to the extreme past-performance portfolios are detected. It should be noted, however, that both portfolios of interest have economically higher average bid-ask spreads than the market portfolio in all cases, which is not surprising given that the differences thereof are between 63% and 160%.

To conclude, most of the employed risk measures suggest that contrarian and momentum strategies for Slovenia (LJSE) are accompanied by above market-average risk, especially when returns become negative. Although the market microstructure analysis did not reveal any statistically and economically significant abnormalities in most cases, it is not improbable that trading the lowest past-return portfolio's stocks, in particular, will be associated with a liquidity premium. Therefore, the second alternative hypothesis is rejected for Slovenia (LJSE).

4.4.13. THE EU12 STOCK MARKET

This subsection provides information on the investment characteristics of extreme past-performance, arbitrage and market portfolios for the EU12 stock market. Herein, investment characteristics comprise two constituent parts: risk characteristics and market microstructure characteristics. The objective of the ensuing, two-part analysis is to verify if past-return-based strategies are associated with either excess risk or excess market microstructure frictions in the stock market under consideration.

4.4.13.1. RISK CHARACTERISTICS

As in all previous subsections of this section, the risk analysis of past-return-based portfolios involves the examination of both return-volatility-based statistics (see Table 100 and Table 101, pp. 395-396) as well as ME statistics (see Table 102, p. 397).[88]

[88] In addition to the beta statistics in this part of the subsection, Appendix I provides test-period beta estimates adjusted for infrequent trading using the Dimson's (1979) method.

TABLE 100. EU12 STOCK MARKET: INVESTMENT CHARACTERISTICS – STANDARD DEVIATION STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio, P1/P10 is the arbitrage portfolio, and Pm is the market portfolio. No distinction is made between long and short investment positions, on account of the fact that the standard deviation of returns will be exactly the same for both positions in a given portfolio. The remaining four columns report conventional standard deviation and downside standard deviation statistics for both the formation period as well as the test period. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Standard deviation of returns** (formation period)	**Downside standard deviation of returns** (formation period)	**Standard deviation of returns** (test period)	**Downside standard deviation of returns** (test period)
P1	1.12	N/A	0.29	0.18
P10	0.15	0.46	0.27	0.11
P1/P10	1.09	N/A	0.37	N/A
Pm	0.15	0.05	0.11	0.04

TABLE 101. EU12 STOCK MARKET: INVESTMENT CHARACTERISTICS – CAPM-RELATED STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the long-short investment positions that generate positive test-period returns, are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The remaining columns report CAPM-related statistics, with the exception of CAPM alphas presented and discussed *vis-à-vis* Hypothesis One, for both the formation period as well as the test period. In particular, the last two columns show the probability (p) associated with an F-test, with a right-tailed distribution, for the overall significance of the CAPM regression line. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**CAPM beta** (formation period)	**Downside beta** (formation period)	**CAPM beta** (test period)	**Downside beta** (test period)	**Standard error** (formation period CAPM)	**Standard error** (test period CAPM)	**Adjusted R^2** (formation period CAPM)	**Adjusted R^2** (test period CAPM)	***p*-value** (formation period CAPM)	***p*-value** (test period CAPM)
P1L	6.54	-23.08	1.74	2.60	0.5054	0.2213	0.7953	0.3897	0.0000	0.0005
P10L	0.63	11.32	0.82	-7.25	0.1177	0.2622	0.3758	0.0775	0.0009	0.1192
P1S/P10L	-5.90	34.78	-0.91	-9.49	0.6173	0.3680	0.6800	0.0290	0.0000	0.2121
PmL	1.00	1.00	1.00	1.00	0.0000	0.0000	1.0000	1.0000	-	-

TABLE 102. EU12 STOCK MARKET: INVESTMENT CHARACTERISTICS – ME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average market value of equity (ME) for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average ME is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average ME** (formation period)	***p*-value** (formation period ME)	***Δ*-value** (formation period ME)	**Average ME** (test period)	***p*-value** (test period ME)	***Δ*-value** (test period ME)	***p*-value** (formation-test period ME)
P1	132.63	0.7291	0.1722	155.22	0.6924	0.2042	0.0097
P10	55.99	0.0000	1.5117	42.95	0.0000	1.8239	0.0057
Pm	142.49	-	-	143.92	-	-	-

The test-period conventional standard deviation figures indicate that past-return-based portfolios might be more volatile than the market portfolio by 145% to 236%, depending on which portfolio is being investigated. The test-period conventional beta figures suggest that the excess risk detected by the standard deviations might be unsystematic in nature, due to the fact that the available P10L and P1S/P10L betas are well below PmL betas, which implies below-market-average systematic risk. This appears to apply to P1L as well, since even though the portfolio's beta is larger than PmL's beta, the difference in betas is still substantially smaller than the difference in standard deviations.

The above results may seem surprising given that the extreme past-performance portfolios are composed of, on average, as many as 193 stocks (see Table 28) that could potentially come from up to 12 countries. Solnik (1974), using stock returns from seven European countries and the US, found that the diversification benefit of, and by implication the unsystematic risk associated with, holding a portfolio of more than 30 stocks is negligible. These findings were largely corroborated by, among others, Fisher and Lorie (1970) as well as Statman (1987), while Evans and Archer (1968) expressed doubts concerning "(…) the economic justification of increasing portfolio sizes beyond 10 or so securities (…)" (p. 767). Of course, Solnik (1974), similarly to most researchers in the area of portfolio diversification, studied developed countries and selected stocks randomly, which is different to the present case. Therefore, it is possible that, for example, the above-cited effect does not hold in less-developed countries or that all of the 193 stocks were issued by companies in the same, or related, industry. The unusually high proportion of the unsystematic component of total investment risk in the case of past-return-based portfolios would then be consistent with the hypothesis that it is the overreaction to firm-specific information that is responsible for the abnormal profitability of the strategy based on P10.

An alternative, but not necessarily mutually exclusive, interpretation of the above-described differences between standard deviations and betas is that, rather than P1L, P10L and P1S/P10L being associated with very high unsystematic risk, CAPM itself could be incorrectly specified and it does not capture all systematic risk (see *e.g.*, Chen *et al.*, 1986; Fama and French, 1993). This possibility is supported to some extent by the extremely low explanatory power of the market factor, especially in the test period, as signalled by the standard errors, adjusted *R*-squared and *p*-values of the CAPM regression.

The ME statistics in Table 102 add to the foregoing evidence by showing some support for a risk-based explanation of the anomaly observed for the lowest past-return portfolio. Specifically, the portfolio's average ME is statistically and economically lower than the average ME of the market portfolio, at $p < 0.01$ and $\Delta > 1.5$, in both the formation period as well as the test period. In addition, the discussed figures decrease between the two periods in a statistically significant manner, which suggests that if ME is, indeed, a proxy for risk and/or the size effect, then the investing consequences therefrom are likely to be more pronounced in the test period than it was projected from the formation-period data available at the time of making the investment. However, it is critical to reiterate at this point that the risk premium associated with company size can explain less than 20% of the documented abnormal return, as discussed in Subsection 4.3.13. of this chapter.

4.4.13.2. MARKET MICROSTRUCTURE CHARACTERISTICS

Following risk assessment, three market microstructure characteristics will now be considered for past-return-based strategies implemented in the EU12 stock market. These characteristics are price, volume and the bid-ask spread. The pertinent data is presented in a tabular form and is available in Table 103 (p. 401), Table 104 (p. 402) and Table 105 (p. 403).[89]

[89] In addition to the price statistics in this part of the subsection, Appendix D provides the frequency distributions of average stock prices for each stock market.

TABLE 103. EU12 STOCK MARKET: INVESTMENT CHARACTERISTICS – PRICE STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average price for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, and Δ-values are the Glass's Effect Sizes. The probability (p) associated with the Student's Paired t-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average price is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average price** (formation period)	***p*-value** (formation period price)	***Δ*-value** (formation period price)	**Average price** (test period)	***p*-value** (test period price)	***Δ*-value** (test period price)	***p*-value** (formation-test period price)
P1	20.48	0.0132	1.3772	24.37	0.0773	0.9865	0.0145
P10	12.90	0.0000	2.0570	11.67	0.0000	2.0936	0.0479
Pm	35.82	-	-	35.68	-	-	-

TABLE 104. EU12 STOCK MARKET: INVESTMENT CHARACTERISTICS – VOLUME STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average volume for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where *p*-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) *t*-Test, based on the two-tailed distribution, and *Δ*-values are the Glass's Effect Sizes. The probability (*p*) associated with the Student's Paired *t*-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average volume is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average volume** (formation period)	***p*-value** (formation period volume)	***Δ*-value** (formation period volume)	**Average volume** (test period)	***p*-value** (test period volume)	***Δ*-value** (test period volume)	***p*-value** (formation-test period volume)
P1	2639.26	0.5207	0.2479	2409.15	0.9052	0.0409	0.1294
P10	1891.36	0.2932	0.3967	2343.25	0.8270	0.0967	0.0189
Pm	2351.60	-	-	2457.56	-	-	-

TABLE 105. EU12 STOCK MARKET: INVESTMENT CHARACTERISTICS – BID-ASK SPREAD STATISTICS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest are listed in the first column. P1 is the highest past-return portfolio, P10 is the lowest past-return portfolio and Pm is the market portfolio. Importantly, the concepts of long, short and arbitrage investment positions are not applicable in the present context as the following statistics relate to the portfolios underlying the long-short positions and not to the long-short positions *per se*. Columns two and five report the average bid-ask spread for the formation and test periods, respectively. The results presented in columns three, four, six and seven show the corresponding statistical and economic significance, where p-values are the probabilities associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, and Δ-values are the Glass's Effect Sizes. The probability (p) associated with the Student's Paired t-Test, based on the two-tailed distribution, for the difference between the formation-period and the test-period average bid-ask spread is reported in the last column. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average bid-ask spread** (formation period)	***p*-value** (formation period bid-ask spread)	***Δ*-value** (formation period bid-ask spread)	**Average bid-ask spread** (test period)	***p*-value** (test period bid-ask spread)	***Δ*-value** (test period bid-ask spread)	***p*-value** (formation-test period bid-ask spread)
P1	21.28%	0.2064	0.4687	22.42%	0.2686	0.4982	0.8089
P10	27.99%	0.0040	1.2904	25.48%	0.0370	0.8920	0.2562
Pm	17.46%	-	-	18.56%	-	-	-

The market microstructure analysis reveals that only P10 appears to have less favourable price and bid-ask spread (but not volume) characteristics than Pm, with the differences between the investment portfolio and the benchmark portfolio of all stocks being both statistically and economically significant.

In particular, the average price of a Pm stock is roughly three times that of a P10 stock in both the formation period as well as the test period. However, it might be argued that this result is unlikely to have any adverse consequences for the investor. With the average price between €12.90 and €11.67 per share and market-average liquidity, it is doubtful that P10 stocks will be associated with oversensitivity to microstructure effects, as proposed by, among others, Ball *et al.* (1995).

In terms of the average bid-ask spread, while the difference between P10 and Pm is substantial in the formation period (*i.e.*, about 60%), it diminishes significantly in the test period to below 38%. It should be emphasised at this point that it is the test-period results that are important here as the investment strategy based on P10 would involve buying P10 stocks at the beginning of the test period and selling P10 stocks at the end of the test period. Another fact to note is that the discussed strategy is solely based on a long position in the portfolio of interest and, therefore, it is less direct-transaction-cost intensive than a strategy based on a short or arbitrage arrangement.

Incidentally, as all strategies presented in this thesis are based on a buy-and-hold investing approach, as specified in the 'Methodology' chapter, a strategy executed in the six-month/six-month timeframe involves one instance of two-way (or 'round-trip') transaction costs within the six-month investment (or 'test') period. This means that investing in P10 would be connected with a substantial bid-ask spread of 25.48%, on average. However, this would still leave about 1.09% per month (*i.e.*, 32%/6 – 25.48%/6) in bid-ask-spread-adjusted terms. Only after simultaneous risk adjustment, which reduces the abnormal six-monthly profit to 21% (using CAPM) or 17% (using the two-factor model), and transaction-cost adjustment is the equal-weighted, decile portfolio-size group, six-month/six-month, lowest past-return contrarian strategy for the EU12 stock market no longer profitable.

To conclude, past-return-based portfolios appear to be more risky than the benchmark portfolio of all stocks traded on the EU12 stock market. It is possible that this excess risk is mainly unsystematic in nature, which would be consistent with the overreaction hypothesis, and/or that CAPM does not capture all systematic risk, which is supported to some extent by the CAPM-related statistics. In addition, the assessment of market microstructure revealed that statistically and economically significant differences only arise between the lowest past-return portfolio and the market portfolio. In particular, a strategy based on the lowest past-return portfolio is likely to be associated with above-market-average transaction costs. Therefore, the second alternative hypothesis of no difference between past-return-based portfolios and the market portfolio is rejected for the EU12 stock market.

4.5. CONCLUSION

The purpose of this chapter has been to present, analyse and discuss the empirical results generated with the aim of addressing the two main hypotheses of the present research, which are defined in the 'Methodology' chapter. This process was divided into three stages, each corresponding to one section, which are as follows: (1) contextualising hypothesis number one and two (covered in Section 4.2.); (2) testing hypothesis number one (covered in Section 4.3.); and (3) testing hypothesis number two (covered in Section 4.4.).

From the analysis of the US, UK and EU12 investment environments in Section 4.2., it has been revealed that although the EU12 stock markets are still underdeveloped, undervalued and under-researched as compared to their US and UK counterparts, the level of risk associated with those investment environments is, in fact, appropriate even for conservative investors. What is more, the EU12 investment environment as a whole shows similar characteristics to the UK investment environment, when the difference in price levels is correctly accounted for and relative measures appropriate for comparing stock markets at different stages of development are used. As far as the EU12 stock markets' relative immaturity is concerned, it is no doubt rooted in the troublesome history of the 12 constituent countries. This fact, *nota bene*, complicates research design as it creates difficulties with, among others, determining the most appropriate time period for analysis or the currency of denomination, which helps to understand the lack of academic attention in the discipline of finance for the less-developed regions of the world. However, with increasing network integration on the part of stock market operators and progressing globalisation, the once unrecognised and underrated EU12 economies are now becoming within easy reach of investors worldwide and, due to the mostly untapped growth potential thereof, the related stock markets constitute an attractive investment destination.

Rather than investigating investment opportunities in the US, UK and EU12 in general, the explicit focus of this research has been on the performance and the investment characteristics of contrarian and momentum strategies in the stock markets of US (NYSE-AMEX), US (NASDAQ), UK (LSE), Bulgaria (BSE-Sofia), Cyprus (CSE), Czech republic (PSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania

(BVB), Slovakia (BSSE), Slovenia (LJSE) and the EU12 as a group. Section 4.3. explored the former, and at the same time the most fundamental, aspect of the two investing approaches by analysing returns to portfolios stratified on the basis of past performance for each of the 13 stock universes. The main finding therein has been that although contrarian and momentum strategies are mostly unsuccessful in the investigated populations, there is one notable exception.

Overall, out of the total of 39 extreme past-performance and arbitrage portfolios examined for all stock markets under consideration, only about 28.21% generate either a contrarian or a momentum average return that is associated with, at least, statistical significance at $p \leqslant 0.05$, which result shows high country-to-country variation between 0% and 100%. The higher standard of proof of significance adopted by this study, requiring both statistical significance at $p \leqslant 0.05$ and economic significance at $\Delta \geqslant 0.5$, is met by only five contrarian and momentum strategies in total, which represents a mere 12.82% of the qualifying portfolio universe, and it is detected in only three out of the 13 stock markets of interest. These are: Bulgaria (BSE-Sofia), Czech Republic (PSE), and the EU12 stock market. However, of the three stock markets listed only in the case of the last one is there a strategy that persists after controlling for market risk using CAPM, as indicated by statistical significance of CAPM alpha at $p \leqslant 0.05$. This means that the first alternative hypothesis of the present research is only accepted for the aggregate EU12 stock market and it is rejected for the remaining 12 stock populations. It should be noted, nonetheless, that the profitability of the one strategy that does meet the 'statistical and economic significance' standard set by Hypothesis One is, indeed, spectacular, with the average return of 5.33% **per month** in absolute terms, 3.5% **per month** in CAPM-adjusted terms or 2.83% **per month** in two-factor-model-adjusted terms during the time period studied.

Interestingly, little difference can be observed between the developed stock markets of US (NYSE-AMEX), US (NASDAQ) and UK (LSE), and the less-developed stock markets of the EU12. Consequently, the gathered evidence suggests that, on average, the nine less-developed stock markets do not outperform the three developed stock markets, at least insofar as contrarian and momentum strategies are concerned. It should be pointed out, though, that a greater sample of countries would be needed to generalise the above findings, concerning the relative performance of the developed and the less-developed stock markets, beyond the studied context.

The above evaluation is supported by the results of past-return-based strategies' risk and market microstructure analysis for each of the 13 stock markets studied, as presented in Section 4.4. of this chapter. In particular, the inspection of a wide range of investment characteristics reveals that, regardless of the stock market under consideration, contrarian and momentum strategies are typically exposed to a certain degree of excess risk and excess market microstructure frictions relative to the benchmark portfolio of all stocks. Thus, the second alternative hypothesis is rejected for all 13 stock populations. While in the case of the 12 stock markets that are not associated with an exploitable contrarian or momentum effect, as indicated by the results in Section 4.3., this fact is of little practical consequence, in the case of the aggregate EU12 stock market, for which one potentially profitable investment opportunity exists, further examination is needed.

From the analysis in Section 4.3., it is clear that the equal-weighted, decile portfolio-size group, six-month/six-month, lowest past-return contrarian strategy for the EU12 stock market remains highly profitable even after adjustment for risk using CAPM or a two-factor model based on the market factor as well as the size factor. However, the results in Section 4.4. indicate that the lowest past-return portfolio underlying the contrarian strategy has two unfavourable investment characteristics: (1) it is primarily composed of stocks issued by companies of below market-average market value of equity; and (2) it is primarily composed of stocks with extremely high and reliably above market-average bid-ask spreads. While the excess risk or the size effect potentially associated with the former characteristic has already been accounted for through a proxy in the form of the size factor in the two-factor model, the latter characteristic appears to fully explain the documented abnormal profitability.

Lastly, asymmetric mean reversion patterns have been documented in virtually all of the studied stock markets of the US and Europe. This result is consistent with the extensive body of economic literature on negative autocorrelation in stock returns (see *e.g.*, DBT, 1989; Fama and French, 1988; Kim *et al.*, 1991). Specifically, in line with Nam *et al.* (2002) it has been found that negative returns, on average, revert more quickly and with a greater reverting magnitude to positive returns than positive returns revert to negative returns.

5. CONCLUSION

5.1. STOCK MARKET EFFICIENCY REVISITED

It has been over 40 years since the efficient market hypothesis was formulated and, despite being disputed by many theorists and practitioners, it still remains the main proposition in finance and economics. The primary objective of this study has been to perform a practical test of weak-form efficiency for the US, UK and EU12 stock markets by considering the viability of contrarian and momentum strategies in each of the inspected investment environments. Specifically, having surveyed the existing studies on the subject, the present research aimed to address a number of limitations found in the literature within the framework of two main questions, which are the following: (1) 'Is either the contrarian or the momentum effect present in the stock markets of the US, UK and EU12?'; and (2) 'Are the strategies that exploit the contrarian and momentum effects associated with either excess risk exposure or excess market microstructure frictions as compared to the market-average level?'.

The results of this enquiry suggest that all stock markets considered are weak-form efficient. Specifically, in the case of US (NYSE-AMEX), US (NASDAQ), UK (LSE), Cyprus (CSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania (BVB), Slovakia (BSSE) and Slovenia (LJSE) all equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based strategies generate statistically and, in the vast majority of cases also economically, insignificant returns. While there is, at least, one past-return-based strategy for Bulgaria (BSE-Sofia) and Czech Republic (PSE) that is associated with statistically and economically significant returns, the perceived inefficiency is no longer statistically significant after controlling for risk using CAPM. The collective universe of all EU12 stocks is the only stock market in this study for which a past-return-based strategy produces (1) statistically and economically significant returns; as well as (2) a positive and statistically significant CAPM alpha. In fact, not only is the strategy robust to a risk adjustment using CAPM, but also to a risk adjustment using a two-factor model. However, once market microstructure frictions are considered in addition to risk, the abnormal profitability disappears.

5.2. SUMMARY AND DISCUSSION OF THE RESULTS

Commencing with the works of DBT (1985; 1987), and JT (1993), a substantial body of literature has developed that looked into the persistence of the return reversal and the return continuation effects as well as the profitability of the two corresponding investment methods, labelled as contrarian and momentum strategies, respectively. While the weight of the existing empirical evidence leans in favour of confirming the validity of the proposed phenomena, and by implication towards the rejection of the weak-form efficient market hypothesis, research in this branch of finance still remains considerably underdeveloped and conflicting in many areas.

The aforesaid underdevelopment is not only reflected by gaps in spatial coverage, but also by gaps in temporal coverage. In the former case, it should be pointed out that very little attention has been paid towards developing stock markets, especially the increasingly important EU12 stock markets, and, surprisingly, also to some of the world's largest stock markets, such as The NASDAQ Stock Market. In the latter case, of note is the fact that no US-stock-market-based study on contrarian investing has covered a sample period beyond the late 1980s.

In terms of conflicting results, these are likely to be a result of methodological discrepancies across, often small-scale, studies. What is particularly interesting is that extremely few scholars have looked at the combined framework of contrarian and momentum strategies, despite the fundamental similarity of the two concepts.

This thesis has sought to address the above-mentioned, and other, limitations of the existing literature as well as to uniquely contribute to the debate on the subject. In particular, the objective of the present research was to determine if, in recent years, it has been possible to systematically earn abnormal returns in the stock markets of the US, UK and EU12 by following either a contrarian or a momentum strategy. Under investigation was the time period from the beginning of January 2000 up to the end of December 2011 and the following 13 stock markets: US (NYSE-AMEX), US (NASDAQ), UK (LSE), Bulgaria (BSE-Sofia), Cyprus (CSE), Czech Republic (PSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania (BVB), Slovakia (BSSE), Slovenia (LJSE) and the EU12.

To begin with, it has been found that although the EU12 stock markets are still underdeveloped, undervalued and under-researched in comparison to the more mature US and UK stock markets, all of the studied investment environments are suitable even for conservative investors. What is more, when appropriate economic measures for cross-country analysis are used, the aggregate EU12 investment environment emerges as comparable to the UK investment environment, which already implies that the former context provides an alternative, if not directly competitive with the latter context, source of investment opportunities for investors worldwide. This is especially the case for two reasons. First, as discussed in Sections 1.2. and 4.2., the EU12 region is of growing economic importance internationally, due to an increasingly integrated Europe and increasingly integrated global financial markets. Second, as discussed in Appendix A, Principal Components Analysis, a statistical method commonly used in the context of evaluating the portfolio diversification potential of global financial markets, suggests that the EU12 stock market can provide US and UK investors with substantial diversification benefits.

Furthermore, the first alternative hypothesis, testing for a contrarian or momentum investment strategy with statistically and economically significant returns as well as a positive and statistically significant CAPM alpha, is rejected for 12 out of the 13 stock markets investigated. Specifically, in the case of US (NYSE-AMEX), US (NASDAQ), UK (LSE), Lithuania (VSE) and Slovenia (LJSE) all past-return-based portfolios generate returns that are neither statistically nor economically different from zero. The results for Cyprus (CSE), Hungary (BSE) and Poland (WSE) show that only the arbitrage portfolio's returns are associated with statistical significance, but not with economic significance. Exclusively economic significance of returns, on the other hand, can be observed for exactly one portfolio in the case of Romania (BVB) and Slovakia (BSSE). While, at least, one portfolio for each Bulgaria (BSE-Sofia) and Czech Republic (PSE) produces statistically and economically significant returns, it would seem that the perceived abnormal profitability can be explained by CAPM. Although the same applies to the highest past-return portfolio formed from the aggregate pool of all EU12 stocks, the contrarian effect associated with the lowest past-return portfolio for the EU12 stock market remains strong after a risk adjustment using CAPM (leaving 3.5% per month) or even after a risk adjustment using a two-factor model based on the market factor and the size factor (leaving 2.83% per month). Therefore, the equal-weighted, decile portfolio-size group, six-month/six-month, lowest past-return contrarian strategy for the EU12 stock market is the only strategy in this study that fulfils the requirements set by the first alternative hypothesis.

The second alternative hypothesis, testing for no difference in risk or market microstructure frictions between past-return-based portfolios and the market portfolio, is rejected for all stock market studied. This means that contrarian and momentum strategies, which are based on past-return-based portfolios, tend to be associated with excess risk and excess market microstructure frictions relative to the benchmark portfolio of all stocks. While in the case of the 12 stock markets that are not associated with a successful contrarian or momentum strategy, at least by the adopted specifications and standards, this fact is of little practical consequence, the same does not apply to the EU12 stock market, for which one potentially successful contrarian strategy exists. The risk and market microstructure analysis performed for the portfolio underlying the aforementioned strategy reveals two unfavourable investment characteristics. First, the portfolio is mainly composed of stocks issued by companies of below market-average market value of equity. Second, the portfolio is mainly composed of stocks with extremely high and reliably above market-average bid-ask spreads. While the excess risk or the size effect that could potentially be associated with the first characteristic has already been accounted for through the use of a proxy in the form of the size factor in the two-factor model (which leaves, as mentioned earlier, 2.83% per month), the latter characteristic appears to fully explain the documented abnormal profitability.

In addition to considering different proxies for risk and market microstructure, the above results are robust to, among others, non-normal distributions, heteroscedasticity, autocorrelation, time periods, macroeconomic risk and exchange rate risk.

As can be seen from the above list, there are no viable contrarian or momentum investment options for US (NYSE-AMEX), which is interesting considering that the stock market has been previously associated with powerful past-return-based effects on many investment horizons (see *e.g.*, DBT, 1985; 1987; JT, 1993, 2001). One possible, and at the same time the most credible, rationalisation of this discrepancy is that the earlier-documented abnormal profitability has already been discounted by the market, which eventuality is not without precedent as it was reported for, among others, the size effect, the book-to-market effect, the dividend yield effect and the weekend effect (see *e.g.*, Schwert, 2003). Another potential explanation could be that the exceptionally stringent criteria adopted by this study, which require both statistical as well as economic significance of returns, increase Type II error rates. However, a close inspection of the results reveals that not only would lowering the standard of proof of significance set by the first alternative hypothesis leave the overall conclusion of virtually no market inefficiency unchanged, but also the main findings pertinent to the first hypothesis would remain the same. Specifically, if the only requirement for a successful past-return-based strategy were the statistical significance of its returns and the statistical significance of its CAPM alpha, then only the same one strategy for the aggregate EU12 stock market would qualify.

Moreover, there is no noticeable difference in terms of the effectiveness of contrarian and momentum strategies and the level of stock market development. The EU12 stock markets do not appear to significantly outperform the stock markets of the US and the UK, especially after excess risk and market microstructure frictions are considered. This can be interpreted as either evidence against the hypothesis that developing stock markets are less informationally efficient than developed stock markets (see *e.g.*, Schatzberg and Reiber, 1992; Antoniou *et al.*, 1997) or evidence questioning the categorisation of the EU12 stock markets as developing by the Dow Jones Indexes Country Classification System (S&P Dow Jones Indexes, 2011). However, especially in the former case, a greater sample of countries would need to be investigated in order to reach a more definitive conclusion.

Despite the fact that no past-return-based strategy complies with both the first and the second alternative hypothesis of the present research for any of the stock markets studied, there appears to be a strong mean reversion pattern in virtually all of the studied stock markets of the US and Europe, with negative returns, on average, reverting more quickly and with a greater magnitude to positive returns than positive returns reverting to negative returns. This result is in line with the extensive body of economic literature on negative autocorrelation in stock returns (see *e.g.*, DBT, 1989; Fama and French, 1988; Kim *et al.*, 1991).

To conclude, the EU12 investment environments are not meaningfully more risky than their more mature US and UK counterparts and the EU12 stock markets are not relatively more inefficient. Consequently, investing in the EU12 is suitable even for conservative investors, especially those seeking international diversification. As regards contrarian and momentum opportunities *per se*, these appear to be no longer present, which suggests that, like many other similar anomalies, the two past-return-based effects have been arbitraged away.

5.3. RECOMMENDATIONS FOR FURTHER WORK

Despite the fact that this study has been comprehensive in scope by design in order to, *inter alia*, address the problem of methodological discrepancies in the contrarian and momentum literature, there are still a number of ways in which the present research could be meaningfully expanded. Specifically, two areas deserve future academic attention.

First, this study documents asymmetric mean reversion patterns in virtually all of the examined populations. Although this phenomenon has been extensively researched in the developed stock markets, still relatively few studies exist for developing stock markets (see *e.g.*, Akarim and Sevim, 2013), especially the EU12 stock markets. Considering the fact that mean reversion is a time-series phenomenon, unlike the contrarian and momentum effects which are partly cross-sectional in nature (see *e.g.*, Lo and MacKinlay, 1990; Lewellen, 2002), a time-series analysis would be more appropriate in this context.

Second, in order to determine whether developing stock markets are less informationally efficient than the developed stock markets, especially as regards weak-form efficiency, a greater sample of economies would need to be analysed. The evidence presented in this thesis, suggesting that, on average, there is no meaningful difference between the two types of stock markets, is largely consistent with Rouwenhorst (1999) and De Groot *et al.* (2012). However, it might be argued that still too few studies have addressed this issue to date so as to justify such far-reaching conclusions.

APPENDIX A

Principal Components Analysis (PCA) is a non-parametric statistical procedure that transforms, through eigen decomposition, a single set of possibly correlated variables into subsets of linearly uncorrelated (or orthogonal) variables called principal components (or eigenvectors). When used in the context of evaluating the portfolio diversification potential of global financial markets (see *e.g.*, Meric, Ratner, Lentz and Meric, 2005; Meric, Ratner and Lentz, 2006; 2008), PCA clusters investments (or in the present case stock markets) into principal component portfolios on the basis of similarities in return movements. Stock markets from the same principal component portfolio are closely correlated, which means that they provide low diversification, whereas stock markets with high factor loadings in different principal component portfolios provide high diversification.

In order to group stock markets into principal component portfolios and estimate factor loadings, it is first necessary to organise data (in the present case average monthly stock market returns) into a *d*-dimensional dataset (in the present case 13-dimensional, with each dimension corresponding to the data from one of the stock markets investigated). From the *d*-dimensional dataset one can derive the *d*-dimensional mean vector and generate a covariance matrix (or, alternatively, the scatter matrix). It is then possible to calculate eigenvectors (or principal components) and the corresponding eigenvalues. Eigenvectors are sorted by decreasing eigenvalues, which gives principal components order of significance. As in Meric *et al.* (2008), components of lesser significance, *i.e.* with eigenvalues less than one, are excluded from analysis.

One of the main advantages of PCA over the conventional correlation analysis is that it makes possible to (1) compare more than two stock markets at a time; and to (2) detect more complex underlying structure in the data that have a large number of characteristics (*e.g.*, the dividend yield, the P/E ratio or market capitalisation). However, one of its limitations is that even though PCA can detect complex underlying structure in data, the underlying pattern itself cannot be identified.

For the set of all the stock markets examined in this study Table 106 on the next page shows the factor loadings of the statistically significant principal components with eigenvalues (λ) greater than one, *i.e.* Comp1 ($\lambda \approx 3.60$), Comp2 ($\lambda \approx 1.87$), Comp3 ($\lambda \approx 1.15$), Comp4 ($\lambda \approx 1.09$) and Comp5 ($\lambda \approx 1.01$). The calculations therein are based on the correlation matrix of 13[90] aggregate stock market returns for this study's entire time period under analysis (*i.e.*, 01/01/2000 - 30/12/2011).

The results of the PCA indicate that Cyprus (CSE), Hungary (BSE), Poland (WSE), US (NYSE-AMEX) and US (NASDAQ) all have their highest factor loadings in Comp1. This means that while, in general, having stocks from the aforementioned stock markets in the same portfolio will provide limited diversification due to the presence of high correlation, diversification benefits can be substantially increased by including stocks from the other six individual EU12 stock markets, the aggregate EU12 stock market or UK (LSE). Most importantly, though, by investing in a US stock market, UK (LSE) and the aggregate EU12 stock market investors could obtain the greatest diversification, on account of the fact that the three stock markets have their highest factor loadings in different principal components. In particular, the collective EU12 stock universe appears to be only slightly correlated with US (NYSE-AMEX), US (NASDAQ) and UK (LSE).

[90] As noted in footnote 2 on page 24, the individual results for Estonia (TSE), Latvia (RSE) and Malta (MSE) have been excluded from this study upon the request of viva voce examiners and doctoral supervisors. Therefore, the correlation matrix is based on the aggregate stock market returns for US (NYSE-AMEX), US (NASDAQ), UK (LSE), Bulgaria (BSE-Sofia), Cyprus (CSE), Czech Republic (PSE), Hungary (BSE), Lithuania (VSE), Poland (WSE), Romania (BVB), Slovakia (BSSE), Slovenia (LJSE) and the EU12.

TABLE 106. PRINCIPAL COMPONENTS ANALYSIS (PCA) – FACTOR LOADINGS OF THE PRINCIPAL COMPONENTS.

Stock market	**Comp1**	**Comp2**	**Comp3**	**Comp4**	**Comp5**
US (NYSE-AMEX)	**0.4375**	-0.1316	-0.2051	0.1093	-0.0088
US (NASDAQ)	**0.4163**	-0.1451	-0.2034	0.1009	-0.0528
UK (LSE)	0.1262	-0.0440	**0.5056**	0.0666	0.4790
Bulgaria (BSE-Sofia)	-0.0618	**0.6197**	0.0717	0.1262	-0.3003
Cyprus (CSE)	**0.2123**	0.0094	0.1978	-0.6176	-0.2542
Czech Republic (PSE)	0.2856	-0.0577	-0.2377	**0.3238**	-0.1945
Hungary (BSE)	**0.3550**	-0.0059	-0.0310	0.0537	-0.1313
Lithuania (VSE)	0.2903	-0.0528	0.2253	0.1229	**0.3193**
Poland (WSE)	**0.4193**	0.0326	0.0818	-0.0794	-0.1458
Romania (BVB)	0.2557	0.1556	**0.3082**	-0.2919	0.1592
Slovakia (BSSE)	0.0393	0.2497	-0.5699	-0.1902	**0.6350**
Slovenia (LJSE)	0.0308	0.1962	0.2781	**0.5687**	0.0749
EU12	0.1869	**0.6658**	-0.0683	-0.0467	0.0185

APPENDIX B

As specified in Chapter One, the explicit focus of this thesis is on the practical implications of the contrarian and momentum effects.

What this means is that the primary consideration herein is given to the issues that are of direct relevance to the investment community. This orientation is based on the premise that the main role of finance research should be to inform and guide finance practice, rather than to pursue 'dry' theoretical debates or to produce theories that lack real-world relevance and as such are of little interest to investors. While this is not to suggest that pure, non-applied research is unnecessary or that research should exclusively focus on servicing the immediate needs of practice, finance is ultimately an applied discipline and it should inform practice if it is to be of value[91].

What the aforementioned emphasis on practical aspects does not mean, however, is that the present study is detached from academic research, academic theories or academic methodologies and, therefore, does not meaningfully contribute to the development of the academic discipline of finance. Indeed, the two past-return-based stock market anomalies that are the primary object of analysis and discussion in this thesis represent a product of academic theory, but one with wide-ranging practical implications. Similarly, the aim of the present research is to contribute to knowledge in a way that adds value to finance practice.

With the above-described philosophy in mind, the 'Literature review' chapter provides a review of the publications on the contrarian and momentum effects with an explicit focus on the issues relevant to finance practice. The practical aspects thereof principally encompass the magnitude and significance of the documented profits as well as the risk and market microstructure considerations associated with generating those profits. However, for completeness, this appendix briefly discusses

[91] The problem of the gap between theory and practice has been addressed in several publications from various fields of study. A few prominent examples from the disciplines of finance and management include Baker, Singleton and Veit (2010); Mitchell (2002); and Van De Ven and Johnson (2006).

the theoretical aspects of the contrarian and momentum effects, most importantly the effects' 'theoretical sources'[92].

In line with DBT (1985) and JT (1993), referred to extensively in Chapter Two, several publications point towards behavioural factors as a possible source of past-return-based anomalies. In particular, Barberis, Shleifer and Vishny (1998); Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) all developed theories that are largely consistent with the available empirical findings. Despite drawing on distinct psychological ideas, the first two papers proposed models based on the concept of a single representative investor whose biased beliefs essentially reflect 'consensus forecasts'. The last paper, on the other hand, focused on the interaction between two different types of investors with bounded rationality.

Barberis *et al.* (1998) suggested that, in accordance with, among others, Tversky and Kahneman (1974), Edwards (1968), and Griffin and Tversky (1992), investors rely on the representativeness heuristic as well as conservatism when making decisions or judgements about the probability of an event under uncertainty.

As far as the former bias is concerned, it is argued that investors tend to attach too much weight to relatively unlikely events that are erroneously seen as representative of a class and too little weight to relatively likely events that are erroneously seen as less representative of a class, thereby ignoring the laws of probability. Consequently, a history of consistently high returns, potentially along with positive analyst recommendations, might lead investors to believe that a stock's past performance is representative of its future performance, rather than that it is a chance occurrence which is unlikely to repeat itself in the future. In time, this will cause the stock to become over-valued and, once investors realise that the forecasts are not going to

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[92] As opposed to 'practical sources', such as risk or market microstructural factors, 'theoretical sources' are taken herein to mean the hypothesised sources of the studied phenomena that have limited or no immediate implications for finance practice.

It is also important to mention that this review focuses on the seminal contributions on the subject of the potential 'theoretical sources' behind the contrarian and momentum effects. Other notable research efforts in this area include, among others, the studies on the disposition effect (see *e.g.*, Frazzini, 2006; Grinblatt and Han, 2005; Hur, Pritamani and Sharma, 2010; Shefrin and Statman, 1985), the positive feedback strategies (see *e.g.*, De Long *et al.*, 1990) and the moderated confidence phenomenon (see *e.g.*, Bloomfield, Libby and Nelson, 2000).

materialise, subsequently a price correction. This mechanism is consistent with overreaction and the contrarian effect.

In terms of the latter bias, it would seem that as new information arrives to the stock market investors update their beliefs in the correct direction but by too little relative to a rational Bayesian. As a result, investors may partially disregard new information and only adjust stock valuations to some extent, thereby still partially depending on outdated information. This incomplete response to new information will lead to underreaction, which is commonly associated with the momentum effect.

Although the authors' model is mainly based on the two aforementioned biases, other closely related behavioural traits include overconfidence, overoptimism, anchoring, the clustering illusion, the confirmation bias or the availability heuristic.

Similarly to Barberis *et al.* (1998), Daniel *et al.* (1998) proposed that stock market overreaction and underreaction, presumably underlying the contrarian and momentum effects, may be driven by two well-known psychological biases, *i.e.* overconfidence and biased self-attribution.

However, rather than being overconfident about prior information, as suggested by the previously-discussed publication, investors and analysts are here said to be overconfident about their ability to generate accurate forecasts. This, in conjunction with the fact that finance practitioners are more likely to be overconfident about the information that is generated by them personally, rather than the information that is available publically, causes stock prices to overreact, which overreaction subsides slowly over time as more public information arrives to the stock market. Thus, it is argued that stock prices overreact to private information, but underreact to public information.

In addition to overconfidence, as Daniel *et al.* (1998) explained, investors are subject to biased self-attribution, which causes asymmetric shifts in confidence as a function of investment outcomes. Attribution theory (see *e.g.*, Bem, 1965) states that individuals in general tend to interpret events in a manner that attributes internal, controllable factors for success and external, non-controllable factors for failure (a psychological phenomenon also known as the self-serving bias). In the context of financial markets this means that the confidence of investors trading on private information will rise markedly if subsequent public information is favourable, but fall only modestly if subsequent public information is unfavourable. Therefore, new public information will, on average, rise confidence, thereby adding to the overreaction associated with preceding private information. The result of such continuing overreaction will at first be the momentum effect, but then, as more public information arrives to the stock market and stock prices are drawn towards fundamentals, the contrarian effect.

In contrast to Barberis *et al.* (1998) and Daniel *et al.* (1998), who proposed two main psychological biases that affect the typical investor, Hong and Stein (1999) argued that there are two types of investors with bounded rationality, *i.e.* 'news-watchers' and 'momentum traders'. With neither type of investor being fully rational, each type is assumed to have information-processing abilities limited to a subset of the available public information. In particular, the former investors produce forecasts based on privately observed signals about future fundamentals, but do not condition on current or past prices, while the latter investors do condition on past price changes, but can only produce forecasts that are a simple, univariate function of past prices. With the additional (third) assumption of private information diffusing gradually across the 'news-watcher' population, the authors showed that when 'news-watchers' are active prices adjust slowly to new information, thereby creating underreaction. Due to the fact that 'momentum traders' are assumed to solely use simple strategies, which do not factor in all public information[93], this underreaction is not efficiently arbitraged away, but as a result of an accelerated move of prices towards fundamentals is only eliminated at the expense of creating overreaction. Consequently, in the model developed by Hong and Stein (1999) it is the interplay between two types of investors under the conditions of gradual diffusion of information about fundamentals that is responsible for both the momentum effect and the contrarian effect.

[93] In particular, it is assumed that 'momentum traders' are not able to condition on the timing of new information arrival, which means that it is not possible for them to determine whether new information has already been fully incorporated into prices or not. This will result in momentum trades pushing prices beyond long-term equilibrium values and, therefore, overreaction.

Thus far, the discussion in this appendix has been concerned with behavioural theories about the potential 'theoretical sources' of past-return-based anomalies. However, a fundamentally different perspective on this issue was put forward by Lo and MacKinlay (1990)[94], who showed that if returns on some stocks systematically lead or lag returns on other stocks, then a strategy that sells the highest past-return portfolio and buys the lowest past-return portfolio can produce positive expected returns, even in the absence of negative autocorrelation that is central to virtually all models of overreaction.

Indeed, it might be argued that most contrarian strategies (most notably, DBT 1985; 1987), conceivably based on a premise that 'what goes up must come down', and vice versa, implicitly focus on exploiting the negative own-autocorrelations of individual securities, which are then primarily attributed to overreaction. However, the authors questioned the reverse implication of the overreaction hypothesis, namely, that the profitability of contrarian investment strategies necessarily implies stock market overreaction and asserted that forecastability across securities is, at least, as important a source of contrarian profits both in principle and in fact.

To test this hypothesis, the authors employed a **short-term** contrarian strategy based on **weekly** equal-weighted and value-weighted returns indexes obtained from CRSP daily returns files for the period from 1962 to 1987.

The findings suggest that, contrary to the overreaction hypothesis, weekly returns are generally weakly negatively auto-correlated, which effect is also confirmed for daily and monthly returns, where similar patterns were observed.

Furthermore, to show the relationship between short-term contrarian profits and the cross effects that were argued here to be apparent in the data, Lo and MacKinlay

[94] It should be stressed, however, that the findings presented by Lo and MacKinlay (1990) as well as Jegadeesh and Titman (1995), discussed later in this appendix, are based on short-term strategies, rather than intermediate-term strategies, such as those examined by JT (1993), or long-term strategies, such as those examined by DBT (1985; 1987). Here, 'short-term' is taken to mean under one month, 'intermediate-term' is taken to mean between one month and one year, while 'long-term' is taken to mean beyond one year.

(1990) examined the expected profits of one such strategy under various return-generating processes. It was speculated (*ibid.*, p. 184) that:

> (If) returns are positively cross-autocorrelated, then a return-reversal strategy will yield positive profits on average, even if individual security returns are serially independent! The presence of stock market overreaction, that is, negatively autocorrelated individual returns, enhances the profitability of the return-reversal strategy, but it is not required for such a strategy to earn positive expected returns.

Accordingly, a simple return-generating process was constructed in which each security's return seemed to be serially independent and yet still yielded positive expected profits for a portfolio strategy that buys losers and sells winners. Thus, it would appear that short-term contrarian portfolio strategies benefit from positive cross-autocovariances across securities.

This result, Lo and MacKinlay (1990) argued, highlights the importance of the cross effects, since although each security is individually unpredictable, a contrarian strategy may still profit if securities are positively cross-correlated at various leads and lags. Incidentally, one possible source of such cross effects, as identified by the authors, is what has come to be known as the 'non-synchronous trading', 'thin-trading' or 'non-trading' problem.

Nonetheless, although the authors presented evidence against overreaction as the only source of contrarian profits, a contrarian investment strategy is still found to be "a convenient tool for exploring the autocorrelation properties of stock returns" (*ibid*., p. 178). Furthermore, Lo and MacKinlay (1990) emphasised that: "inferences concerning the performance of the long-horizon strategies cannot be drawn directly from results such as ours. Because our analysis of the contrarian investment strategy (...) uses only weekly returns, we have little to say about the behavior of long-horizon returns" (p. 200).

By sharp contrast, Jegadeesh and Titman (1995) argued that it is, in fact, stock price overreaction that contributes most to the **short-term** contrarian profit, while the delayed reactions to common factors which give rise to a size-related lead-lag effect in stock returns can account for only a small fraction of this profit.

Principally, the authors showed that the average cross-serial covariance, which according to Lo and MacKinlay (1990) measures the contribution of the lead-lag structure to contrarian profits, may be a misleading measure. Therefore, in this paper stock price reactions to common factors and firm-specific information were examined separately, thereby presenting a decomposition model that: "directly relates the different components of contrarian profits to their sources, identified based on how stock prices respond to information" (Jegadeesh and Titman, 1995, p. 975).

To begin with, having analysed the method of decomposing contrarian profits employed by the preceding paper, Jegadeesh and Titman (1995) proved that Lo and MacKinlay's (1990) decomposition counts the effect of delayed reactions twice, "once in the own-autocovariance term and once in the cross-serial covariance term" (Jegadeesh and Titman, 1995, p. 982). This double counting, the authors stated, leads to misleading inferences.

Further investigation revealed that, overall, the upper boundary on the contribution of the lead-lag relation is approximately 13.12%. However, the authors noted that in the likely event of there being only a partial reaction, the contrarian profit due to this delayed reaction will be significantly smaller. Thus, the primary source of observed contrarian profits would appear to be the reversal of the firm-specific component of returns, which is consistent with the overreaction hypothesis.

Jegadeesh and Titman (1995) concluded that stock prices react with a delay to common factors, but overreact to firm-specific information. While consistent with Lo and MacKinlay (1990) the delayed reactions to common factors give rise to the lead-lag effect in stock returns which, in principle, together with overreaction could lead to the profitability of contrarian strategies, the results indicate that the delayed reactions cannot be exploited by contrarian trading strategies.

APPENDIX C

TABLE 107. CHARACTERISTICS OF MONTHLY TOTAL STOCK INDEX RETURNS FOR DATASTREAM ADVANCE AND CRSPSIFT DATA.

	R						
	Minimum	**Maximum**	**Average**[95]	**Median**	**Standard deviation**	**Skewness**	**Kurtosis**
US (NYSE-AMEX)	-0.2997	0.2578	0.0123	0.0143	0.07	-0.39	2.76
US (NASDAQ)	-0.2655	0.3589	0.0100	0.0088	0.09	0.25	1.87
UK (LSE)	-0.0962	0.6899	0.0056	0.0025	0.06	8.99	97.55
Bulgaria (BSE-Sofia)	-0.0645	2.4127	0.0900	0.0303	0.28	6.91	52.11
Cyprus (CSE)	-0.2575	0.6596	-0.0009	-0.0039	0.09	2.46	17.34
Czech Republic (PSE)	-0.0548	0.0553	0.0056	0.0052	0.02	-0.38	1.19
Hungary (BSE)	-0.1497	0.1505	0.0103	0.0098	0.05	0.21	1.10
Lithuania (VSE)	-0.1830	0.2775	0.0142	0.0154	0.06	0.79	4.37
Poland (WSE)	-0.1927	0.2278	0.0098	0.0095	0.07	0.32	0.70
Romania (BVB)	-0.1272	0.2819	0.0403	0.0329	0.07	1.13	2.46
Slovakia (BSSE)	-0.0572	5.8860	0.0915	0.0081	0.53	9.67	101.74
Slovenia (LJSE)	-0.0522	0.8572	0.0317	0.0105	0.11	5.74	37.59
EU12	-0.0563	0.4447	0.0328	0.0261	0.06	3.49	19.93

[95] The time series of average monthly total stock index returns are available in Figure 5 - Figure 11.

FIGURE 5. AVERAGE MONTHLY RETURNS FOR US (NYSE-AMEX) AND US (NASDAQ).

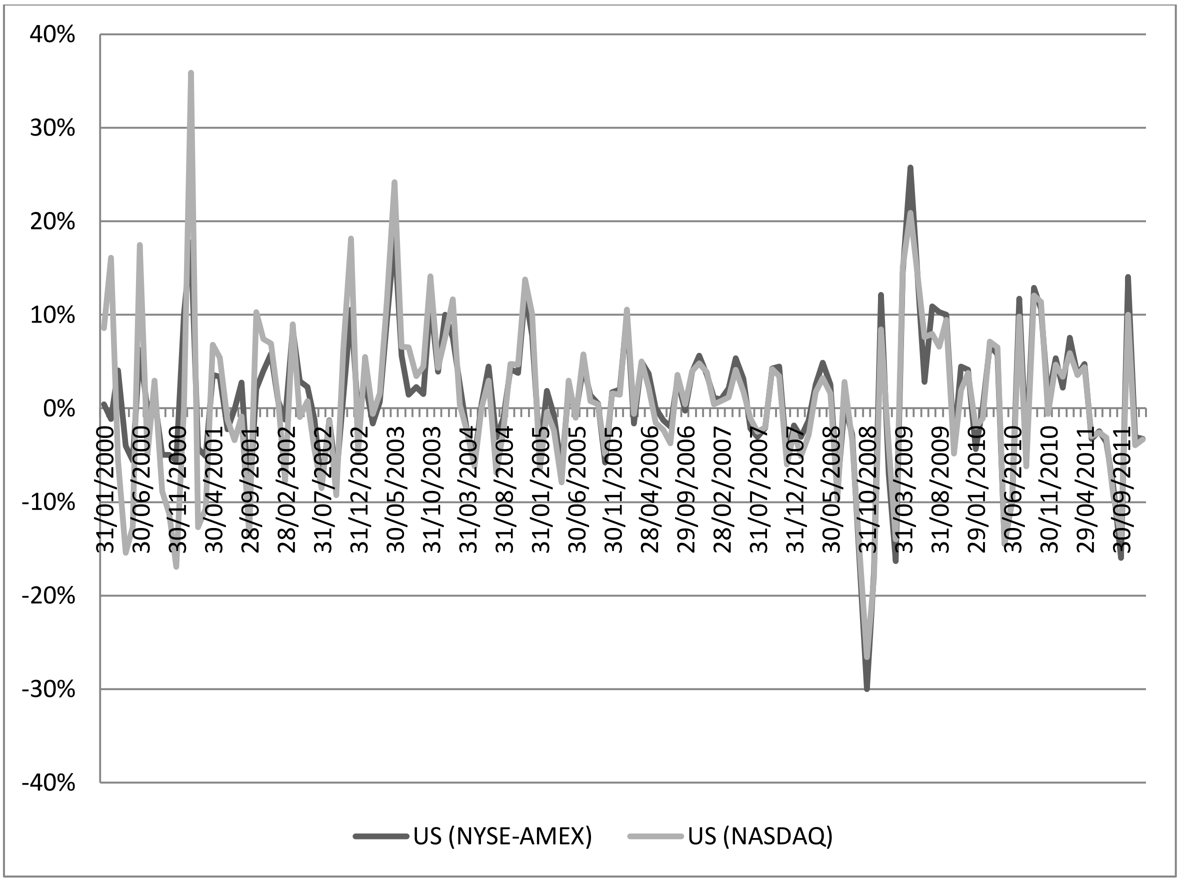


FIGURE 6. AVERAGE MONTHLY RETURNS FOR UK (LSE) AND EU12.

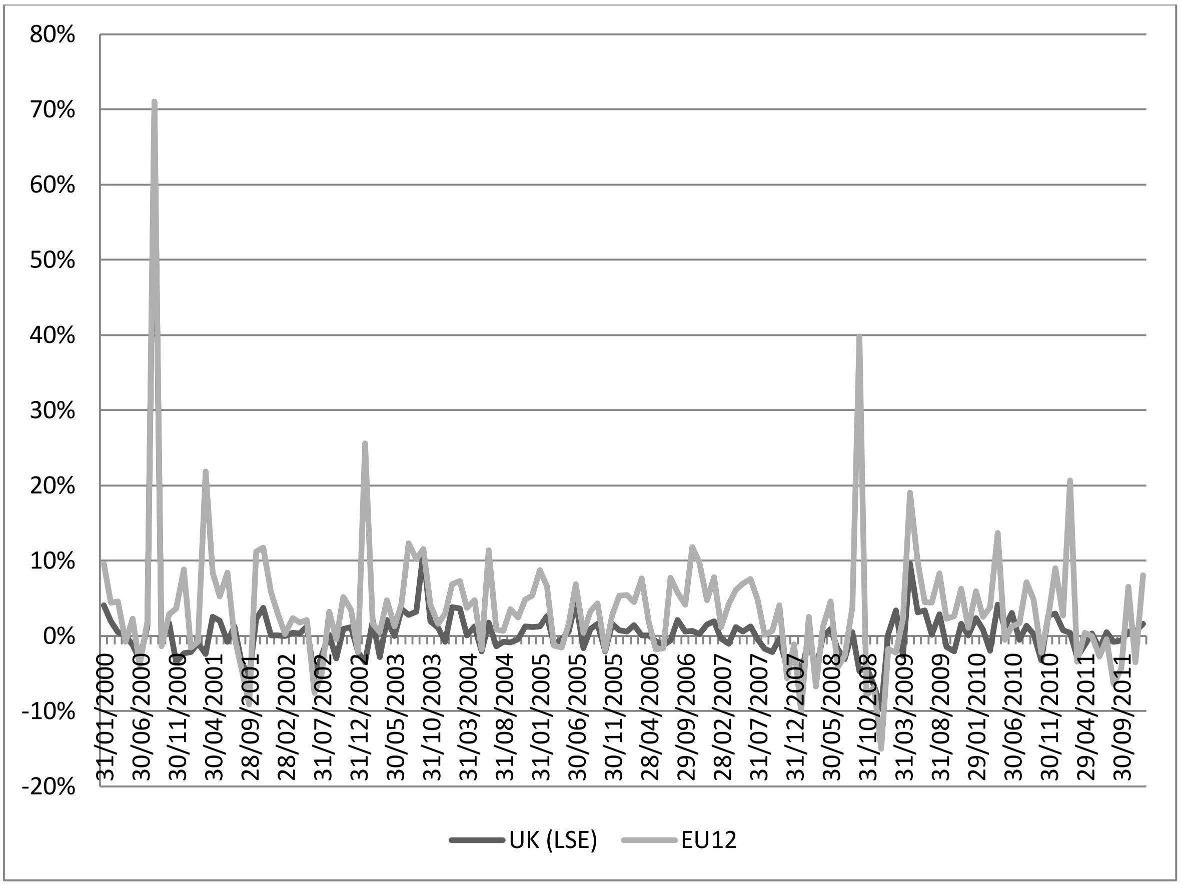


FIGURE 7. AVERAGE MONTHLY RETURNS FOR BULGARIA (BSE-SOFIA) AND CYPRUS (CSE).

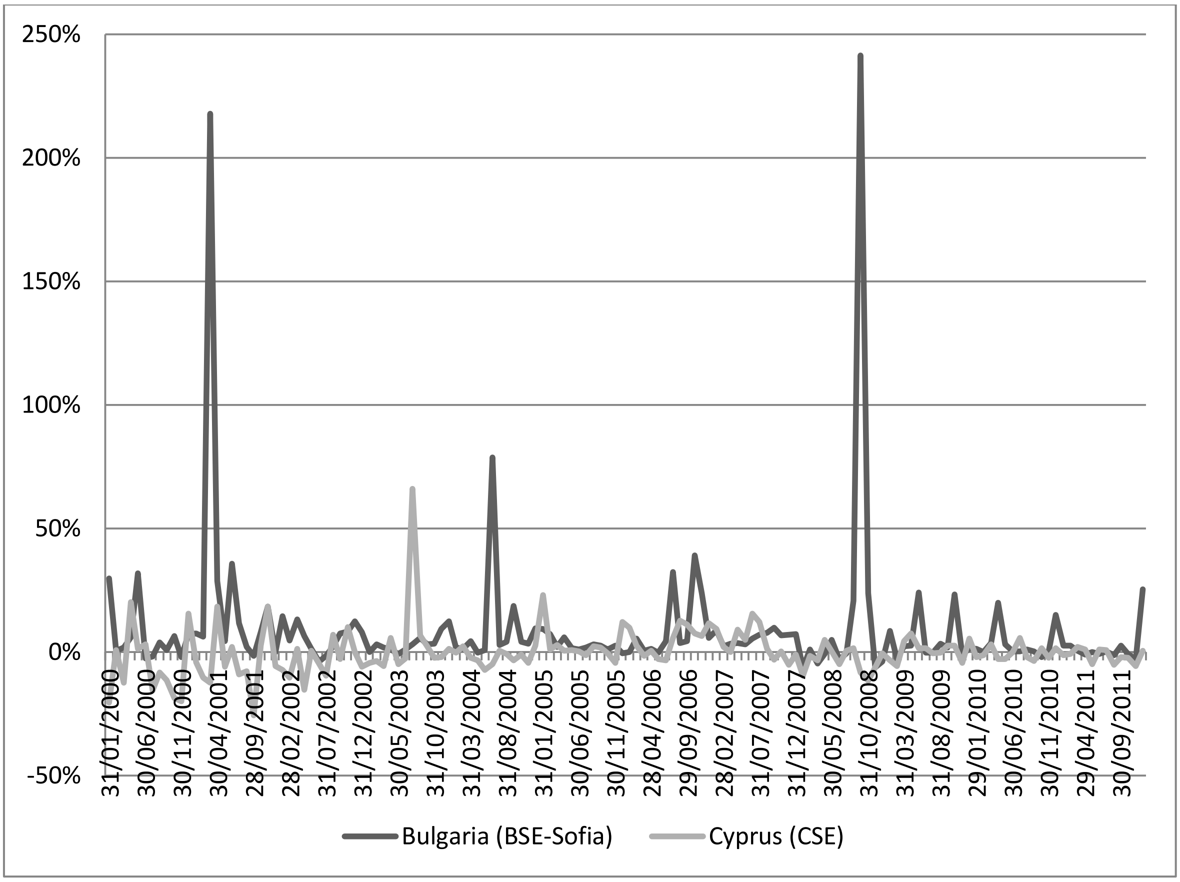


FIGURE 8. AVERAGE MONTHLY RETURNS FOR CZECH REPUBLIC (PSE) AND HUNGARY (BSE).

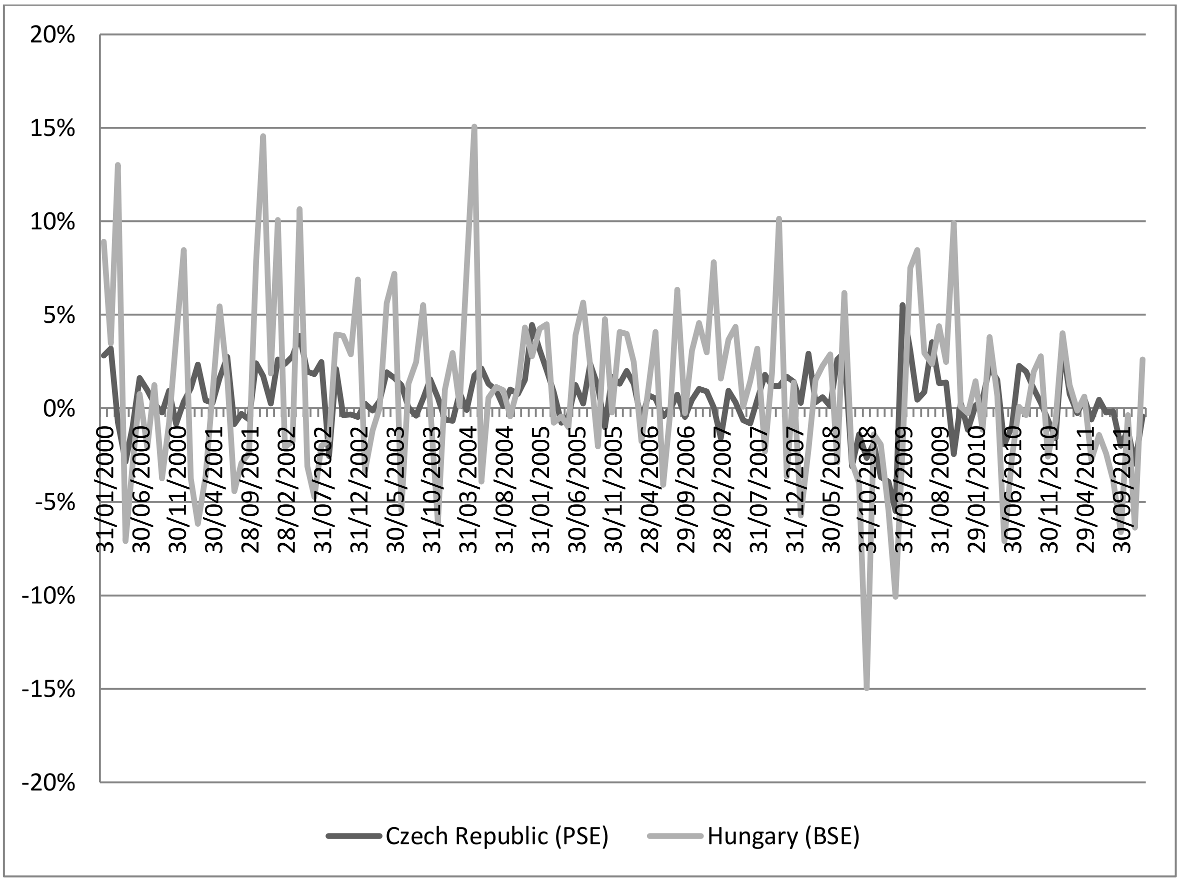


FIGURE 9. AVERAGE MONTHLY RETURNS FOR LITHUANIA (VSE).

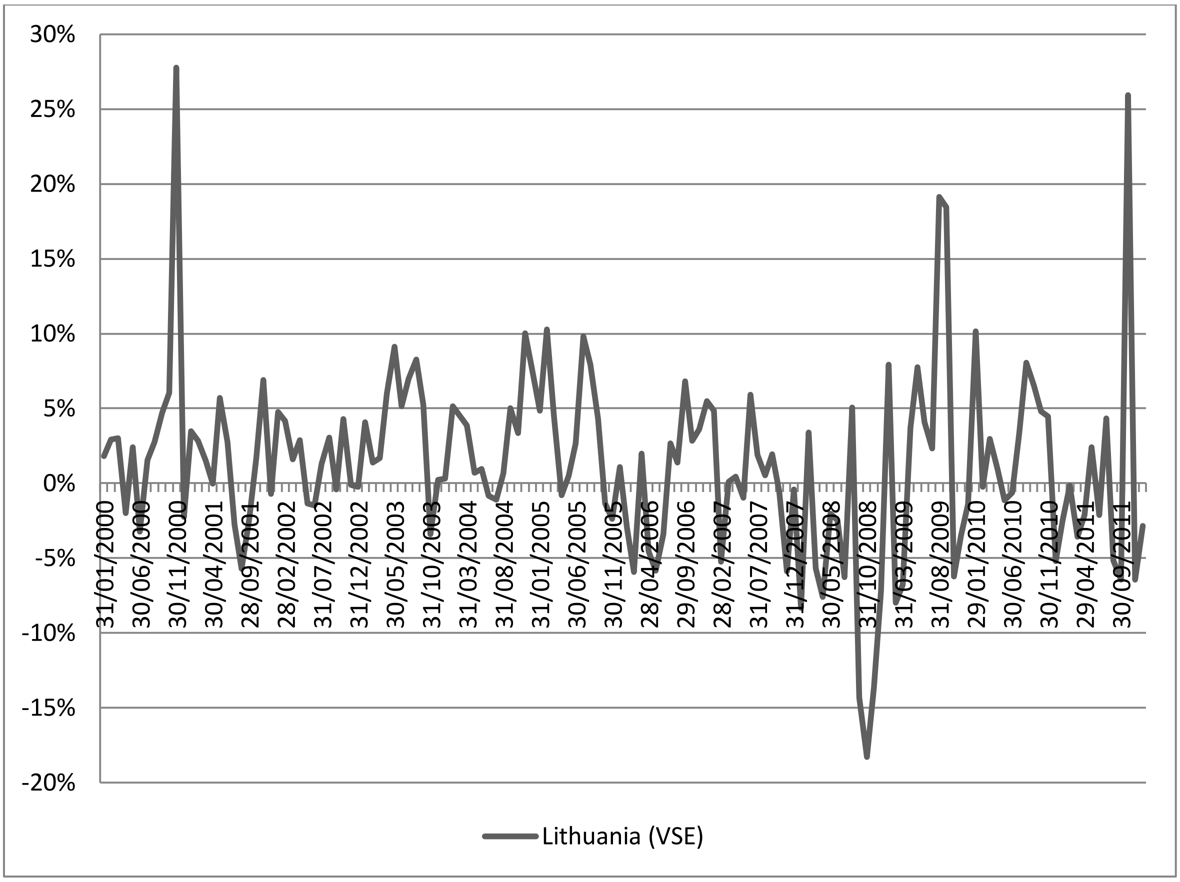


FIGURE 10. AVERAGE MONTHLY RETURNS FOR POLAND (WSE) AND ROMANIA (BVB).

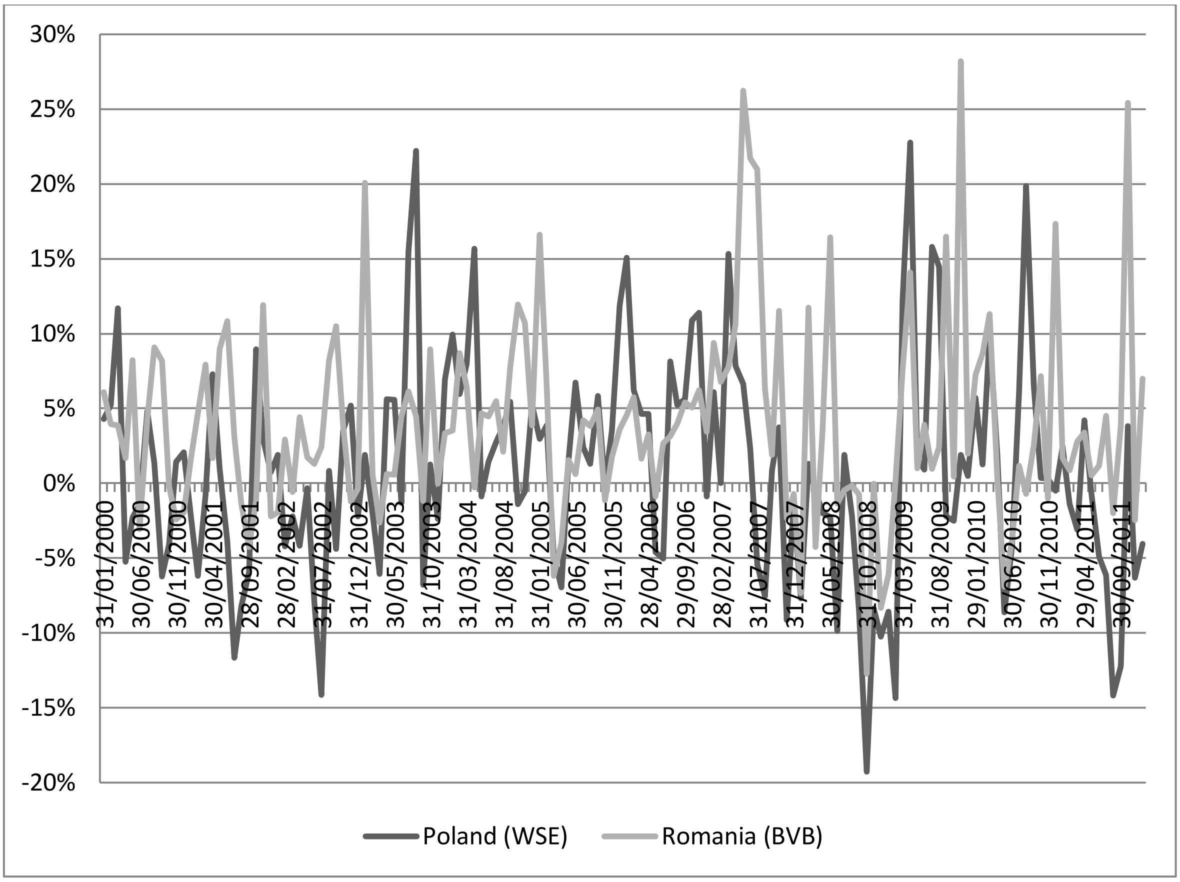
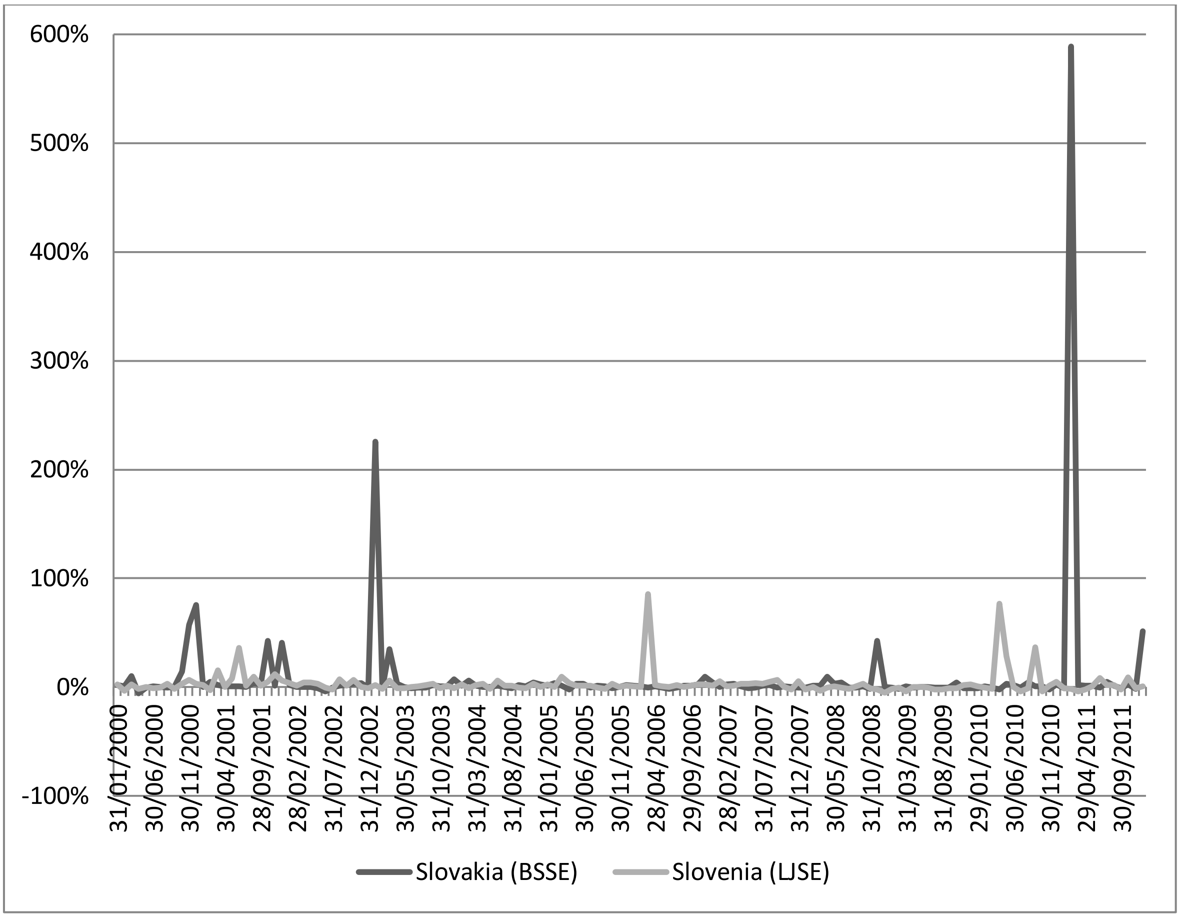


FIGURE 11. AVERAGE MONTHLY RETURNS FOR SLOVAKIA (BSSE) AND SLOVENIA (LJSE).



APPENDIX D

To provide further evidence concerning the prevalence of low-priced (or 'penny') stocks in the studied stock markets and the potential for bias therefrom, this appendix offers the frequency distributions of average stock prices for each stock market, beginning with Figure 12 (p. 437) and ending with Figure 24 (p. 449). Average prices for each stock are derived from monthly price data for the entire time period under analysis (*i.e.*, 01/01/2000 - 30/12/2011).

At this point it is important to reiterate that there is no universally accepted definition of a 'penny' stock. The US Securities and Exchange Commission (2013), also referred to as SEC, generally defines a 'penny' stock as a security issued by a very small company that trades at less than $5 per share. However, the formal definition of a 'penny' stock provided by SEC contains several more specific conditions that need to be met, which are in many cases only pertinent to the US stock markets (see §240.3a51-1 in Securities Exchange Act of 1934). Notwithstanding the aforementioned limitations, for the purposes of the ensuing analysis the SEC's general definition of a 'penny' stock will be adopted. Furthermore, to allow international comparisons, currency conversion to a common unit needs to be performed (see Chapter Three for details). The highest USD/EUR exchange rate during the time period under analysis was 1.17 (*N.B.,* $5 x 1.17 = €5.85), while the average exchange rate was 0.85 (*N.B.,* $5 x 0.85 = €4.25). Therefore, the USD/EUR exchange rate of 1 is adopted to convert the above-mentioned cut-off point of $5 to euros.

As can be seen from the histograms, stocks listed on US (NYSE-AMEX) and US (NASDAQ) tend to have much higher prices in absolute terms than stocks listed on the European stock markets after prices are converted to a common currency of euro. What is particularly interesting, though, is that this tendency does not only apply to the smaller stock markets of the EU12, but it also applies to the much larger UK (LSE). Thus, while only between 20% and 28% of the US stocks are priced at €5 or less on average, this figure amounts to 77% in the case of UK (LSE) and 73% in the case of the aggregate EU12 stock market. It should be noted that this finding is in line with the conclusions of Section 4.2., which, among others, found the aggregate EU12 investment environment to be comparable to the UK investment environment. The variability in frequency of average stock prices at €5 or below among the studied individual EU12 stock markets ranges from -33 percentage points to 21 percentage points of the figure for the aggregate EU12 stock market. Czech Republic (PSE), Hungary (BSE), Slovakia (BSSE) and Slovenia (LJSE) all have a lower percentage of stocks priced at €5 or less than UK (LSE), whereas Bulgaria (BSE-Sofia), Cyprus (CSE), Lithuania (VSE) and Romania (BVB) have a higher percentage of stocks priced at €5 or less than UK (LSE). The figure for Poland (WSE) is roughly equal to the figure for UK (LSE). Therefore, although there appears to be a noticeable difference between the US stock markets and the EU stock markets in terms of stock prices, no such difference can be seen between the developed EU stock market of UK (LSE) and the investigated less-developed EU stock markets.

In addition to the earlier-examined price statistics that are directly relevant to the studied contrarian and momentum strategies (see Section 4.4.), the histograms in this appendix provide further evidence that low-priced stocks are unlikely to be a cause for concern in the EU12 investment context. However, it should be stressed that, as discussed in Section 4.2., any comparisons of absolute prices, such as those drawn herein, are very likely to be misleading. This is mainly due to differences in price levels across countries and, in this particular case, different stock pricing practices across countries. The same does not apply to the price statistics in Section 4.4., which are context specific.

FIGURE 12. HISTOGRAM OF AVERAGE STOCK PRICE FOR US (NYSE-AMEX).

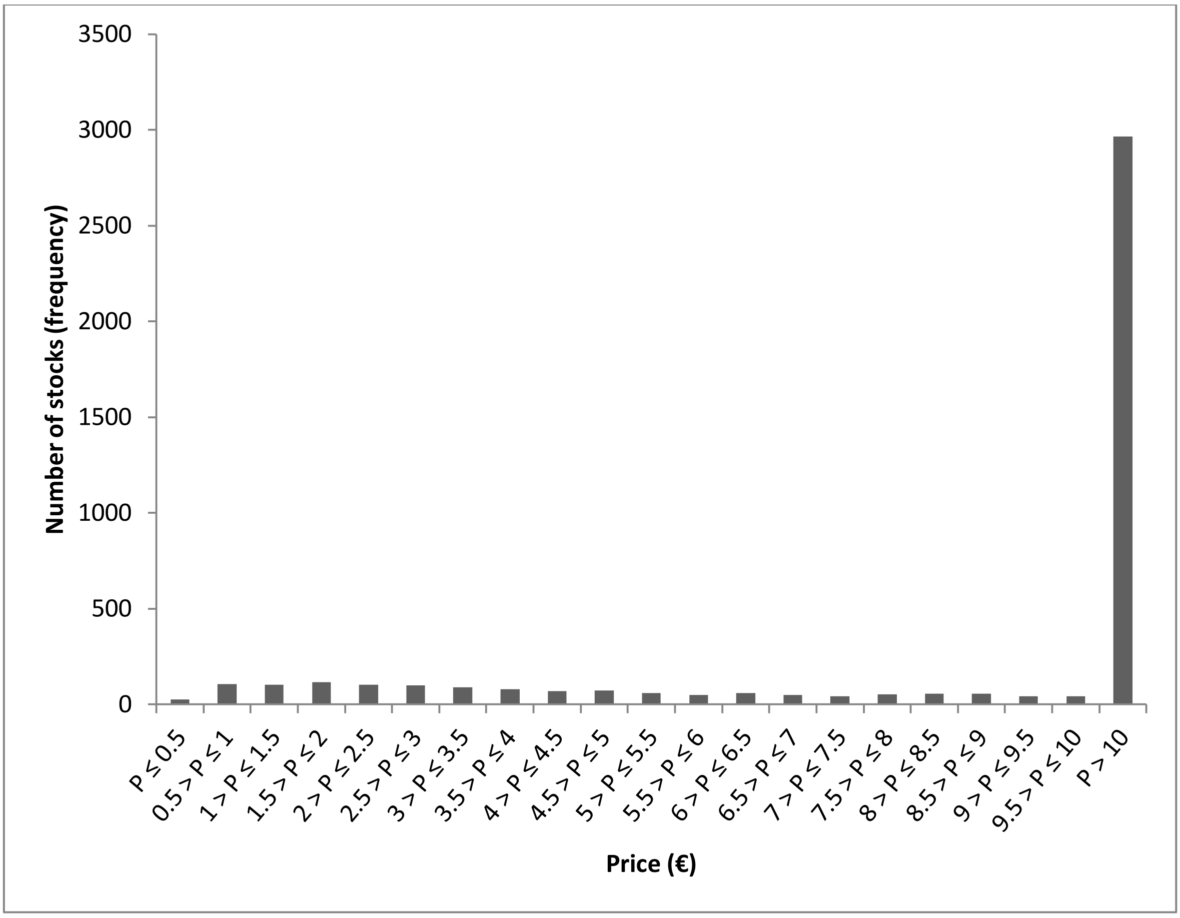


FIGURE 13. HISTOGRAM OF AVERAGE STOCK PRICE FOR US (NASDAQ).

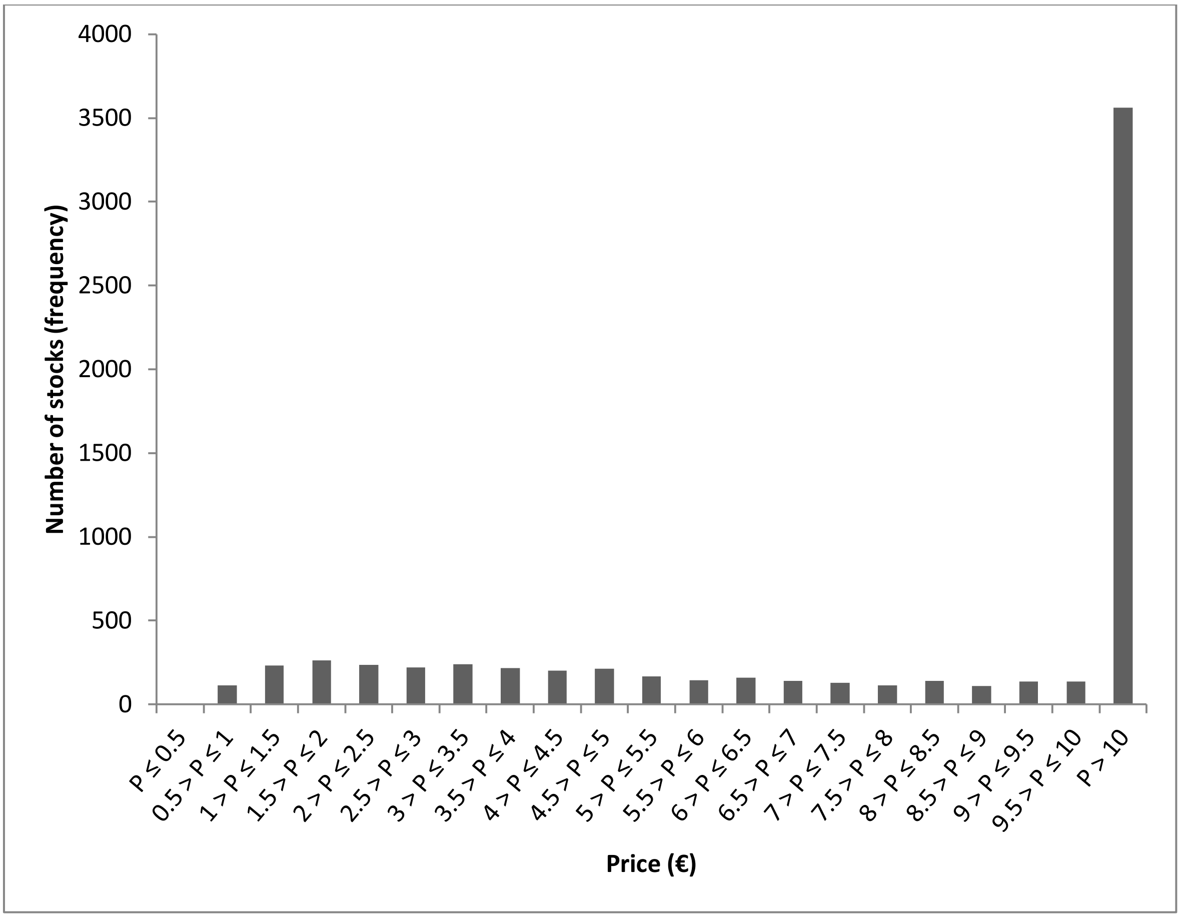


FIGURE 14. HISTOGRAM OF AVERAGE STOCK PRICE FOR UK (LSE).

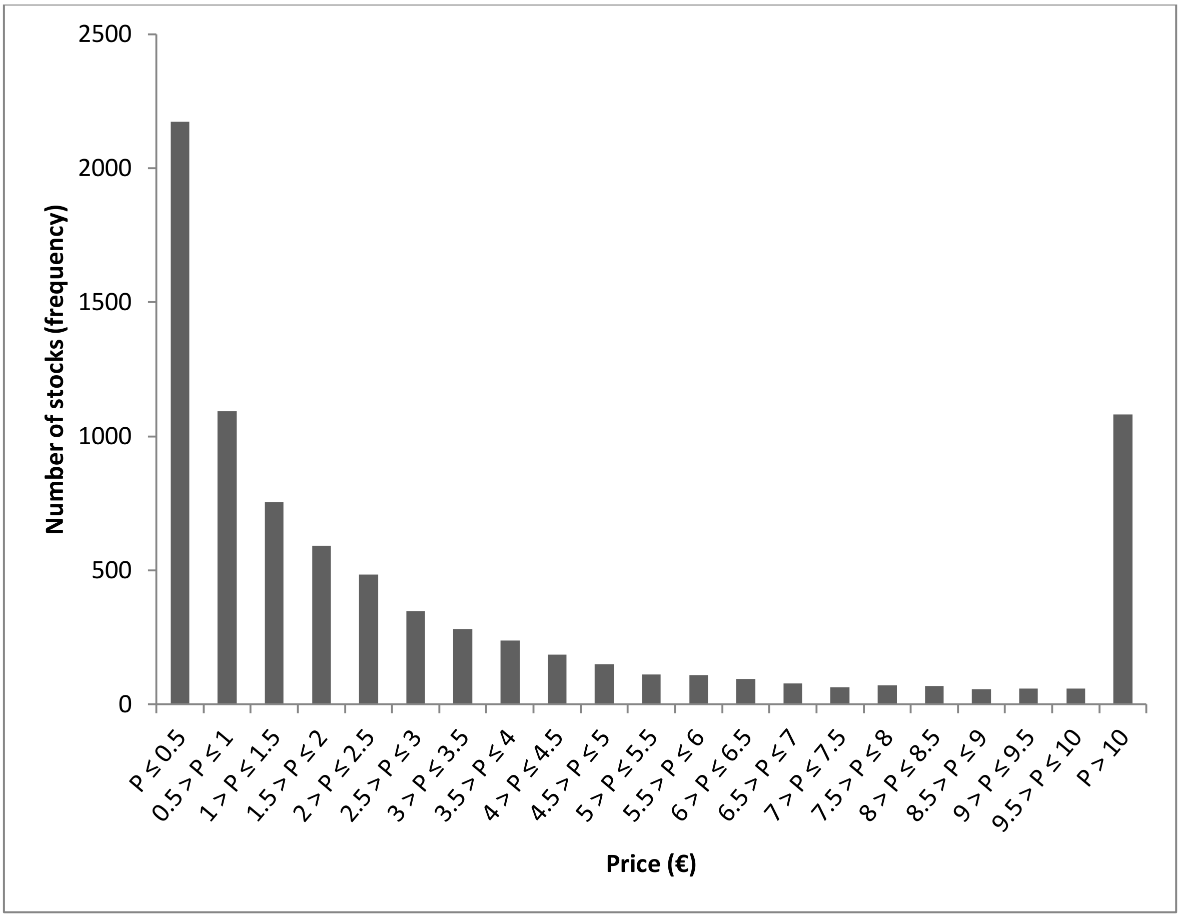


FIGURE 15. HISTOGRAM OF AVERAGE STOCK PRICE FOR BULGARIA (BSE-SOFIA).

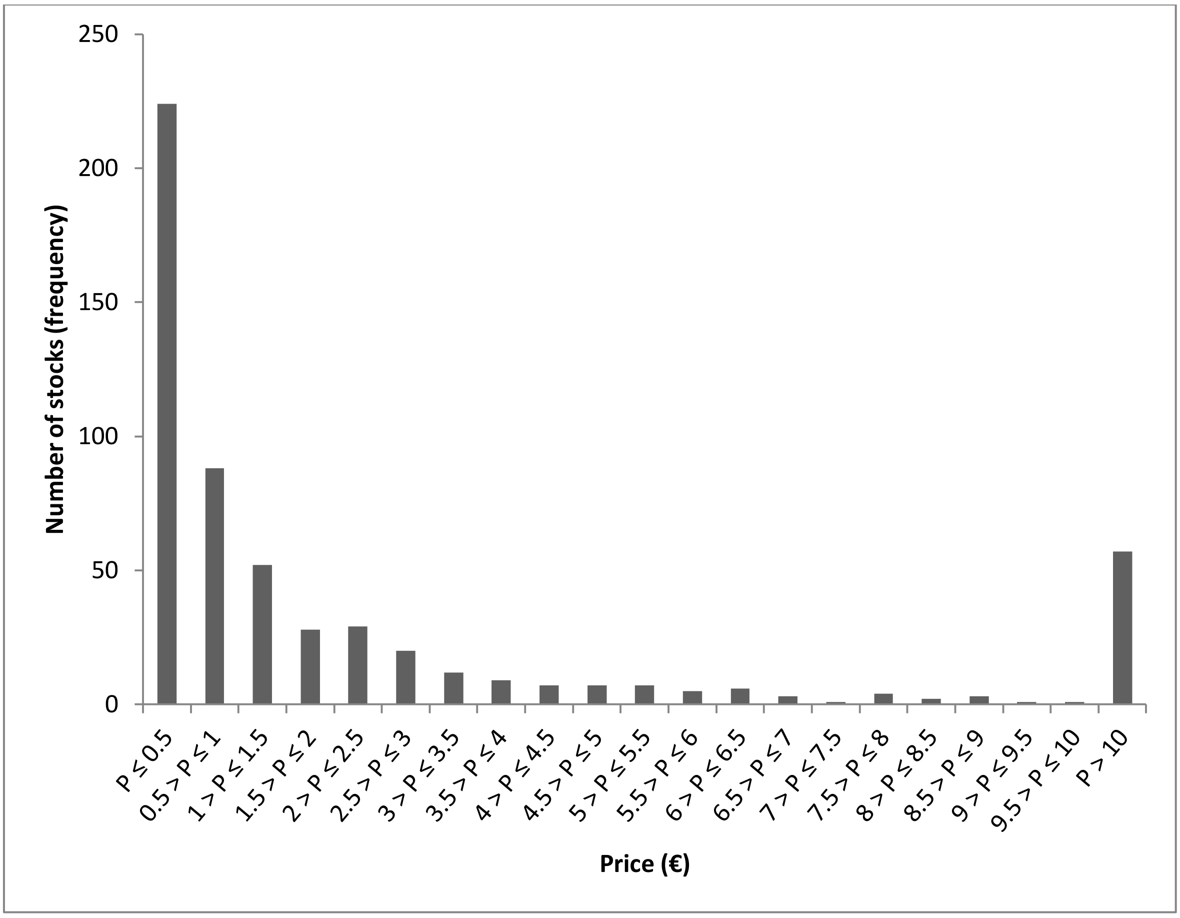


FIGURE 16. HISTOGRAM OF AVERAGE STOCK PRICE FOR CYPRUS (CSE).

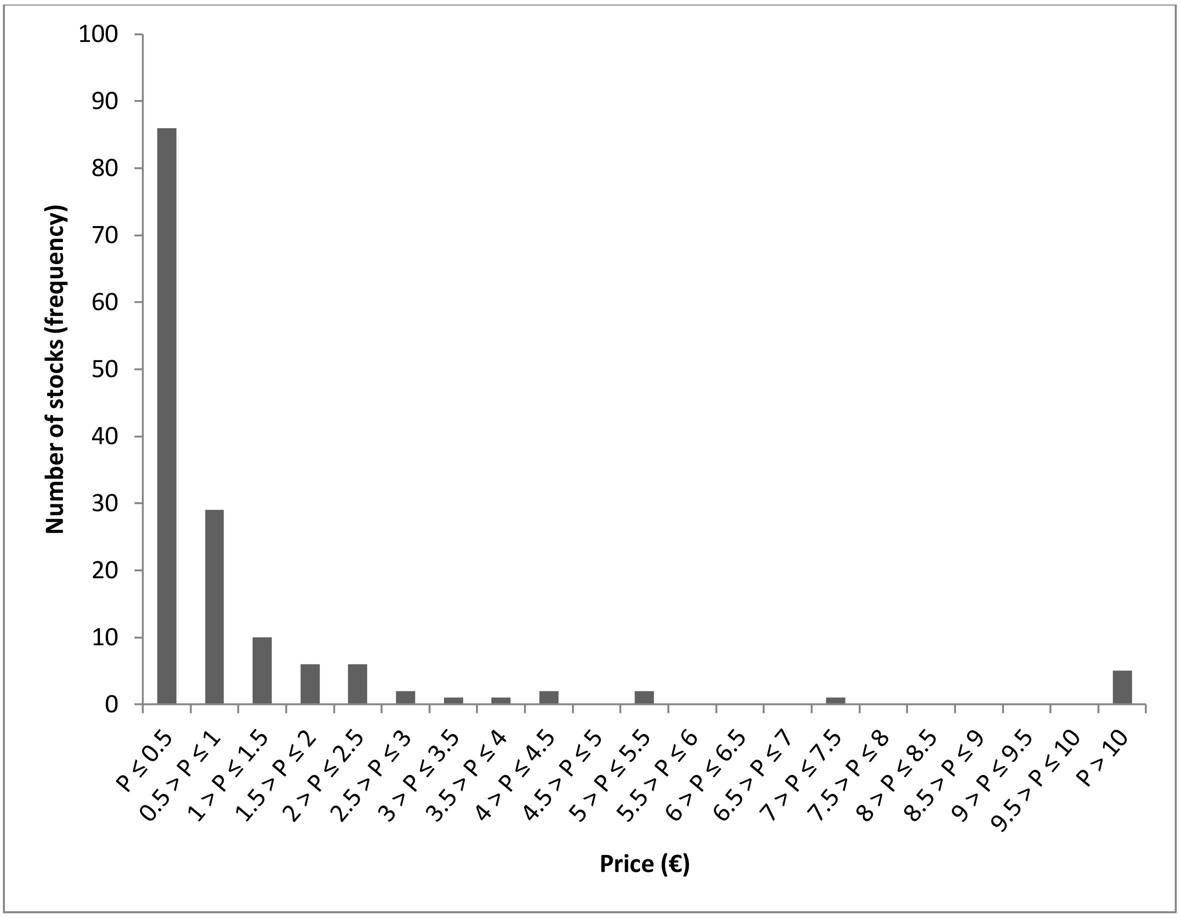


FIGURE 17. HISTOGRAM OF AVERAGE STOCK PRICE FOR CZECH REPUBLIC (PSE).

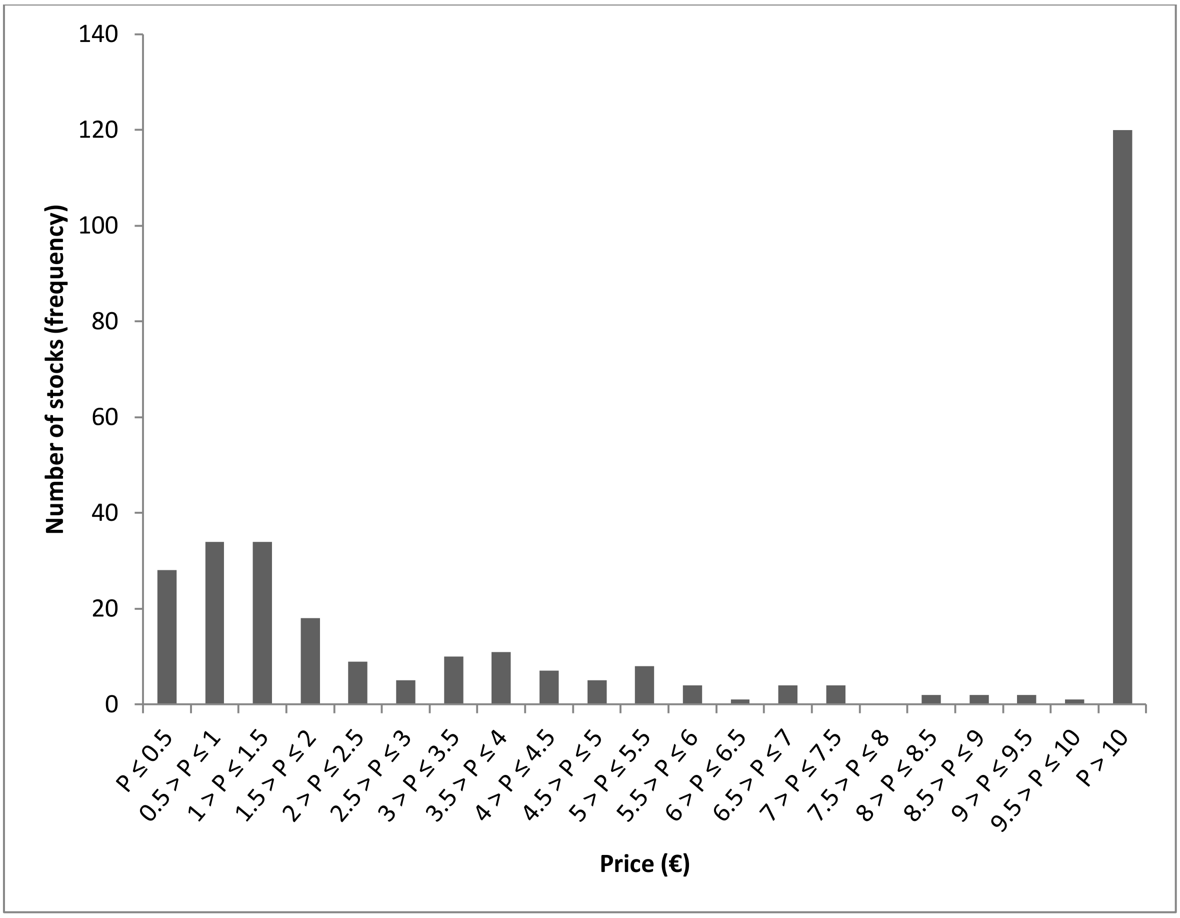


FIGURE 18. HISTOGRAM OF AVERAGE STOCK PRICE FOR HUNGARY (BSE).

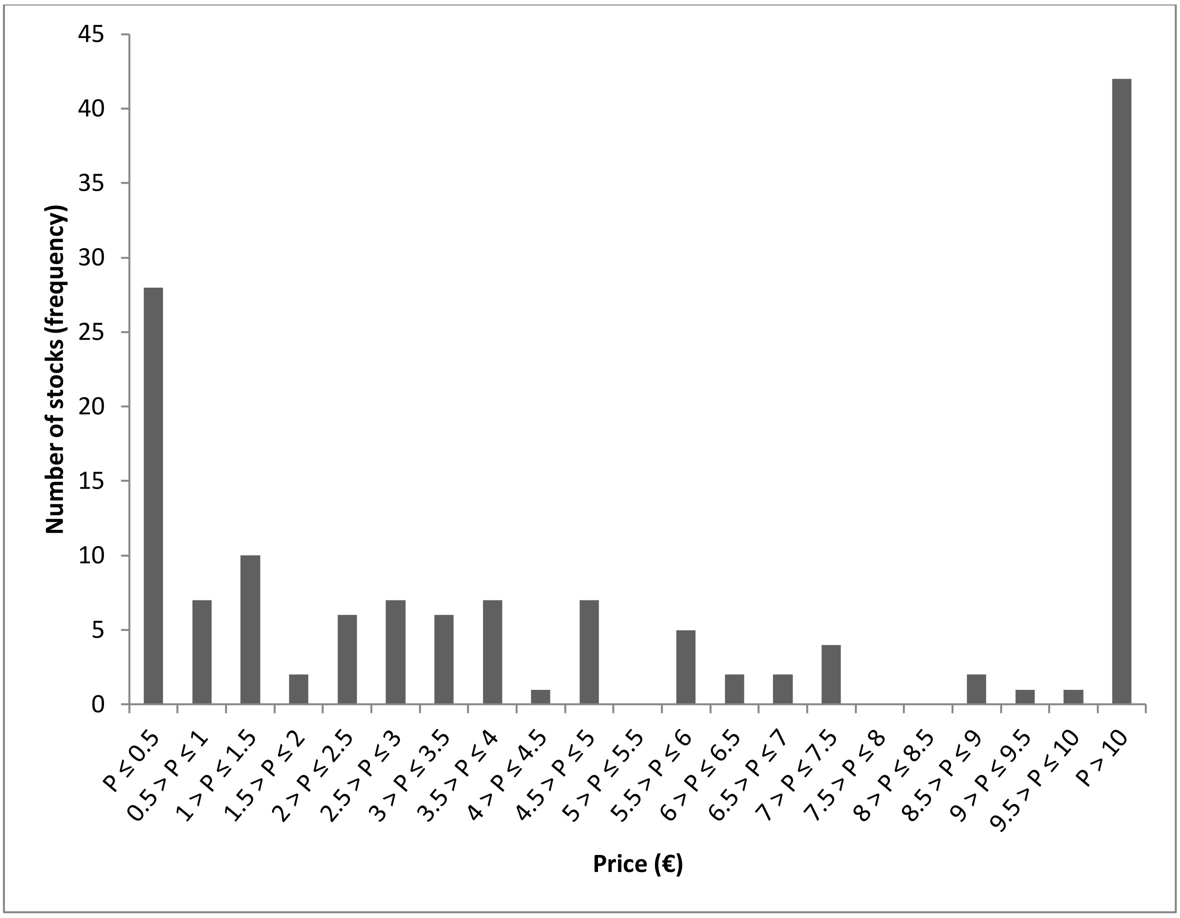


FIGURE 19. HISTOGRAM OF AVERAGE STOCK PRICE FOR LITHUANIA (VSE).

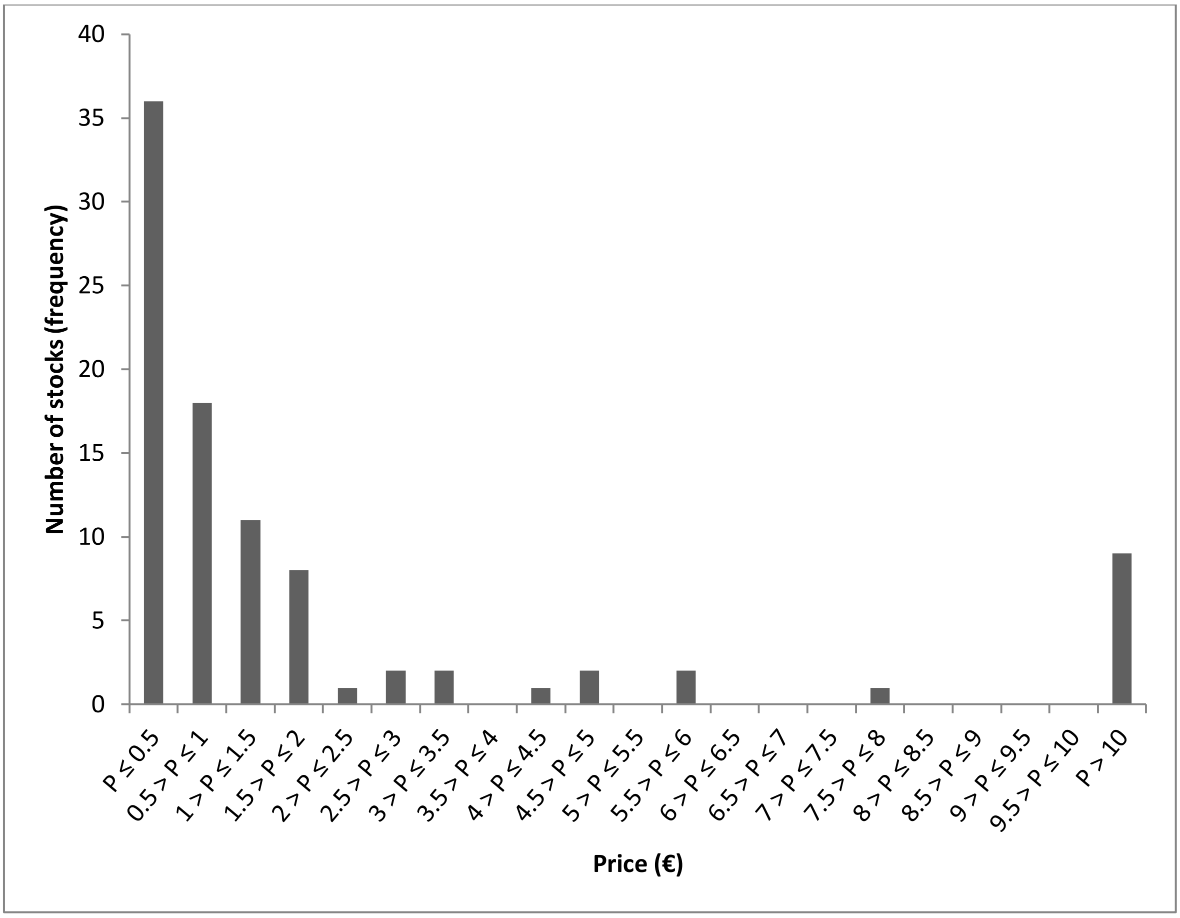


FIGURE 20. HISTOGRAM OF AVERAGE STOCK PRICE FOR POLAND (WSE).

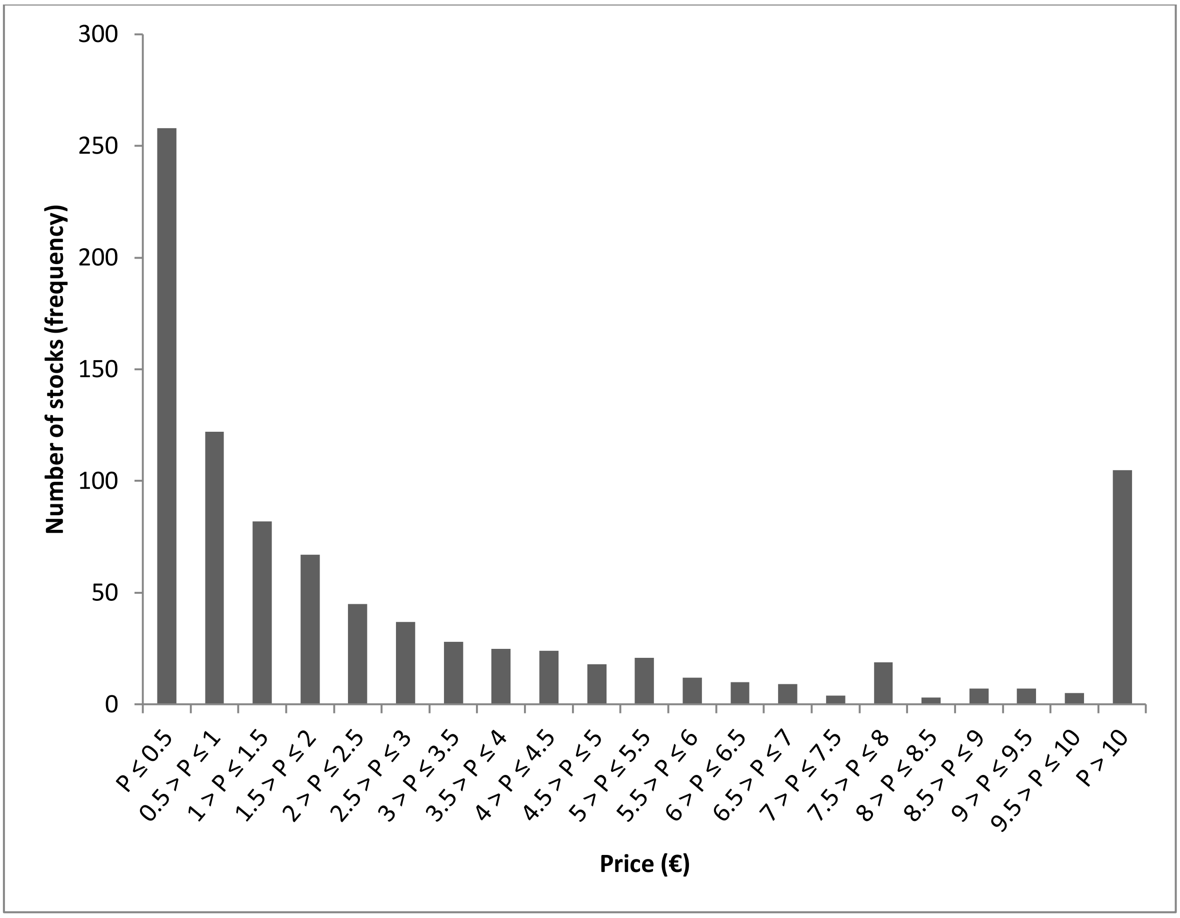


FIGURE 21. HISTOGRAM OF AVERAGE STOCK PRICE FOR ROMANIA (BVB).

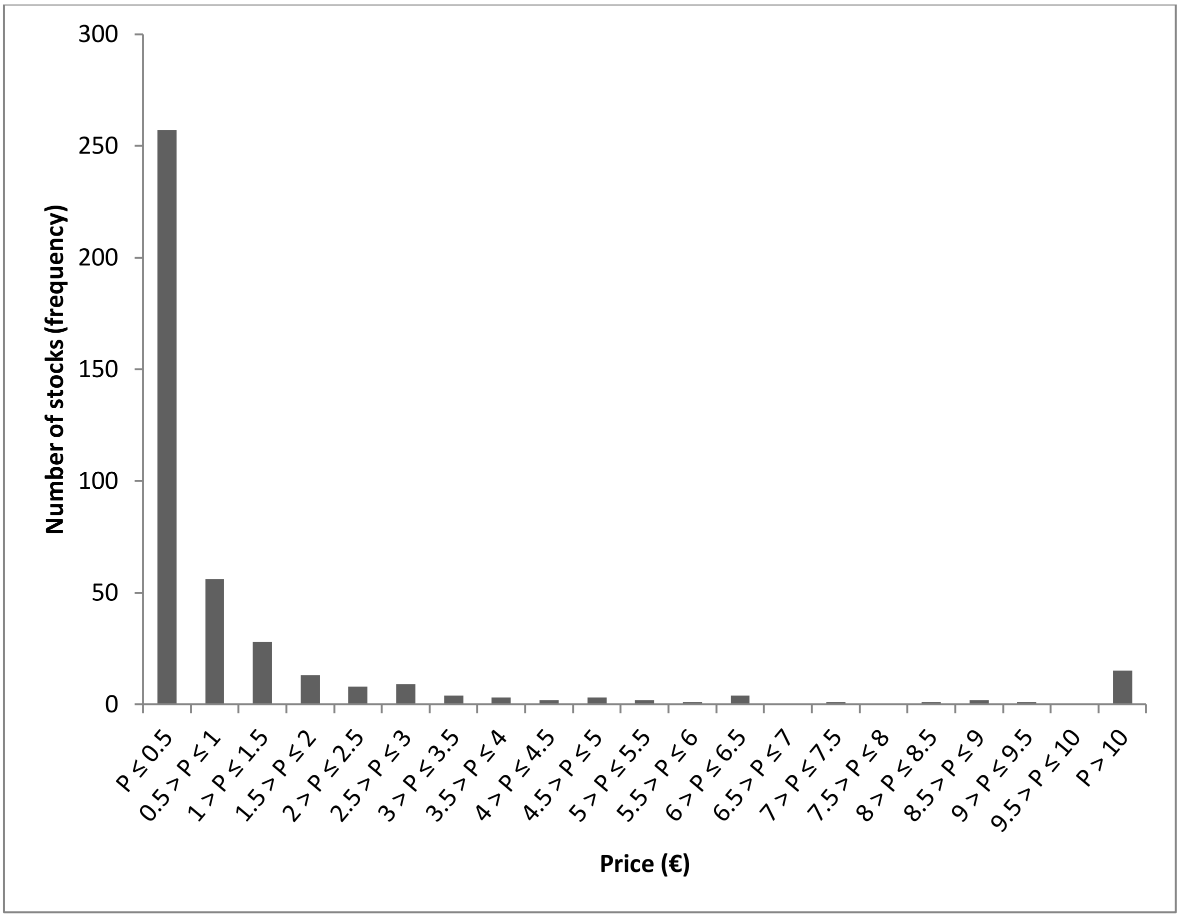


FIGURE 22. HISTOGRAM OF AVERAGE STOCK PRICE FOR SLOVAKIA (BSSE).

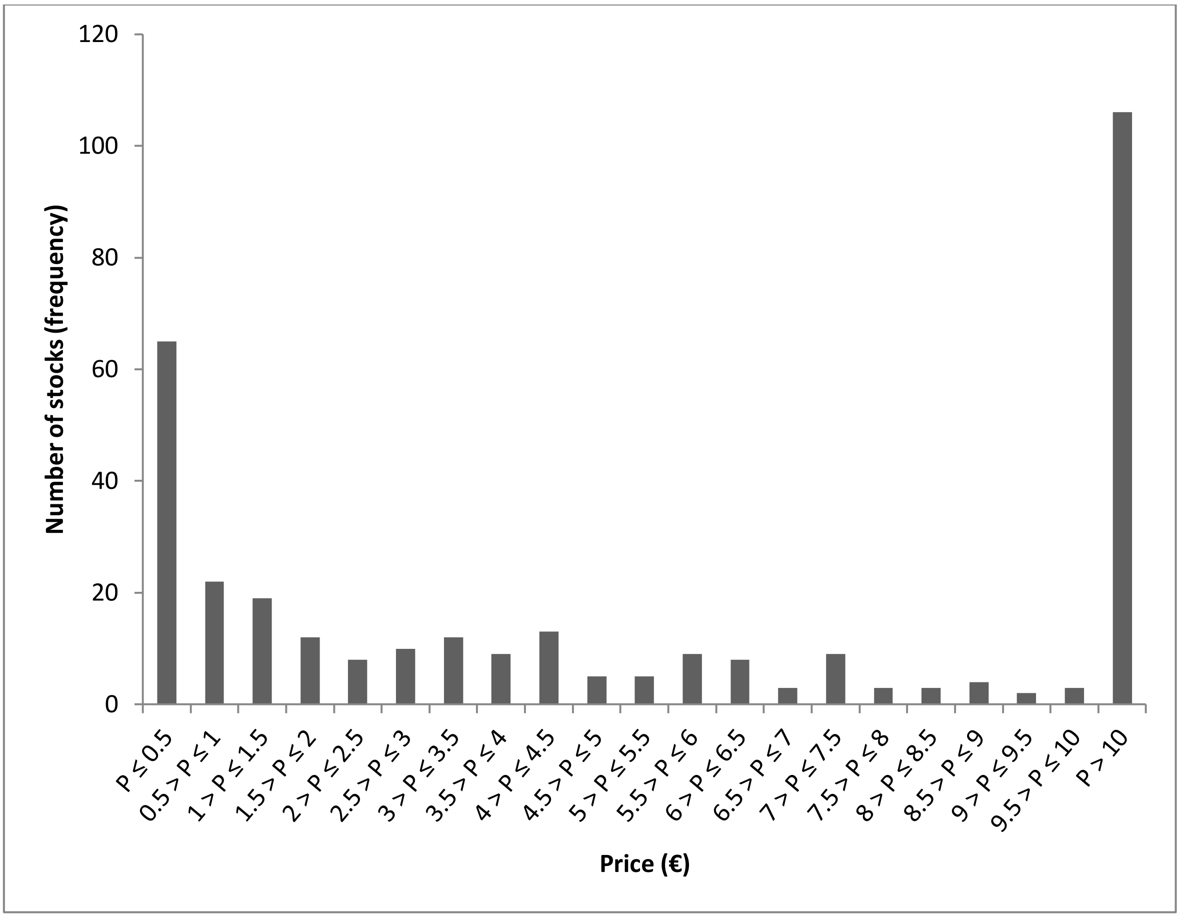


FIGURE 23. HISTOGRAM OF AVERAGE STOCK PRICE FOR SLOVENIA (LJSE).

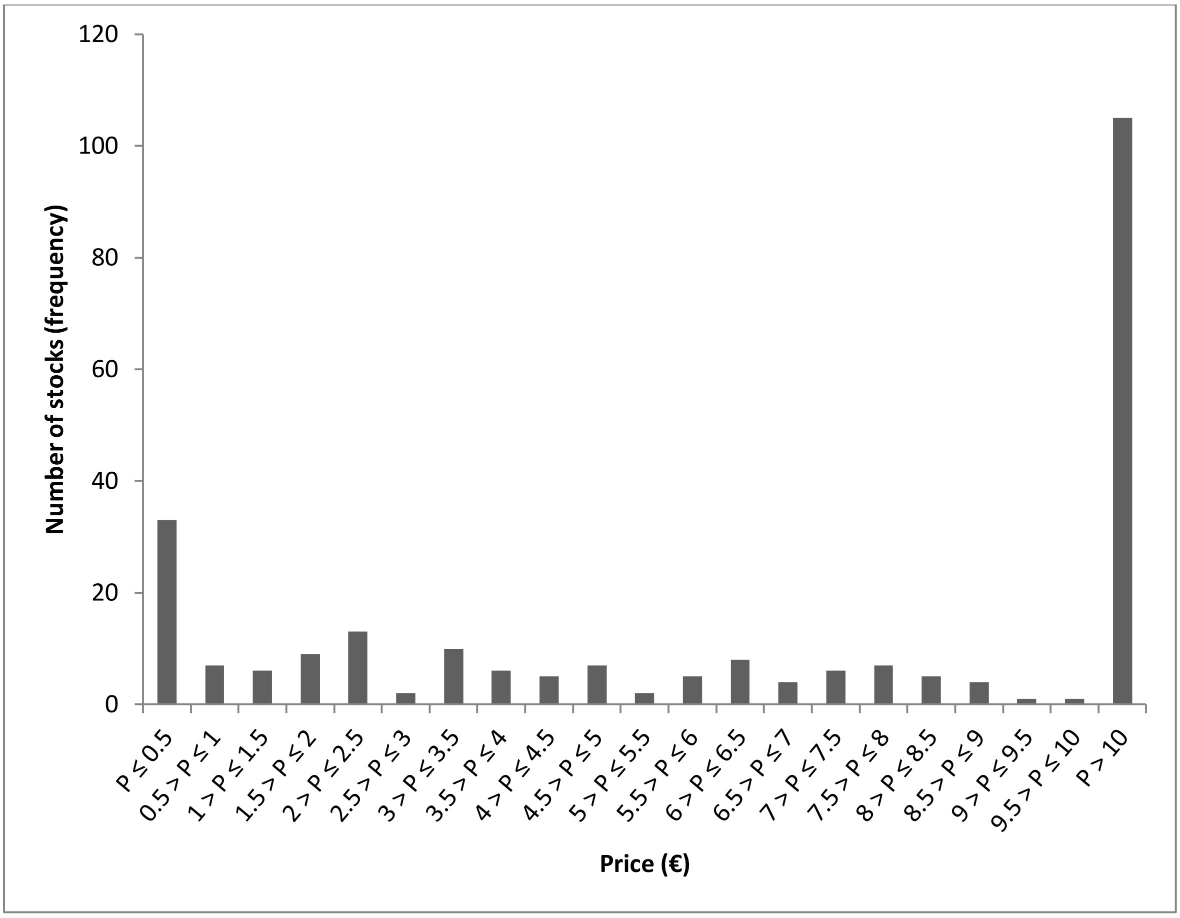
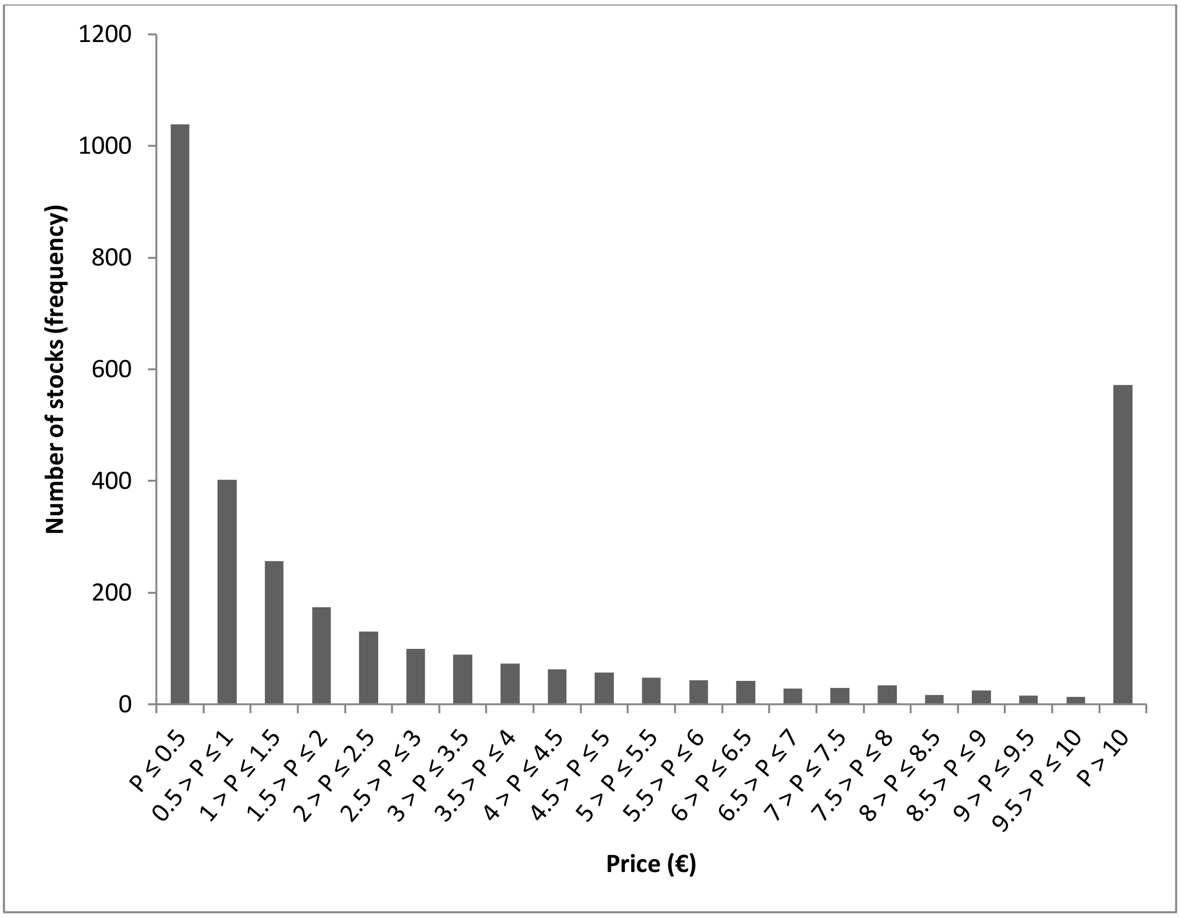


FIGURE 24. HISTOGRAM OF AVERAGE STOCK PRICE FOR THE EU12 STOCK MARKET.



APPENDIX E

This appendix provides information on the performance of the contrarian and momentum investment strategies examined in Sections 4.3. and 4.4. during two time sub-periods of the present study's time period under analysis, which extends from 01/01/2000 to 31/12/2011. The first time sub-period (spanning 90 months, from 01/01/2000 to 29/06/2007) covers the months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis, whereas the second time sub-period (spanning 54 months, from 01/07/2007 to 31/12/2011) covers the months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis. The purpose of this inquiry is to determine if the two crises could potentially have had any short-term or long-term impact on the performance of past-return-based strategies and, by implication, if the findings presented in Section 4.3. are still valid once those events are accounted for.

It should be noted at this point that the specification of the two time sub-periods has been based on (1) the information provided by the National Bureau of Economic Research (2013) as well as (2) the examination of the data in Appendix C. While the expansionary phase of the business cycle that began in November 2001 did not officially end until December 2007 in the US (*ibid.*), the effects of the Global Financial Crisis on financial markets, such as a sharp decline in aggregate stock returns, can be observed a few months earlier. Incidentally, this underscores the distinction between business cycles and market states, which may occur non-synchronously or even independently of each other. An additional consideration in specifiying the two sub-periods has been the fact that the contrarian and momentum strategies studied herein are based on six-monthly formation and test periods, which means that choosing mid-year as the end of the first sub-period and the beginning of the second sub-period is beneficial in terms of both consistency with the results in Section 4.3. as well as efficiency in the use of data.

The pre-crises and the peri-/post-crises results (see Table 108 - Table 133, pp. 453-478) indicate that only two out of the 13 stock markets examined are associated with, at least, one $H_{1(1)}$-compliant strategy in, at least, one time sub-period, *i.e.* Slovenia

(LJSE) and the aggregate EU12 stock market. In both cases, there is only one past-return-based portfolio in the peri-/post-crises sub-period, and none in the pre-crises sub-period, that can be considered to constitute a basis for a successful strategy in the context of the requirements set by Hypothesis One. However, what is of paramount importance is that the Slovenian strategy (based on P1S[96]) is not associated with any significance of returns, be it statistical or economic, either during this study's entire time period, when it generates negligible gains both in absolute terms and in CAPM-adjusted terms, or during the pre-crises sub-period, when it generates losses both in absolute terms and in CAPM-adjusted terms. The EU12 stock market's strategy based on P10L[97], on the other hand, consistently generates statistically and economically significant returns in all three time (sub-)periods, but in the pre-crises sub-period it is associated with a statistically insignificant, albeit meaningfully positive at 0.05, CAPM alpha. A closer investigation of the data thereof revealed that the reason for the aforementioned lack of significance is not due to a poor performance of the portfolio of interest, but rather due to an exceptional performance of the benchmark (*i.e.*, the market portfolio), which returned, on average, about 3% per month in the pre-crises period.

Furthermore, Table 134 (p. 479), Table 135 (p. 480) and Table 136 (p. 481) indicate that the pre-crises and the peri-/post-crises test-period returns on roughly 80% of all investment portfolios are not statistically different at $p \leq 0.05$ across the two periods. In the case of the remaining 20% of investment portfolios, with the exception of the earlier-discussed Slovenian strategy based on P1S, the pre-crises test-period returns are always statistically higher (at $p \leq 0.05$) than the peri-/post-crises test-period returns. This result, however, is not surprising and it underscores the very limited usefulness of the statistical tests for the difference between the pre-crises and the peri-/post-crises returns in the present context. To clarify, the reason why the tests are generally unhelpful is as follows.

The pre-crises sub-sample and the post-crises sub-sample may very well be statistically different as determined by a statistical test, but that does not say much

[96] That is, a short position in the highest past-return portfolio (or past 'winners').

[97] That is, a long position in the lowest past-return portfolio (or past 'losers').

about the consistency of contrarian/momentum profitability across the three periods. In particular, the pre-crises average returns are higher in general as compared to the post-crises average returns. Given the experiment's design, especially the definition of the pre-crises and the peri-/post-crises period, this is the expected outcome and it can be seen by looking at the results, among others, in Table 134, Table 135 and Table 136, especially the figures for the market portfolio of all stocks (*i.e.*, PmL). On account of the fact that average returns are generally higher in the first period as compared to the second period (in 92% of cases), the average returns for contrarian/momentum portfolios may very well also be, and indeed are, generally higher in the first period as compared to the second period (in 77% of cases). However, the question posed in this appendix is not whether contrarian/momentum strategies generate different returns during the two (or three) periods, but whether contrarian/momentum strategies are similarly profitable (or unprofitable) in all three periods. If contrarian/momentum strategies are similarly profitable (or unprofitable) in all three periods (*i.e.*, if the results are consistent across all sub-periods), which they indeed are, then this means that the crises did not have a meaningful effect on the results based on the collective sample, which sample was used for the main tests in the thesis. If the results based on the collective sample are not meaningfully affected by the crises, then those results would be expected to be valid regardless of whether the crises would have occurred or not.

Overall, the results presented and discussed in this appendix can be seen as consistent with the findings of Section 4.3., considering that the ramifications of the Global Financial and Eurozone Crises do not appear to meaningfully alter this study's main conclusion, which is that, with the exception of the EU12 stock market, past-return-based strategies are unprofitable prior to market microstructure adjustment in the stock markets of US, UK and EU12, at least by the adopted specifications and standards.

TABLE 108. US (NYSE-AMEX): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns that are calculated over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six consecutive months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	228	0.86	0.12	0.0158	0.7415	0.00	0.6373
P10L	228	-0.41	0.05	0.4164	0.2243	-0.10	0.0811
P1L /P10S	-	1.26	0.07	0.0986	0.4755	0.09	0.0648
PmL	2272	0.11	0.11	-	-	0.00	-

TABLE 109. US (NYSE-AMEX): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns that are calculated over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six consecutive months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	198	0.93	-0.01	0.9524	0.0219	-0.05	0.3427
P10L	198	-0.45	0.06	0.7325	0.1258	0.01	0.9176
P1L /P10S	-	1.38	-0.07	0.5811	0.2045	-0.06	0.6134
PmL	1978	0.07	0.04	-	-	0.00	-

TABLE 110. US (NASDAQ): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	342	1.15	0.09	0.1743	0.3841	-0.01	0.7593
P10L	342	-0.53	0.03	0.7680	0.0805	-0.10	0.0019
P1L /P10S	-	1.68	0.06	0.1018	0.4705	0.08	0.0349
PmL	3415	0.10	0.09	-	-	0.00	-

TABLE 111. US (NASDAQ): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (*p*) associated with the Student's One-Sample *t*-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (*Δ*), respectively. CAPM alpha and the probability (*p*) associated with the Student's Regression Coefficient *t*-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	267	1.08	-0.05	0.5898	0.1997	-0.07	0.2549
P10L	267	-0.55	0.07	0.7395	0.1223	0.04	0.7659
P1L /P10S	-	1.63	-0.12	0.5299	0.2336	-0.11	0.5314
PmL	2663	0.05	0.02	-	-	0.00	-

TABLE 112. UK (LSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	636	1.08	0.08	0.0125	0.7739	0.06	0.0917
P10L	636	-0.35	0.01	0.8172	0.0630	-0.01	0.8312
P1L/ P10S	-	1.43	0.07	0.1500	0.4089	0.05	0.3526
PmL	6350	0.07	0.06	-		0.00	-

TABLE 113. UK (LSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (*p*) associated with the Student's One-Sample *t*-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (*Δ*), respectively. CAPM alpha and the probability (*p*) associated with the Student's Regression Coefficient *t*-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	781	0.50	0.03	0.5794	0.2055	0.04	0.4522
P10L	781	-0.37	0.05	0.7615	0.1116	0.08	0.3112
P1L/ P10S	-	0.87	-0.01	0.9163	0.0385	-0.06	0.5465
PmL	7805	-0.02	0.00	-		0.00	-

TABLE 114. BULGARIA (BSE-SOFIA): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	18	5.58	0.23	0.01 <= p <= 0.05	0.5714	0.26	0.0956
P10L	18	-0.47	1.36	p < 0.01	0.8571	-0.21	0.7032
P1S/P10L	-	-6.04	1.13	0.01 <= p <= 0.05	0.2857	-0.49	0.4273
PmL	175	0.54	0.31	-	-	0.00	-

TABLE 115. BULGARIA (BSE-SOFIA): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	48	3.16	-0.03	$p > 0.05$	0.2500	-0.04	0.7460
P10L	48	-0.52	0.92	$0.01 <= p <= 0.05$	0.5000	-0.25	0.5673
P1S/P10L	-	-3.68	0.95	$0.01 <= p <= 0.05$	0.7500	-0.22	0.6199
PmL	477	0.24	0.16	-	-	0.00	-

TABLE 116. CYPRUS (CSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10S is the lowest past-return portfolio (based on a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1S	13	-1.38	0.04	$p > 0.05$	0.1429	0.04	0.4410
P10S	12	0.56	-0.01	$p > 0.05$	0.1429	-0.01	0.8646
P1S/ P10L	-	-1.94	0.06	$p < 0.01$	0.1429	0.04	0.4625
PmL	123	0.01	0.04	-	-	0.00	-

TABLE 117. CYPRUS (CSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10S is the lowest past-return portfolio (based on a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1S	12	-0.50	0.16	0.01 <= p <= 0.05	0.7500	0.05	0.5409
P10S	12	0.49	0.12	p > 0.05	0.5000	-0.07	0.4457
P1S/ P10L	-	-0.98	0.04	p > 0.05	0.0000	0.11	0.4746
PmL	118	-0.07	-0.10	-	-	0.00	-

TABLE 118. CZECH REPUBLIC (PSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	30	0.47	0.14	$p < 0.01$	0.7143	0.06	0.1814
P10L	30	-0.13	0.09	$p < 0.01$	0.7143	0.01	0.5437
P1L/P10S	-	0.60	0.05	$p > 0.05$	0.0000	0.03	0.5869
PmL	294	0.05	0.05	-	-	0.00	-

TABLE 119. CZECH REPUBLIC (PSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	30	0.12	0.01	p > 0.05	0.2500	0.00	0.7817
P10L	30	-0.08	0.00	p > 0.05	0.5000	0.00	0.9367
P1L/P10S	-	0.19	0.01	p > 0.05	0.2500	-0.01	0.6515
PmL	295	0.02	0.00	-	-	0.00	-

TABLE 120. HUNGARY (BSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	8	0.83	0.09	p > 0.05	0.2857	-0.03	0.5565
P10L	8	-0.32	0.21	0.01 <= p <= 0.05	0.4286	0.04	0.6793
P1S/P10L	-	-1.16	0.12	p > 0.05	0.5714	0.06	0.6633
PmL	77	0.06	0.07	-	-	0.00	-

TABLE 121. HUNGARY (BSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	11	0.47	-0.02	$p > 0.05$	0.5000	0.03	0.3510
P10L	11	-0.34	-0.12	$p > 0.05$	0.5000	-0.06	0.2854
P1S/P10L	-	-0.81	-0.10	$p > 0.05$	0.7500	-0.11	0.1238
PmL	106	0.00	-0.04	-	-	0.00	-

TABLE 122. LITHUANIA (VSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	7	1.11	0.30	0.01 <= p <= 0.05	0.4286	0.00	0.9978
P10L	7	-0.32	0.12	0.01 <= p <= 0.05	0.2857	-0.04	0.2946
P1L/P10S	-	1.43	0.18	0.01 <= p <= 0.05	0.2857	0.02	0.7998
PmL	62	0.16	0.16	-	-	0.00	-

TABLE 123. LITHUANIA (VSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	6	0.58	0.04	$p > 0.05$	0.2500	0.05	0.3989
P10L	6	-0.43	0.12	$p > 0.05$	0.2500	0.13	0.4457
P1L/P10S	-	1.00	-0.08	$p > 0.05$	0.2500	-0.09	0.6519
PmL	51	0.00	0.00	-	-	0.00	-

TABLE 124. POLAND (WSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	27	1.18	0.31	0.01 <= p <= 0.05	0.2857	0.06	0.2138
P10L	26	-0.42	0.17	p > 0.05	0.2857	-0.04	0.5546
P1L/ P10S	-	1.59	0.14	0.01 <= p <= 0.05	0.4286	0.08	0.3253
PmL	361	0.13	0.16	-	-	0.00	-

TABLE 125. POLAND (WSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	54	0.63	0.00	$p > 0.05$	0.2500	0.05	0.1870
P10L	54	-0.48	-0.04	$p > 0.05$	0.0000	0.04	0.4415
P1L/ P10S	-	1.12	0.03	$p > 0.05$	0.7500	0.00	0.9694
PmL	535	-0.03	-0.05	-	-	0.00	-

TABLE 126. ROMANIA (BVB): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	27	1.90	0.36	$p < 0.01$	0.7143	-0.14	0.1819
P10L	27	-0.39	0.55	$p < 0.01$	0.8571	0.22	0.2513
P1S/ P10L	-	-2.29	0.19	$p > 0.05$	0.1429	0.34	0.1734
PmL	268	0.21	0.29	-	-	0.00	-

TABLE 127. ROMANIA (BVB): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	40	2.04	-0.10	0.01 <= p <= 0.05	0.7500	-0.17	0.0037
P10L	40	-0.54	0.72	p > 0.05	0.7500	0.19	0.5726
P1S/ P10L	-	-2.59	0.82	0.01 <= p <= 0.05	0.7500	0.34	0.3581
PmL	395	0.11	0.09	-	-	0.00	-

TABLE 128. SLOVAKIA (BSSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	**δ-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	19	3.57	0.83	$p < 0.01$	0.5714	0.15	0.8467
P10L	19	-0.28	1.63	$p < 0.01$	0.7143	-0.71	0.5003
P1S/ P10L	-	-3.85	0.80	$p > 0.05$	0.0000	-0.87	0.6073
PmL	190	0.35	0.37	-	-	0.00	-

TABLE 129. SLOVAKIA (BSSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	15	7.58	-0.09	$p > 0.05$	0.0000	-0.12	0.1916
P10L	15	-0.31	0.09	$p > 0.05$	0.2500	0.08	0.3421
P1S/ P10L	-	-7.89	0.18	$p > 0.05$	0.5000	0.18	0.1466
PmL	144	0.79	0.80	-	-	0.00	-

TABLE 130. SLOVENIA (LJSE): PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1S	15	-1.53	-0.01	$p > 0.05$	0.1429	-0.02	0.7152
P10L	15	-0.34	0.85	$p < 0.01$	0.5714	-0.33	0.1052
P1S/ P10L	-	-1.87	0.84	$p < 0.01$	0.7143	-0.33	0.1135
PmL	146	0.13	0.14	-	-	0.00	-

TABLE 131. SLOVENIA (LJSE): PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size (δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1S	15	-0.47	0.09	0.01 <= p <= 0.05	1.0000	0.08	0.0048
P10L	15	-0.43	-0.06	p > 0.05	0.2500	0.01	0.8975
P1S/ P10L	-	-0.90	0.03	p > 0.05	0.0000	0.10	0.2773
PmL	147	0.00	-0.02	-	-	0.00	-

TABLE 132. EU12 STOCK MARKET: PRE-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	166	2.21	0.33	0.0010	1.1317	0.03	0.8039
P10L	166	-0.41	0.36	0.0004	1.2641	0.05	0.6961
P1S/P10L	-	-2.62	0.03	0.7688	0.0802	0.00	0.9912
PmL	1660	0.20	0.18	-	-	0.00	-

TABLE 133. EU12 STOCK MARKET: PERI- AND POST-CRISES INVESTMENT RETURNS AND CAPM ALPHAS.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the first column. P1L is the highest past-return portfolio (based on a long position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P1S/P10L is the arbitrage portfolio (based on a long position in P1 and a short position in P10), and PmL is the market portfolio (based on a long position in Pm). The formation-period average number of stocks per portfolio can be found in the second column. Columns three and four report the average, six-monthly return for the formation and test periods, respectively. The results presented in the remaining four columns are based on test period returns. Columns five and six show the probability (p) associated with the Student's One-Sample t-Test, based on the two-tailed distribution, and the Glass's Effect Size Test (Δ), respectively. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS covariance matrix estimators, for the intercept of the CAPM regression line are reported in the two last columns. The procedures employed to generate all of the results are described and discussed in detail in the 'Methodology' chapter.

Portfolio	**Average number of stocks** (formation period)	**Average return** (formation period)	**Average return** (test period)	***p*-value** (test period returns)	***Δ*-value** (test period returns)	**CAPM alpha**	***p*-value** (CAPM alpha)
P1L	235	1.62	0.01	0.9369	0.0290	-0.05	0.5245
P10L	235	-0.49	0.27	0.0299	0.9607	0.29	0.0384
P1S/P10L	-	-2.10	0.26	0.0951	0.6820	0.32	0.0709
PmL	2346	0.09	0.06	-	-	0.00	-

TABLE 134. RESULTS OF STATISTICAL SIGNIFICANCE TESTS FOR THE DIFFERENCE BETWEEN PRE-CRISES AND PERI-/POST-CRISES INVESTMENT RETURNS. PART 1.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns that are calculated over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six consecutive months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated: (1) 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007); and then (2) eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011). The succession of the repetitions is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). Columns three and four report the average, six-monthly return for the pre-crises and the peri-/post-crises test periods, respectively. Probability (p) associated with the Student's Two-Sample (Unequal Variance) t-Test, based on the two-tailed distribution, for the difference between the pre-crises and the peri-/post-crises test-period returns can be found in the last column.

Stock market	**Portfolio**	**Average pre-crisis return** (test period)	**Average peri- and post-crisis return** (test period)	***p*-value** (pre-crisis/peri- and post-crisis test period returns)
US (NYSE-AMEX)	P1L	0.12	-0.01	0.3375
	P10L	0.05	0.06	0.9659
	P1L/P10S	0.07	-0.07	0.3016
	PmL	0.11	0.04	0.5595
US (NASDAQ)	P1L	0.09	-0.05	0.2227
	P10L	0.03	0.07	0.8455
	P1L/P10S	0.06	-0.12	0.3526
	PmL	0.09	0.02	0.5884
UK (LSE)	P1L	0.08	0.03	0.4458
	P10L	0.01	0.05	0.8388
	P1L/P10S	0.07	-0.01	0.5316
	PmL	0.06	0.00	0.3363
EU12	P1L	0.33	0.01	0.0039
	P10L	0.36	0.27	0.4750
	P1S/P10L	0.03	0.26	0.1865
	PmL	0.18	0.06	0.0074

TABLE 135. RESULTS OF STATISTICAL SIGNIFICANCE TESTS FOR THE DIFFERENCE BETWEEN PRE-CRISES AND PERI-/POST-CRISES INVESTMENT RETURNS. PART 2.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns that are calculated over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six consecutive months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated: (1) 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007); and then (2) eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011). The succession of the repetitions is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). Columns three and four report the average, six-monthly return for the pre-crises and the peri-/post-crises test periods, respectively. Probability (p) associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test for the difference between the pre-crises and the peri-/post-crises test-period returns can be found in the last column.

Stock market	**Portfolio**	**Average pre-crisis return** (test period)	**Average peri- and post-crisis return** (test period)	***p*-value** (pre-crisis/peri- and post-crisis test period returns)
Bulgaria (BSE-Sofia)	P1L	0.23	-0.03	$p > 0.05$
	P10L	1.36	0.92	$p > 0.05$
	P1S/P10L	1.13	0.95	$p > 0.05$
	PmL	0.31	0.16	$p > 0.05$
Cyprus (CSE)	P1S	0.04	0.16	$p > 0.05$
	P10S	-0.01	0.12	$p > 0.05$
	P1S/P10L	0.06	0.04	$p > 0.05$
	PmL	0.04	-0.10	$p > 0.05$
Czech Republic (PSE)	P1L	0.14	0.01	$0.01 <= p <= 0.05$
	P10L	0.09	0.00	$p > 0.05$
	P1L/P10S	0.05	0.01	$p > 0.05$
	PmL	0.05	0.00	$p > 0.05$
Hungary (BSE)	P1L	0.09	-0.02	$p > 0.05$
	P10L	0.21	-0.12	$0.01 <= p <= 0.05$
	P1S/P10L	0.12	-0.10	$0.01 <= p <= 0.05$
	PmL	0.07	-0.04	$0.01 <= p <= 0.05$
Lithuania (VSE)	P1L	0.30	0.04	$p > 0.05$
	P10L	0.12	0.12	$p > 0.05$
	P1L/P10S	0.18	-0.08	$p > 0.05$
	PmL	0.16	0.00	$p > 0.05$

TABLE 136. RESULTS OF STATISTICAL SIGNIFICANCE TESTS FOR THE DIFFERENCE BETWEEN PRE-CRISES AND PERI-/POST-CRISES INVESTMENT RETURNS. PART 3.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns that are calculated over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six consecutive months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated: (1) 14 times, which makes full use of the 90 months prior to the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/01/2000 to 29/06/2007); and then (2) eight times, which makes full use of the 54 months after the onset of the Global Financial Crisis and the subsequent Eurozone Crisis (specified herein as from 01/07/2007 to 31/12/2011). The succession of the repetitions is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). Columns three and four report the average, six-monthly return for the pre-crises and the peri-/post-crises test periods, respectively. Probability (*p*) associated with the two-tailed Kolmogorov-Smirnov Two-Sample Test for the difference between the pre-crises and the peri-/post-crises test-period returns can be found in the last column.

Stock market	**Portfolio**	**Average pre-crisis return** (test period)	**Average peri- and post-crisis return** (test period)	***p*-value** (pre-crisis/peri- and post-crisis test period returns)
Poland (WSE)	P1L	0.31	0.00	$p > 0.05$
	P10L	0.17	-0.04	$p > 0.05$
	P1L/P10S	0.14	0.03	$p > 0.05$
	PmL	0.16	-0.05	$p > 0.05$
Romania (BVB)	P1L	0.36	-0.10	$p < 0.01$
	P10L	0.55	0.72	$p > 0.05$
	P1S/P10L	0.19	0.82	$p > 0.05$
	PmL	0.29	0.09	$p > 0.05$
Slovakia (BSSE)	P1L	0.83	-0.09	$0.01 <= p <= 0.05$
	P10L	1.63	0.09	$p > 0.05$
	P1S/P10L	0.80	0.18	$p > 0.05$
	PmL	0.37	0.80	$p > 0.05$
Slovenia (LJSE)	P1S	-0.01	0.09	$0.01 <= p <= 0.05$
	P10L	0.85	-0.06	$0.01 <= p <= 0.05$
	P1S/P10L	0.84	0.03	$p > 0.05$
	PmL	0.14	-0.02	$p < 0.01$

APPENDIX F

TABLE 137. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. TAXATION DATA (AS AT 31/05/2012). PART 1.

The information provided in the table below was sourced from Eurostat (2013a), PWC (2012) and Tax Foundation (2012a; 2012b). The conversion of local currencies into euro (€), if not officially provided at source, was computed using the average annual exchange rate in 2009.

Country	Personal income tax	Capital gains tax	Corporate tax	Double taxation treaties
US	Federal progressive tax rates: 10%, 15%, 25%, 28%, 33% and 35%on taxable income over €295,037; State and local governments tax rate: 1% - 11.36%;	Short-term capital gains (*i.e.*, investments held for a year or less before being sold) are taxed at the investor's ordinary income tax rate; Long-term capital gains (*i.e.*, gains on dispositions of assets held for more than one year) are taxed at 15%; this rate is reduced to 5% for individuals in the lowest two income tax brackets;	Federal progressive tax rates:15%, 25%, 34%, 39%, 34%, 35%, 38% and 35% (above €14.27m); State and local governments tax rates: 0% - 12%;	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia, UK and 54 other countries
UK	Progressive tax rates: 20% (basic rate), 40% (higher rate) and 50% (additional rate) on taxable income over €172,853; Dividends are taxed at 10% for basic rate taxpayers; at 32.5% for higher rate taxpayers; and at 42.5% for additional rate taxpayers; 10% tax credit applies;	Capital gains tax of 18% applies to basic rate taxpayers; Capital gains tax of 28% applies to higher and additional rate taxpayers;	Progressive tax rates: 20% and 24% (above €365,670)	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia, US and 110 other countries
Bulgaria	Flat-rate tax: 10%	Flat-rate tax: 10% However, an exemption of 100% applies to capital gains from disposal of shares traded on the Bulgarian and EU stock exchange (no participation exemption or holding period requirements)	Flat-rate tax: 10%	Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia, UK, US and 56 other countries

TABLE 138. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. TAXATION DATA (AS AT 31/05/2012). PART 2.

The information provided in the table below was sourced from Eurostat (2013a), PWC (2012) and Tax Foundation (2012a; 2012b). The conversion of local currencies into euro (€), if not officially provided at source, was computed using the average annual exchange rate in 2009.

Country	Personal income tax	Capital gains tax	Corporate tax	Double taxation treaties
Cyprus	Progressive tax rates: 20%, 25%, 30% and 35% on taxable income over €60,000	Flat-rate tax: 0%	Flat-rate tax: 10%	Bulgaria, Czech Republic, Hungary, Malta, Poland, Romania, Slovakia, Slovenia, UK, US and 39 other countries
Czech Republic	Flat-rate tax: 15%	Flat-rate tax: 15%	Flat-rate tax: 19%	Bulgaria, Cyprus, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia, UK, US and 65 other countries
Estonia	Flat-rate tax: 21%	Flat-rate tax: 21%	Flat-rate tax: 21%	Bulgaria, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia, UK and 38 other countries
Hungary	Flat-rate tax: 16%	Flat-rate tax: 16%	Progressive tax rates: 10% and 19% (above €1.78m)	Bulgaria, Cyprus, Czech Republic, Estonia, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia, UK, US and 60 other countries
Latvia	Flat-rate tax: 25%	Flat-rate tax: 15%	Flat-rate tax: 15% or 9% of turnover if under €100,387	Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia, UK, US and 39 other countries
Lithuania	Flat-rate tax: 15% However, dividend income is taxed at a 20 %	Flat-rate tax: 15% However, various exemptions for shares apply	Progressive tax rates: 5% and 15% (above €289,625)	Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Malta, Poland, Romania, Slovakia, Slovenia, UK, US and 36 other countries

TABLE 139. BACKGROUND INFORMATION ON THE US, UK AND EU12 INVESTMENT ENVIRONMENTS. TAXATION DATA (AS AT 31/05/2012). PART 3.

The information provided in the table below was sourced from Eurostat (2013a), PWC (2012) and Tax Foundation (2012a; 2012b). The conversion of local currencies into euro (€), if not officially provided at source, was computed using the average annual exchange rate in 2009.

Country	Personal income tax	Capital gains tax	Corporate tax	Double taxation treaties
Malta	Progressive tax rates: 0%,15%, 25% and 35% on taxable income over €60,000	Progressive tax rates: 0%,15%, 25% and 35% on taxable income over €60,000	Flat-rate tax: 35%	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia, UK, US and 47 other countries
Poland	Progressive tax rates: 18% and 32% on taxable income over €19,296	Flat-rate tax: 19%	Flat-rate tax: 19%	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Romania, Slovakia, Slovenia, UK, US and 71 other countries
Romania	Flat-rate tax 16%	Flat-rate tax: 16%	Flat-rate tax: 16% or 3% of turnover if under €100,000	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia, UK, US and 73 other countries
Slovakia	Flat-rate tax: 19%	Flat-rate tax: 19%	Flat-rate tax: 19%	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovenia, UK, US and 51 other countries
Slovenia	Progressive tax rates: 16%, 27% and 41% on taxable income over €18,960	Flat-rate tax: 20%	Flat-rate tax: 18%	Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, UK, US and 38 other countries

APPENDIX G

TABLE 140. SOVEREIGN CREDIT RATING CLASS DESCRIPTION (AS AT 31/12/2011).

The information provided in the table below was sourced from Trading Economics (2012), S&P's (2012), Fitch Rating (2012) and Moody's Investor Service (2012).

<table>
<tr><th>General sovereign credit rating class</th><th>Standard and Poor's</th><th>Fitch Ratings</th><th>Moody's</th></tr>
<tr><td>Highest grade</td><td>AAA</td><td>AAA</td><td>Aaa</td></tr>
<tr><td rowspan="3">High grade</td><td>AA+</td><td>AA+</td><td>Aa1</td></tr>
<tr><td>AA</td><td>AA</td><td>Aa2</td></tr>
<tr><td>AA-</td><td>AA-</td><td>Aa3</td></tr>
<tr><td rowspan="3">Upper medium grade</td><td>A+</td><td>A+</td><td>A1</td></tr>
<tr><td>A</td><td>A</td><td>A2</td></tr>
<tr><td>A-</td><td>A-</td><td>A3</td></tr>
<tr><td rowspan="3">Lower medium grade</td><td>BBB+</td><td>BBB+</td><td>Baa1</td></tr>
<tr><td>BBB</td><td>BBB</td><td>Baa2</td></tr>
<tr><td>BBB-</td><td>BBB-</td><td>Baa3</td></tr>
<tr><td rowspan="3">Speculative</td><td>BB+</td><td>BB+</td><td>Ba1</td></tr>
<tr><td>BB</td><td>BB</td><td>Ba2</td></tr>
<tr><td>BB-</td><td>BB-</td><td>Ba3</td></tr>
<tr><td rowspan="3">Highly speculative</td><td>B+</td><td>B+</td><td>B1</td></tr>
<tr><td>B</td><td>B</td><td>B2</td></tr>
<tr><td>B-</td><td>B-</td><td>B3</td></tr>
<tr><td>Substantial risks</td><td>CCC+</td><td rowspan="5">CCC</td><td>Caa1</td></tr>
<tr><td>Extremely speculative</td><td>CCC</td><td>Caa2</td></tr>
<tr><td>In default with little prospect for recovery</td><td>CCC-</td><td>Caa3</td></tr>
<tr><td rowspan="3">In default</td><td>CC</td><td>Ca</td></tr>
<tr><td>C</td><td rowspan="2">C</td></tr>
<tr><td>D</td><td>DDD</td></tr>
</table>

APPENDIX H

Table 141 (p. 497), Table 142 (p. 498) and Table 143 (p. 499) presented in this appendix are meant to complement the information in Section 4.3. with the Fama and French's (1996) three-factor model alpha, together with its associated *p*-value, and the Carhart's (1997) four-factor model alpha, together with its associated *p*-value, for all the combinations of past-return-based portfolios and long-short investment positions that are considered in Sections 4.3. and 4.4. of the thesis.

For the US stock markets, the three-factor model is specified as in Fama and French (1996), with the only difference being that the **factors were discounted from an annual to a semi-annual form** to match the six-monthly portfolio return data examined in the present study. Exactly the same conditions apply to the four-factor model that is specified as in Carhart (1997). For the UK and all the EU12 stock markets, the three-factor model as well as the four-factor model is specified as in Gregory, Tharyan and Christidis (2013), with the only difference being that the **UK size, value and momentum factors** were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and **used in both the UK regressions as well as all the EU12 regressions**. As explained in the 'Methodology' chapter, the reason for not using EU12 factors in the EU12 regressions is that the data necessary for calculating the factors, in particular the value factor, is mostly unavailable for the EU12 stock markets. During the entire time period under consideration by the present research, companies' book values **in any form** are available for **one month or more** only in the case of about 40% of all the EU12 stocks. It should be noted, however, that the return on all strategies investigated in Section 4.3. can be fully explained by a combination of the robustness tests that are already employed in Sections 4.3. and 4.4. of the thesis.

The statistics presented in this appendix suggest that, at least for the regressions estimated herein, CAPM alphas are as conservative as the three-factor model alphas and the four-factor model alphas in terms of statistical significance.

Specifically, all three models showed statistically significant alphas at $p \leqslant 0.05$ in the case of P1L for Poland (WSE), P1L for Romania (BVB) and P10L for the EU12 stock market. However, both P1L for Poland (WSE) and P1L for Romania (BVB) are associated with test-period investment returns that are neither statistically nor economically different from zero at $p \leq 0.05$ and $\delta \geq 0.5$, as indicated by the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size Test (see Subsections 4.3.9. and 4.3.10.). Additionally, all three alphas in the case of P1L for Romania (BVB) are negative. The result for the EU12 stock market is the only result in this study for which a past-return-based strategy produces (1) statistically and economically significant returns (see Subsection 4.3.13.); (2) a positive and statistically significant CAPM alpha; (3) a positive and statistically significant two-factor model alpha (see Subsection 4.3.13.); (4) a positive and statistically significant three-factor model alpha; and (5) a positive and statistically significant four-factor model alpha. Yet, once market microstructure frictions are considered in addition to risk, the abnormal profitability disappears (see Subsection 4.4.13.).

In addition to the case of P1L for Poland (WSE), P1L for Romania (BVB) and P10L for the EU12 stock market discussed above, statistical significance at $p \leq 0.05$ of CAPM alpha only is detected in the case of P1S/P10L for Romania (BVB). As discussed in Subsection 4.3.10., nonetheless, this result is associated with test-period investment returns that are neither statistically nor economically different from zero at $p \leq 0.05$ and $\delta \geq 0.5$, as indicated by the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size Test.

Lastly, positive and statistically significant (at $p \leq 0.05$) alphas of the four-factor model only can be observed in the cases of P1L for Czech Republic (PSE), P1L for Lithuania (VSE) and P1S/P10L for the EU12 stock market. The results for Lithuania (VSE) and the EU12 stock market are associated with test-period investment returns that are neither statistically nor economically different from zero. In the case of Lithuania (VSE), this is demonstrated by the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size Test (see Subsection 4.3.8.). In the case of the EU12 stock market, this is demonstrated by the two-tailed Student's One-Sample t-Test and the Glass's Effect Size Test (see Subsection 4.3.13.). Interestingly, the results for Czech Republic (PSE) are associated with test-period investment returns that are both statistically different from zero at $p < 0.01$ and economically different from zero at $\delta \geq 0.5$, , as indicated by the two-tailed Wilcoxon Signed-Ranks Test and the Cliff's Effect Size Test. This means that, market microstructure considerations aside, a strategy based on P1L in Czech Republic (PSE) could be considered to be successful under the four-factor model, at least by the adopted specifications and standards. However, any results for the four-factor model (or the three-factor model for that matter) are very likely to be unreliable. The reason for this is that, as mentioned before, the specification of both the three-factor model and the four-factor model is such that (1) **the factors used are discounted from an annual to a semi-annual form to match the six-monthly portfolio return data**; and (2) **the factors used are the factors for the UK stock market and not for Czech Republic (PSE)**. In fact, either one of the two aforementioned (mis-)specifications is by itself able to render the regression results unreliable.

To conclude, the results reported and analysed in this appendix indicate that in the present context the choice of the asset pricing model makes little difference as far as the standards set by Hypothesis One are concerned. All three models considered, *i.e.* CAPM, the three-factor model and the four-factor model, generate similar results in terms of statistical significance and, thus, lead to very similar conclusions. However, the Carhart's (1997) model is clearly the least conservative model here in the sense that it occasionally detects statistical significance where CAPM and the Fama and French's (1996) model do not. In any case, out of the three models here only CAPM is correctly specified and, therefore, only the estimates thereof can be seen as reliable.

TABLE 141. CAPM ALPHAS, F&F ALPHAS AND CARHART ALPHAS. PART 1.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely. Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). The results presented in the remaining six columns are based on test period returns. Column three reports the average, six-monthly return for the test period. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS estimators, are reported in columns four and five. The alpha of the Fama and French's (1996) three-factor model and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS estimators, are reported in columns six and seven. The alpha of the Carhart's (1997) four-factor model and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS estimators, are reported in the last two columns.

Stock market	**Portfolio**	**Average return** (test period)	**CAPM alpha**	***p*-value** (CAPM alpha)	**F&F model alpha**	***p*-value** (F&F model alpha)	**Carhart model alpha**	***p*-value** (Carhart model alpha)
US (NYSE-AMEX)	P1L	0.07	-0.01	0.6373	0.00	0.9914	0.00	0.9849
	P10L	0.05	-0.06	0.0811	-0.04	0.3515	-0.04	0.3468
	P1L/P10S	0.03	0.04	0.4644	0.02	0.6822	0.03	0.6794
	PmL	0.08	0.00	-	0.00	-	0.00	-
US (NASDAQ)	P1L	0.04	-0.02	0.4905	-0.02	0.4683	-0.02	0.4575
	P10L	0.03	-0.05	0.2377	-0.01	0.8523	-0.01	0.8898
	P1L/P10S	0.01	0.02	0.7369	-0.02	0.7621	-0.03	0.7328
	PmL	0.06	0.00	-	0.00	-	0.00	-
UK (LSE)	P1L	0.06	0.03	0.2595	0.05	0.1130	0.04	0.2146
	P10L	0.01	-0.01	0.8066	0.01	0.9027	0.06	0.3430
	P1L/P10S	0.04	0.03	0.6084	0.02	0.6862	-0.04	0.4479
	PmL	0.03	0.00	-	0.00	-	0.00	-
EU12	P1L	0.22	-0.02	0.8261	0.02	0.8121	-0.01	0.9370
	P10L	0.32	0.21	0.0221	0.20	0.0341	0.26	0.0090
	P1S/P10L	0.11	0.20	0.0953	0.17	0.1538	0.25	0.0407
	PmL	0.14	0.00	-	0.00	-	0.00	-

Notes: For the US stock markets, the three-factor model is specified as in Fama and French (1996), with the only difference being that the factors, obtained from French (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data. For the UK and all the EU12 stock markets, the three-factor model is specified as in Gregory *et al.* (2013), with the only difference being that the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors, obtained from Xfi Centre (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and applied to both the UK and all the EU12 regressions.

For the US stock markets, the four-factor model is specified as in Carhart (1997), with the only difference being that the factors, obtained from French (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data. For the UK and all the EU12 stock markets, the four-factor model is specified as in Gregory *et al.* (2013), with the only difference being that the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors, obtained from Xfi Centre (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and applied to both the UK and all the EU12 regressions.

TABLE 142. CAPM ALPHAS, F&F ALPHAS AND CARHART ALPHAS. PART 2.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely. Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). The results presented in the remaining six columns are based on test period returns. Column three reports the average, six-monthly return for the test period. CAPM alpha and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS estimators, are reported in columns four and five. The alpha of the Fama and French's (1996) three-factor model and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS estimators, are reported in columns six and seven. The alpha of the Carhart's (1997) four-factor model and the probability (p) associated with the Student's Regression Coefficient t-Test, based on the two-tailed distribution and standard OLS estimators, are reported in the last two columns.

Stock market	**Portfolio**	**Average return** (test period)	**CAPM alpha**	***p*-value** (CAPM alpha)	**F&F model alpha**	***p*-value** (F&F model alpha)	**Carhart model alpha**	***p*-value** (Carhart model alpha)
Bulgaria (BSE-Sofia)	P1L	0.22	0.07	0.6381	0.12	0.4172	0.08	0.6311
	P10L	1.18	-0.12	0.7564	-0.19	0.6563	0.09	0.8360
	P1S/P10L	0.95	-0.21	0.6648	-0.32	0.5277	0.00	0.9937
	PmL	0.27	0.00	-	0.00	-	0.00	-
Cyprus (CSE)	P1S	0.08	0.06	0.0952	0.05	0.1780	0.05	0.2907
	P10S	0.03	0.00	0.9825	-0.01	0.7846	-0.01	0.7727
	P1S/P10L	0.05	0.04	0.2700	0.05	0.2470	0.04	0.3424
	PmL	-0.01	0.00	-	0.00	-	0.00	-
Czech Republic (PSE)	P1L	0.09	0.04	0.0980	0.04	0.1384	0.05	0.0219
	P10L	0.06	0.01	0.5767	0.00	0.9913	0.00	0.8045
	P1L/P10S	0.03	0.02	0.5617	0.02	0.4707	0.03	0.2454
	PmL	0.04	0.00	-	0.00	-	0.00	-
Hungary (BSE)	P1L	0.05	0.01	0.7259	0.03	0.3952	0.05	0.1791
	P10L	0.09	0.04	0.4782	0.02	0.7266	0.05	0.4388
	P1S/P10L	0.04	0.01	0.8546	-0.02	0.7820	-0.01	0.8990
	PmL	0.03	0.00	-	0.00	-	0.00	-
Lithuania (VSE)	P1L	0.20	0.07	0.1344	0.08	0.1035	0.10	0.0379
	P10L	0.11	0.01	0.8512	0.01	0.8871	0.03	0.7093
	P1L/P10S	0.10	0.04	0.6255	0.05	0.5784	0.06	0.5455
	PmL	0.09	0.00	-	0.00	-	0.00	-

Notes: For the US stock markets, the three-factor model is specified as in Fama and French (1996), with the only difference being that the factors, obtained from French (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data. For the UK and all the EU12 stock markets, the three-factor model is specified as in Gregory *et al.* (2013), with the only difference being that the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors, obtained from Xfi Centre (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and applied to both the UK and all the EU12 regressions.

For the US stock markets, the four-factor model is specified as in Carhart (1997), with the only difference being that the factors, obtained from French (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data. For the UK and all the EU12 stock markets, the four-factor model is specified as in Gregory *et al.* (2013), with the only difference being that the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors, obtained from Xfi Centre (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and applied to both the UK and all the EU12 regressions.

TABLE 143. CAPM ALPHAS, F&F ALPHAS AND CARHART ALPHAS. PART 3.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely. Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). The results presented in the remaining six columns are based on test period returns. Column three reports the average, six-monthly return for the test period. CAPM alpha and the probability (*p*) associated with the Student's Regression Coefficient *t*-Test, based on the two-tailed distribution and standard OLS estimators, are reported in columns four and five. The alpha of the Fama and French's (1996) three-factor model and the probability (*p*) associated with the Student's Regression Coefficient *t*-Test, based on the two-tailed distribution and standard OLS estimators, are reported in columns six and seven. The alpha of the Carhart's (1997) four-factor model and the probability (*p*) associated with the Student's Regression Coefficient *t*-Test, based on the two-tailed distribution and standard OLS estimators, are reported in the last two columns.

Stock market	**Portfolio**	**Average return** (test period)	**CAPM alpha**	***p*-value** (CAPM alpha)	**F&F model alpha**	***p*-value** (F&F model alpha)	**Carhart model alpha**	***p*-value** (Carhart model alpha)
Poland (WSE)	P1L	0.17	0.07	0.0275	0.07	0.0395	0.08	0.0346
	P10L	0.08	-0.01	0.7834	-0.01	0.8701	0.01	0.8979
	P1L/P10S	0.09	0.07	0.2134	0.06	0.2940	0.06	0.3750
	PmL	0.07	0.00	-	0.00	-	0.00	-
Romania (BVB)	P1L	0.18	-0.19	0.0108	-0.21	0.0146	-0.22	0.0185
	P10L	0.61	0.32	0.1128	0.25	0.2502	0.29	0.2218
	P1S/P10L	0.43	0.49	0.0463	0.44	0.1070	0.49	0.0997
	PmL	0.22	0.00	-	0.00	-	0.00	-
Slovakia (BSSE)	P1L	0.49	0.36	0.4531	0.02	0.9603	-0.10	0.8142
	P10L	1.03	0.58	0.5263	0.28	0.7654	0.71	0.4967
	P1S/P10L	0.54	0.21	0.8406	0.25	0.8132	0.80	0.4883
	PmL	0.50	0.00	-	0.00	-	0.00	-
Slovenia (LJSE)	P1S	0.01	0.01	0.6792	0.00	0.9317	-0.01	0.7444
	P10L	0.51	-0.10	0.4555	-0.08	0.5451	0.01	0.9676
	P1S/P10L	0.53	-0.07	0.6112	-0.06	0.6524	0.01	0.9450
	PmL	0.09	0.00	-	0.00	-	0.00	-

Notes: For the US stock markets, the three-factor model is specified as in Fama and French (1996), with the only difference being that the factors, obtained from French (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data. For the UK and all the EU12 stock markets, the three-factor model is specified as in Gregory *et al.* (2013), with the only difference being that the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors, obtained from Xfi Centre (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and applied to both the UK and all the EU12 regressions.

For the US stock markets, the four-factor model is specified as in Carhart (1997), with the only difference being that the factors, obtained from French (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data. For the UK and all the EU12 stock markets, the four-factor model is specified as in Gregory *et al.* (2013), with the only difference being that the UK size (*i.e.*, SMB), value (*i.e.*, HML) and momentum (*i.e.*, UMD) factors, obtained from Xfi Centre (2013), were discounted from an annual to a semi-annual form to match the six-monthly portfolio return data and applied to both the UK and all the EU12 regressions.

APPENDIX I

The information provided in this appendix is complementary to Section 4.4., specifically the CAPM beta statistics thereof. In addition to the conventional CAPM betas that are reported and analysed in Section 4.4., Table 144 (p. 497), Table 145 (p. 498) and Table 146 (p. 499) report test-period betas adjusted for infrequent trading. The purpose of the adjustment is to verify if thin trading could meaningfully bias beta estimates for the investigated past-return-based strategies during the period when investment takes place. This potential problem may be particularly pertinent to the less-developed stock markets of the EU12.

All test-period betas are adjusted using the exact method described by Dimson (1979). Therefore, the reader is referred to the original source for a detailed description of the underlying principles and the calculation procedures involved. The number of lagged and leading market terms has been determined on the basis of the evidence from Sercu, Vandebroek and Vinaimont (2008). The authors stressed that less thin-trading bias comes at the cost of a higher standard error. Thus, assuming no-trade probability of 0.25 or less, which seems to be conservative for monthly data, the number of lagged and leading variables is set to four. An additional consideration has been the fact that the samples concerned contain only 23 observations.

The results in Table 144 (p. 497), Table 145 (p. 498) and Table 146 (p. 499) surprisingly indicate that the developed stock markets of the US and the UK are, on average, much more likely to have past-return-based portfolios' betas underestimated due to infrequent trading than the less-developed stock markets of the EU12. In particular, all but one portfolio thereof, *i.e.* P10L for US (NASDAQ), had its beta estimate revised upward after the adjustment. Differently, only about one half of all the EU12 past-return-based portfolios had its beta estimate revised upward after the adjustment, whereas the other half had its beta estimate revised downward after the adjustment. This means that roughly 50% of all unadjusted CAPM beta estimates for the EU12 stock markets actually overestimated systematic risk.

However, as far as the magnitude of upward beta adjustments is concerned, the developed stock markets averaged only 0.75, while the less-developed stock markets averaged as high as 5.5. This last result is largely driven by Bulgaria (BSE-Sofia) and Slovakia (BSSE). Once those stock markets are excluded from the sample, the average upward adjustment equals 1.85.

Therefore, it would appear that the less-developed stock markets of the EU12 are less likely to have biased betas on account of infrequent trading as compared to the more developed stock markets of the US and the UK, but when the estimates are biased, then the underestimation in the case of the less-developed stock markets is likely to be substantially greater than it would be expected from a developed stock market.

Of particular interest is the result of beta adjustment for the aggregate EU12 stock market's P10L, since unlike the case of all the other combinations of portfolios and long-short investment positions considered in this study, here both the test-period average return and the test-period CAPM alpha meet the rigorous standards of the first alternative hypothesis (see Subsection 4.3.13.). Significantly, it would seem that adjusting the beta estimate using the Dimson's (1979) method with four lagged and leading market terms noticeably lowers the beta of the P10L by about 28%, from 0.82 to 0.59.

TABLE 144. UNADJUSTED AND ADJUSTED TEST-PERIOD BETAS. PART 1.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). Column three reports unadjusted test-period betas as estimated from the CAPM ordinary least squares regression (see Equation 16, p. 174). The last column reports test-period betas adjusted for infrequent trading using the method described by Dimson (1979). In line with the evidence from Sercu *et al.* (2008), who showed that less thin-trading bias comes at the cost of a higher standard error, the number of lagged and leading variables is set to four. This should be regarded as a conservative choice, especially for monthly data.

Stock market	**Portfolio**	**Unadjusted beta** (test period)	**Adjusted beta** (test period)
US (NYSE-AMEX)	P1L	1.04	1.38
	P10L	1.40	1.61
	P1L/P10S	-0.35	-0.23
	PmL	1	1
US (NASDAQ)	P1L	0.91	1.21
	P10L	1.52	1.22
	P1L/P10S	-0.59	-0.02
	PmL	1	1
UK (LSE)	P1L	0.32	2.54
	P10L	0.66	0.83
	P1L/P10S	-0.33	1.71
	PmL	1	1
EU12	P1L	1.74	3.02
	P10L	0.82	0.59
	P1S/P10L	-0.91	-2.42
	PmL	1	1

TABLE 145. UNADJUSTED AND ADJUSTED TEST-PERIOD BETAS. PART 2.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). Column three reports unadjusted test-period betas as estimated from the CAPM ordinary least squares regression (see Equation 16, p. 174). The last column reports test-period betas adjusted for infrequent trading using the method described by Dimson (1979). In line with the evidence from Sercu *et al.* (2008), who showed that less thin-trading bias comes at the cost of a higher standard error, the number of lagged and leading variables is set to four. This should be regarded as a conservative choice, especially for monthly data.

Stock market	**Portfolio**	**Unadjusted beta** (test period)	**Adjusted beta** (test period)
Bulgaria (BSE-Sofia)	P1L	0.53	-5.91
	P10L	5.08	23.24
	P1S/P10L	4.53	29.15
	PmL	1	1
Cyprus (CSE)	P1S	-0.45	-0.64
	P10S	-0.69	-1.54
	P1S/P10L	0.24	0.90
	PmL	1	1
Czech Republic (PSE)	P1L	1.76	4.31
	P10L	1.64	2.53
	P1L/P10S	0.13	1.78
	PmL	1	1
Hungary (BSE)	P1L	1.60	-0.08
	P10L	2.39	6.27
	P1S/P10L	0.80	6.36
	PmL	1	1
Lithuania (VSE)	P1L	1.51	2.86
	P10L	1.01	1.15
	P1L/P10S	0.50	1.72
	PmL	1	1

TABLE 146. UNADJUSTED AND ADJUSTED TEST-PERIOD BETAS. PART 3.

The results presented in the table below relate to equal-weighted, decile portfolio-size group, six-month/six-month, past-return-based investment strategies. Stocks are first sorted into ten portfolios on the basis of compounded returns over six consecutive months (*i.e.*, the formation period) and then compounded returns to the ten portfolios are calculated over the next six months (*i.e.*, the test period). Stock returns are equal-weighted within portfolios. This process is repeated 23 times, which makes full use of the 144 months of data under investigation (*i.e.*, from 01/01/2000 to 31/12/2011) by following the semi-overlapping calculation method. The calculation method, described and discussed in detail in the 'Methodology' chapter, is such that the subsequent six-monthly formation periods do not overlap at all, while the adjacent six-monthly test and formation periods overlap completely.

Stock markets of interest are listed in the first column. Portfolios of interest, based on the same long-short investment positions as in Sections 4.3. and 4.4., are listed in the second column. P1L is the highest past-return portfolio (based on a long position in P1), P1S is the highest past-return portfolio (based on a short position in P1), P10L is the lowest past-return portfolio (based on a long position in P10), P10S is the lowest past-return portfolio (based on a short position in P10), P1L/P10S is the arbitrage portfolio (based on a long position in P1 and a short position in P10), P1S/P10L is the arbitrage portfolio (based on a short position in P1 and a long position in P10) and PmL is the market portfolio (based on a long position in Pm). Column three reports unadjusted test-period betas as estimated from the CAPM ordinary least squares regression (see Equation 16, p. 174). The last column reports test-period betas adjusted for infrequent trading using the method described by Dimson (1979). In line with the evidence from Sercu *et al.* (2008), who showed that less thin-trading bias comes at the cost of a higher standard error, the number of lagged and leading variables is set to four. This should be regarded as a conservative choice, especially for monthly data.

Stock market	**Portfolio**	**Unadjusted beta** (test period)	**Adjusted beta** (test period)
Poland (WSE)	P1L	1.51	1.15
	P10L	1.35	2.48
	P1L/P10S	0.17	-1.33
	PmL	1	1
Romania (BVB)	P1L	1.73	3.62
	P10L	1.36	-1.03
	P1S/P10L	-0.36	-4.65
	PmL	1	1
Slovakia (BSSE)	P1L	0.24	-0.44
	P10L	0.88	12.14
	P1S/P10L	0.64	12.58
	PmL	1	1
Slovenia (LJSE)	P1S	-0.17	-0.86
	P10L	8.43	3.49
	P1S/P10L	8.26	2.63
	PmL	1	1

LIST OF REFERENCES

Aburachis, A. and Kish, R. (1999). International Evidence on the Comovements Between Bond Yields and Stock Returns: 1984-1994. *Journal of Financial and Strategic Decisions,* 12(2), 67-81.

Affleck-Graves, J. and McDonald, B. (1989). Nonnormalities and tests of asset pricing theories. *The Journal of Finance,* 44(4), 889-908.

Agyei-Ampomah, S. (2007). The Post-Cost Profitability of Momentum Trading Strategies: Further Evidence from the UK. *European Financial Management,* 13(4), 776-802.

Ahn, D.-H., Conrad, J. and Dittmar, R. F. (2003). Risk Adjustment and Trading Strategies. *The Review of Financial Studies,* 16(2), 459-485.

Akarim, Y. D. and Sevim, S. (2013). The impact of mean reversion model on portfolio investment strategies: Empirical evidence from emerging markets. *Economic Modelling,* 31, 453-459.

Albert, R. L. and Henderson, G. V. (1995). Firm size, overreaction, and return reversals. *Quarterly Journal of Business & Economics,* 34(4), 60.

Ali, A., Hwang, L.-S. and Trombley, M. A. (2003). Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics,* 69, 355–373.

Ali, A. and Trombley, M. A. (2006). Short Sales Constraints and Momentum in Stock Returns. *Journal of Business Finance & Accounting,* 33(3/4), 587-615.

Alonso, A. and Rubio, G. (1990). Overreaction in the Spanish equity market. *Journal of Banking & Finance,* 14(2-3), 469-481.

Alwathainani, A. M. (2012). Consistent winners and losers. *International Review of Economics & Finance,* 21(1), 210-220.

American Psychological Association (1994). *Publication Manual of the American Psychological Association*. 4th ed. Washington, DC: American Psychological Association.

American Psychological Association (2001). *Publication Manual of the American Psychological Association*. 5th ed. Washington, DC: American Psychological Association.

American Psychological Association (2009). *Publication Manual of the American Psychological Association*. 6th ed. Washington, DC: American Psychological Association.

Ammann, M., Moellenbeck, M. and Schmid, M. M. (2011). Feasible momentum strategies in the US stock market. *Journal of Asset Management,* 11(6), 362-374.

Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns. *The Journal of Finance,* 61(1), 259-299.

Antoniou, A., Ergul, N. and Holmes, P. (1997). Market Efficiency, Thin Trading and Non-linear Behaviour: Evidence from an Emerging Market. *European Financial Management,* 3(2), 175-190.

Antoniou, A., Galariotis, E. C. and Spyrou, S. I. (2006). Short-term Contrarian Strategies in the London Stock Exchange: Are They Profitable? Which Factors Affect Them? *Journal of Business Finance & Accounting,* 33(5/6), 839-867.

Antoniou, A., Lam, H. Y. T. and Paudyal, K. (2007). Profitability of Momentum Strategies in International Markets: The Role of Business Cycle Variables and Behavioral Biases. *CFA Digest,* 37(3), 56-57.

Arena, M. P., Haggard, K. S. and Yan, X. (2008). Price Momentum and Idiosyncratic Volatility. *Financial Review,* 43(2), 159-190.

Asem, E. (2009). Dividends and price momentum. *Journal of Banking & Finance,* 33(3), 486-494.

Asem, E. and Tian, G. Y. (2010). Market Dynamics and Momentum Profits. *Journal of Financial and Quantitative Analysis,* 45(6), 1549–1562.

Asgharian, H. and Hansson, B. (2009). An analysis of momentum and contrarian anomalies using an orthogonal portfolio approach. *Applied Economics Letters,* 16(6), 625-628.

Avramov, D. and Chordia, T. (2006). Asset Pricing Models and Financial Market Anomalies. *The Review of Financial Studies,* 19(3), 1001-1040.

Avramov, D., Chordia, T., Jostova, G. and Philipov, A. (2007). Momentum and Credit Rating. *The Journal of Finance,* 62(5), 2503-2520.

Badreddine, S., Galariotis, E. C. and Holmes, P. (2012). The relevance of information and trading costs in explaining momentum profits: Evidence from optioned and non-optioned stocks. *Journal of International Financial Markets, Institutions and Money,* 22(3), 589-608.

Balassa, B. (1964). The purchasing-power parity doctrine: a reappraisal. *The Journal of Political Economy,* 72(6), 584-596.

Ball, R. and Kothari, S. P. (1989). Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns. *Journal of Financial Economics,* 25(1), 51-74.

Ball, R., Kothari, S. P. and Shanken, J. (1995). Problems in measuring portfolio performance An application to contrarian investment strategies. *Journal of Financial Economics,* 38(1), 79-107.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics,* 9(1), 3-18.

Barberis, N., Shleifer, A. and Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics,* 49(3), 307-343.

Baytas, A. and Cakici, N. (1999). Do markets overreact: International evidence. *Journal of Banking & Finance,* 23(7), 1121-1144.

Beaver, W. H. and Landsman, W. R. (1981). Note on the behavior of residual security returns for winner and loser portfolios. *Journal of Accounting and Economics,* 3(3), 233-241.

Bem, D. J. (1965). An experimental analysis of self-persuasion. *Journal of Experimental Social Psychology,* 1(3), 199-218.

Bergman, U. M., Bordo, M. D. and Jonung, L. (1998). Historical evidence on business cycles: the international experience. *Federal Reserve Bank of Boston Conference Series*, pp. 65-113. Federal Reserve Bank of Boston.

Bettman, J. L., Maher, T. R. B. and Sault, S. J. (2009). Momentum profits in the Australian equity market: A matched firm approach. *Pacific-Basin Finance Journal,* 17(5), 565-579.

Bhatia, A. V. (2002). Sovereign credit ratings methodology: an evaluation. *IMF Working Papers,* October.

Bhootra, A. (2011). Are momentum profits driven by the cross-sectional dispersion in expected stock returns? *Journal of Financial Markets,* 14(3), 494-513.

Bloomfield, R., Libby, R. and Nelson, M. W. (2000). Underreactions, overreactions and moderated confidence. *Journal of Financial Markets*, 3(2), 113-137.

Blume, M. E. and Stambaugh, R. F. (1983). Biases in computed returns: An application to the size effect. *Journal of Financial Economics,* 12(3), 387-404.

Boynton, W. and Oppenheimer, H. R. (2006). Anomalies in Stock Market Pricing: Problems in Return Measurements*. *The Journal of Business,* 79(5), 2617-2631.

Brailsford, T. and O'Brien, M. A. (2008). Disentangling Size from Momentum in Australian Stock Returns. *Australian Journal of Management (University of New South Wales),* 32(3), 463-484.

Breen, W. J. and Korajczyk, R. (1994). On selection biases in book-to-market based tests of asset pricing models. *Working paper (Kellogg Graduate School of Management, Northwestern University, Chicago, US)*.

Brown, G. (2012). Europe's three-dimensional crisis. *The Guardian*.

Brown, P., Kleidon, A. W. and Marsh, T. A. (1983). New evidence on the nature of size-related anomalies in stock prices. *Journal of Financial Economics,* 12(1), 33-56.

Brush, J. S. (2007). A Flexible Theory of Price Momentum. *Journal of Investing,* 16(1), 36-42.

Bulkley, G. and Nawosah, V. (2009). Can the Cross-Sectional Variation in Expected Stock Returns Explain Momentum? *Journal of Financial & Quantitative Analysis,* 44(4), 777-794.

Bulow, J. and Rogoff, K. (1989). Sovereign Debt: Is to Forgive to Forget? *American Economic Review,* 79(1), 43-50.

Cajueiro, D.O. and Tabak, B.M. (2005). Testing for predictability in equity returns for European transition markets. *Economic Systems*, 30(1): 56-78.

Cantor, R. and Packer, F. (1996). Determinants and impact of sovereign credit ratings. *Economic Policy Review,* 2(2), 37-54.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance,* 52(1), 57-82.

Carlstein, E. (1986). The use of subseries values for estimating the variance of a general statistic from a stationary sequence. *The Annals of Statistics*, 1171-1179.

Carver, R. P. (1978). The case against statistical significance testing. *Harvard Educational Review,* 48(3), 378-399.

Carver, R. P. (1993). The case against statistical significance testing, revisited. *The Journal of Experimental Educational*, 287-292.

Center for Research in Security Prices (2013a). *CRSP Marketing*. Chicago: CRSP.

Center for Research in Security Prices (2013b). *Frequently Asked Questions*. [Online]. Available at: www.crsp.com [Accessed 01/03/2013].

Chakrabarty, B. and Trzcinka, C. (2006). Momentum: Does the database make a difference? *Journal of Financial Research,* 29(4), 441-462.

Chan, K. C. (1988). On the Contrarian Investment Strategy. *Journal of Business,* 61(2), 147-163.

Chan, K. C. and Chen, N. F. (1988). An Unconditional Asset-Pricing Test and the Role of Firm Size as an Instrumental Variable for Risk. *The Journal of Finance,* 43(2), 309-325.

Chan, L. K. C., Jegadeesh, N. and Lakonishok, J. (1995). Evaluating the performance of value versus glamour stocks The impact of selection bias. *Journal of Finance,* 38(3), 269-296.

Chan, L. K. C., Jegadeesh, N. and Lakonishok, J. (1996). Momentum Strategies. *The Journal of Finance,* 51(5), 1681-1713.

Chan, L. K. C., Jegadeesh, N. and Lakonishok, J. (1999). The Profitability of Momentum Strategies. *Financial Analysts Journal,* 55(6), 80-90.

Chan, W. S. (2003). Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of Financial Economics,* 70(2), 223-260.

Chelley-Steeley, P. and Siganos, A. (2004). Momentum profits and macroeconomic factors. *Applied Economics Letters,* 11(7), 433-436.

Chen, C. R. and Sauer, D. A. (1997). Is stock market overreaction persistent over time? *Journal of Business Finance & Accounting,* 24(1), 51-66.

Chen, N.-F., Roll, R. and Ross, S. (1986a). Economic Forces and the Stock Market. *The Journal of Business,* 59(3), 383-403.

Chen, N.-F. and Zhang, F. (1998). Risk and Return of Value Stocks*. *The Journal of Business,* 71(4), 501-535.

Chen, Q., Jiang, Y. and Li, Y. (2012). The state of the market and the contrarian strategy: evidence from China's stock market. *Journal of Chinese Economic and Business Studies,* 10(1), 89-108.

Chopra, N., Lakonishok, J. and Ritter, J. R. (1992). Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics,* 31(2), 235-268.

Chordia, T. and Shivakumar, L. (2002). Momentum, Business Cycle, and Time-varying Expected Returns. *The Journal of Finance,* 57(2), 985-1019.

Chordia, T. and Shivakumar, L. (2006). Earnings and price momentum. *Journal of Financial Economics,* 80(3), 627-656.

Chui, A. C. W., Titman, S. and Wei, K. C. J. (2010). Individualism and Momentum around the World. *Journal of Finance,* 65(1), 361-392.

Claessens, S., Dasgupta, S. and Glen, J. (1995). Return behaviour in emerging Stock Market. *The World Bank Economic Review*, 9(1): 131-151.

Clare, A. and Thomas, S. (1995). The overreaction hypothesis and the UK stockmarket. *Journal of Business Finance & Accounting,* 22(7), 961-973.

Cleary, S. and Inglism, M. (1998). Momentum In Canadian Stock Returns. *Canadian Journal of Administrative Sciences (Canadian Journal of Administrative Sciences),* 15(3), 279-291.

Cliff, N. (1993). Dominance statistics: Ordinal analyses to answer ordinal questions. *Psychological Bulletin,* 114(3), 494-509.

Coe, R. (2002). It's the effect size, stupid: what effect size is and why it is important. *Annual Conference of the British Educational Research Association*. 12-14 September 2002. University of Exeter, England.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, J. (1994). The earth is round (p < .05). *American psychologist,* 49(12), 997.

Conrad, J. and Kaul, G. (1993). Long-Term Market Overreaction or Biases in Computed Returns? *The Journal of Finance,* 48(1), 39-63.

Conrad, J. and Kaul, G. (1998). An Anatomy of Trading Strategies. *Review of Financial Studies,* 11(3), 489.

Coombs, W. T., Algina, J. and Oltman, D. O. (1996). Univariate and multivariate omnibus hypothesis tests selected to control Type I error rates when population variances are not necessarily equal. *Review of Educational Research,* 66(2), 137-179.

Cooper, M. J., Gutierrez, R. C. and Hameed, A. (2004). Market States and Momentum. *The Journal of Finance,* 59(3), 1345-1365.

Copeland, T. E. and Mayers, D. (1982). The value line enigma (1965-1978): A case study of performance evaluation issues. *Journal of Financial Economics,* 10(2), 289-321

Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance,* 53(6), 1839-1885.

Davison, A. C. and Hinkley, D. V. (1997). *Bootstrap methods and their application*. New York: Cambridge University Press.

De Bondt, W. F. M. and Thaler, R. H. (1985). Does the Stock Market Overreact? *Journal of Finance,* 40(3), 793-805.

De Bondt, W. F. M. and Thaler, R. H. (1987). Further Evidence On Investor Overreaction and Stock Market Seasonality. *Journal of Finance,* 42(3), 557-581.

De Groot, W., Pang, J. and Swinkels, L. (2012). The cross-section of stock returns in frontier emerging markets. *Journal of Empirical Finance,* 19(5), 796-818.

De Long, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. The Journal of Finance, 45(2), 379-395.

Demir, I., Muthuswamy, J. and Walter, T. (2004). Momentum returns in Australian equities: The influences of size, risk, liquidity and return computation. *Pacific-Basin Finance Journal,* 12(2), 143.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics,* 7(2), 197-226.

Dissanaike, G. (1994). On the computation of returns in tests of the stock market overreaction hypothesis. *Journal of Banking & Finance,* 18(6), 1083-1094.

Dissanaike, G. (1997). Do stock market investors overreact? *Journal of Business Finance & Accounting,* 24(1), 27-50.

Durand, R. B., Limkirangkrai, M. and Smith, G. (2006). Momentum in Australia--A Note. *Australian Journal of Management (University of New South Wales),* 31(2), 355-364.

Edwards, W. (1968). Conservatism in human information processing. In Kleinmutz, B. (Ed.). *Formal Representation of Human Judgment*. New York: John Wiley and Sons, pp. 17-52.

Efron, B. and Tibshirani, R. (1994). *Introduction to the Bootstrap*. Washington, D.C.: Chapman & Hall.

Ellis, M. and Thomas, D. C. (2004). Momentum and the FTSE 350. *Journal of Asset Management,* 5(1), 25-36.

Ellis, P. D. (2012). *The Essential Guide to Effect Sizes: Statistical Power, Meta-Analysis, and the Interpretation of Research Results.* 1st ed. Cambridge: Cambridge University Press.

European Bank for Reconstruction and Development (EBRD) (2006). *Law in transition 2006*. London: European Bank for Reconstruction and Development.

European Commission (1997). Commission communication on certain legal aspects concerning intra-EU investment. *Official Journal C 220*, 19/07/1997 P. 0015-0018.

European Commission (2013). *The European Union explained: Internal market*. Luxembourg: Publications Office of the European Union.

Eurostat (2013a). *Taxation trends in the European Union. Data for the EU Members, Iceland and Norway*. Luxembourg: Publications Office of the European Union.

Eurostat (2013b). Gross domestic product at market prices. [Online]. Available at: http://epp.eurostat.ec.europa.eu/ [Accessed 02/10/2013].

Eurostat (2013c). *Real GDP growth rate.* [Online]. Available at: http://epp.eurostat.ec.europa.eu/ [Accessed 02/10/2013].

Evans, J. L. and Archer, S. H. (1968). Diversification and the reduction of dispersion: An empirical analysis. *Journal of Finance,* 23(5), 761-767.

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business,* 38(1), 34-105.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work*. *The Journal of Finance,* 25(2), 383-417.

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance,* 46(5), 1575-1617.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics,* 33(1), 3-56.

Fama, E. F. and French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance,* 50(1), 131-155.

Fama, E. F. and French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance,* 51(1), 55-84.

Fama, E. F. and MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *The Journal of Political Economy,* 81(3), 607-636.

Ferri, G., Liu, L. G. and Stiglitz, J. E. (1999). The procyclical role of rating agencies: Evidence from the East Asian crisis. *Economic Notes,* 28(3), 335-355.

Fidler, F., Geoff, C., Mark, B. and Neil, T. (2004). Statistical reform in medicine, psychology and ecology. *The Journal of Socio-Economics,* 33(5), 615-630.

Figelman, I. (2007). Stock return momentum and reversal. *The Journal of Portfolio Management,* 34(1), 51-67.

Fisher, L. and Lorie, J. H. (1970). Some studies of variability of returns on investments in common stocks. *The Journal of Business,* 43(2), 99-134.

Fitch Ratings (2012). *Definitions of Ratings and Other Forms of Opinion*. [Online]. Available at: www.fitchratings.com [Accessed 10/01/2012].

Foerster, S., Prihar, A. and Schmitz, J. (1995). Back to the future. *Canadian Investment Review,* 7(4), 9-13.

Forner, C. and Marhuenda, J. (2003). Contrarian and Momentum Strategies in the Spanish Stock Market. *European Financial Management,* 9(1), 67-88.

Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance*, 61(4), 2017-2046.

French, K.R. (2013). *Kenneth R. French.* [Online]. Available at: http://mba.tuck.dartmouth.edu/ [Accessed 02/10/2013].

French, K.R. and Poterba, J.M. (1991). Investor diversification and international equity markets. *American Economic Review*, 81: 222-226.

Fuertes, A.-M., Miffreb, J. and Tanc, W.-H. (2009). Momentum profits, nonnormality risks and the business cycle. *Applied Financial Economics,* 19(12), 935-953.

Fung, A. K.-W. (1999). Overreaction in the Hong Kong stock market. *Global Finance Journal,* 10(2), 223-230.

Galariotis, E. C. (2010). What should we know about momentum investing? The case of the Australian Security Exchange. *Pacific-Basin Finance Journal,* 18(4), 369-389.

Galariotis, E. C., Holmes, P. and Ma, X. S. (2007). Contrarian and momentum profitability revisited: Evidence from the London Stock Exchange 1964-2005. *Journal of Multinational Financial Management,* 17(5), 432-447.

Gaunt, C. (2000). Overreaction in the Australian equity market: 1974-1997. *Pacific-Basin Finance Journal,* 8(3-4), 375-398.

George, T. J. and Hwang, C.-Y. (2004). The 52-Week High and Momentum Investing. *The Journal of Finance,* 59(5), 2145-2176.

Glaser, M. and Weber, M. (2003). Momentum and turnover: Evidence from the German stock market. *Schmalenbach Business Review (SBR),* 55(2), 108-135.

Glass, G. V., McGaw, B. S. and Smith, M. L. (1981). *Meta-analysis in social research*. Beverly Hills: Sage Publications, Inc.

Goetzmann, W.N., Li, L. and Rouwenhorst, K.G. (2005). Long-term global market correlations. *Journal of Business*, 78(1): 1-38.

Goldsmith, R.W. (1971). Capital Markets and Economic Development. *National symposium on Development of Capital Markets*. September 1971. Rio de Janeiro, Brazil.

Gregory, A., Tharyan, R. and Christidis, A. (2013). Constructing and testing alternative versions of the Fama–French and Carhart models in the UK. *Journal of Business Finance & Accounting,* 40(1-2), 172-214.

Griffin, D. and Tversky, A. (1992). The weighing of evidence and the determinants of confidence. *Cognitive psychology,* 24(3), 411-435.

Griffin, J. M., Ji, X. and Martin, J. S. (2003). Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole. *The Journal of Finance,* 58(6), 2515-2547.

Grinblatt, M. and Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, 78(2), 311-339.

Grossman, S. J. and Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American economic review*, 393-408.

Grundy, B. and Martin, J. (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies,* 14(1), 29-78.

Gujarati, D. and Porter, D. (2009). *Basic Econometrics*. 5th ed. Boston: McGraw-Hill International Edition.

Gunaratne, P. S. M. and Yonesawa, Y. (1997). Return reversals in the Tokyo Stock Exchange: A test of stock market overreaction. *Japan and the World Economy,* 9(3), 363-384.

Gupta, R. and Jithendranathan, T. (2008). Time-Varying Correlations and Optimal Allocation in Emerging Market Equities for Australian Investors: A Study Using East European Depositary Receipts. *International Research Journal of Finance and Economics*, 18: 127-141.

Hall, P. (1985). Resampling a coverage pattern. *Stochastic Processes and their Applications,* 20(2), 231-246.

Hameed, A. and Kusnadi, Y. (2002). Momentum Strategies: Evidence from Pacific Basin Stock Markets. *Journal of Financial Research,* 25(3), 383-397.

Harvey, C.R. (1995). Predictable risk and return in emerging markets. *Review of Financial Studies*, 8(3): 773-816.

Hogan, S., Jarrow, R., Teo, M. and Warachka, M. (2004). Testing market efficiency using statistical arbitrage with applications to momentum and value strategies. *Journal of Financial Economics,* 73(3), 525-565.

Hon, M. T. and Tonks, I. (2003). Momentum in the UK stock market. *Journal of Multinational Financial Management,* 13(1), 43.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance,* 54(6), 2143-2184.

Hunter, J. E. (1997). Needed: A ban on the significance test. *Psychological Science,* 8(1), 3-7.

Hur, J., Pritamani, M. and Sharma, V. (2010). Momentum and the disposition effect: the role of individual investors. *Financial Management*, 39(3), 1155-1176.

Hurn, S. and Pavlov, V. (2003). Momentum in Australian Stock Returns. *Australian Journal of Management (University of New South Wales),* 28(2), 141-155.

Iihara, Y., Kato, H. K. and Tokunaga, T. (2004). The winner-loser effect in Japanese stock returns. *Japan and the World Economy,* 16(4), 471-485.

Ince, O. S. and Porter, R. B. (2006). Individual equity return data from Thomson Datastream: handle with care! *Journal of Financial Research,* 29(4), 463-479.

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *The Journal of Finance,* 45(3), 881-898.

Jegadeesh, N. (1992). Does market risk really explain the size effect? *Journal of Financial and Quantitative Analysis,* 27(3).

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance,* 48(1), 65-91.

Jegadeesh, N. and Titman, S. (1995). Overreaction, delayed reaction, and contrarian profits. *Review of Financial Studies,* 8(4), 973-993.

Jegadeesh, N. and Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *Journal of Finance,* 56(2), 699-720.

Jegadeesh, N. and Titman, S. (2002). Cross-Sectional and Time-Series Determinants of Momentum Returns. *Review of Financial Studies,* 15(1), 143-157.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of Financial Economics,* 6(2), 95-101.

Jensen, M. C. and Benington, G. A. (1970). Random walks and technical theories: Some additional evidence. *The Journal of Finance,* 25(2), 469-482.

Johnson, D. H. (1999). The insignificance of statistical significance testing. *The journal of wildlife management*, 763-772.

Johnson, T. C. (2002). Rational Momentum Effects. *Journal of Finance,* LVII(2), 585-608.

Kang, J., Liu, M.-H. and Ni, S. X. (2002). Contrarian and momentum strategies in the China stock market: 1993–2000. *Pacific-Basin Finance Journal,* 10(3), 243-265.

Karlsson, A. and Norden, L. (2007). Home sweet home: bias and international diversification among individual investors. *Journal of Banking and Finance*, 31: 317-333.

Karolyi, G. A. and Kho, B.-C. (2004). Momentum strategies: some bootstrap tests. *Journal of Empirical Finance,* 11(4), 509-536.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics,* 12(1), 13-32.

Kim, C.-J. and Nelson, C. R. (1999). Has the US economy become more stable? A Bayesian approach based on a Markov-switching model of the business cycle. *Review of Economics and Statistics,* 81(4), 608-616.

Kirk, R. E. (1996). Practical significance: A concept whose time has come. *Educational and Psychological Measurement,* 56(5), 746-759.

Korajczyk, R. A. and Sadka, R. (2004). Are Momentum Profits Robust to Trading Costs? *Journal of Finance,* 59(3), 1039-1082.

Kothari, S. P., Shanken, J. and Sloan, R. G. (1995). Another Look at the Cross-Section of Expected Stock Returns. *Journal of Finance,* 50(1), 185-224.

Kunsch, H. R. (1989). The jackknife and the bootstrap for general stationary observations. *The Annals of Statistics,* 17(3), 1217-1241.

LeBlanc, D. C. (2004). *Statistics: Concepts and Applications for Science*. London: Jones and Bartlett Publishers, Inc.

Lee, C. M. C. and Swaminthan, B. (2000). Price Momentum and Trading Volume. *Journal of Finance,* 55(5), 2017-2069.

Lehmann, B. N. (1990). Fads, martingales and market efficiency. *Quarterly Journal of Economics,* 105(1), 1-28.

Lesmond, D. A., Schill, M. J. and Zhou, C. (2004). The illusory nature of momentum profits. *Journal of Financial Economics,* 71(2), 349-380.

Levy, R. (1967). Relative strength as a criterion for investment selection. *Journal of Finance,* 22(4), 595-610.

Lewellen, J. (2002). Momentum and Autocorrelation in Stock Returns. *Review of Financial Studies,* 15(2), 533-563.

Li, B., Qiu, J. and Wu, Y. (2010). Momentum and seasonality in Chinese stock markets. *Journal of Money, Investment and Banking,* 17, 24-36.

Li, X., Brooks, C. and Miffre, J. (2009). Low-cost momentum strategies. *Journal of Asset Management,* 9(6), 366-379.

Li, X., Miffre, J., Brooks, C. and O'Sullivan, N. (2008). Momentum profits and time-varying unsystematic risk. *Journal of Banking & Finance,* 32(4), 541-558.

Liu, L. X. and Zhang, L. (2008). Momentum Profits, Factor Pricing, and Macroeconomic Risk. *The Review of Financial Studies,* 21(6), 2418-2448.

Lo, A. W. and MacKinlay, A. C. (1990). When Are Contrarian Profits Due to Stock Market Overreaction? *Review of Financial Studies,* 3(2), 175-205.

Lo, A. W. and Wang, J. (2009). *Stock Market Trading Volume*. The handbook of financial econometrics. New York: North-Holland.

London Stock Exchange (2013). *All Companies on the London Stock Exchange*. [Online]. Available at: www.londonstockexchange.com [Accessed 28/02/2013].

Loughran, T. and Ritter, J. R. (1996). Long-Term Market Overreaction: The Effect of Low-Priced Stocks. *Journal of Finance,* 51(5), 1959-1970.

Malkiel, B. G. and Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work*. *The Journal of Finance,* 25(2), 383-417.

Markowitz, H.M. (1952). Portfolio selection*. *Journal of Finance*, 7(1), 77-91.

Markowitz, H.M. (1959). *Portfolio selection: Efficient Diversification of Investments*. New York: Wiley.

Mason, R.T. (1972). The creation of risk aversion by imperfect Markets. *American Economic Review*, 62: 77-86.

Mazouz, K. and Xiafei, L. (2007). The overreaction hypothesis in the UK market: empirical analysis. *Applied Financial Economics,* 17(13), 1101-1111.

McConnell, M. M. and Perez-Quiros, G. (2000). Output fluctuations in the United States: What has changed since the early 1980's? *The American Economic Review,* 90(5), 1464-1476.

Meric, G., Ratner, M., Lentz, C. and Meric, I. (2006). Global portfolio diversification implications of the co-movements of Latin American stock markets with the world's other stock markets. *Journal of Emerging Markets*, 11(3), 32-39.

Meric, I., Ratner, M. and Meric, G. (2005). The co-movements of the world's sector index returns. *International Journal of Finance*, 17(1), 3376-3391.

Meric, I., Ratner, M. and Meric, G. (2008). The co-movements of sector index returns in the world's major stock markets during bull and bear markets: Portfolio diversification implications. *International Review of Financial Analysis*, 17(1), 156-177.

Mobarek, A. and Keasey, K. (2000). Weak-form market efficiency of an emerging Market: Evidence from Dhaka Stock Market of Bangladesh. *ENBS Conference*. May 2000. Oslo, Norway.

Moody's Investor Service (2012). *Rating Symbols and Definitions*. [Online]. Available at: www.moodys.com [Accessed 10/01/2012].

Moody's Investors Service (1995). *Sovereign Supranationals Credit Opinions*. London: IFR Publishing.

Moore, D., Notz, W. I. and Fligner, M. A. (2011). *The Basic Practice of Statistics*. 6th ed. New York: W. H. Freeman.

Moser, B. K. and Stevens, G. R. (1992). Homogeneity of Variance in the Two-Sample Means Test. *The American Statistician,* 46(1), 19-21.

Moskowitz, T. J. and Grinblatt, M. (1999). Do Industries Explain Momentum? *The Journal of Finance,* 54(4), 1249-1290.

Muga, L. and Santamaria, R. (2007a). The Momentum Effect in Latin American Emerging Markets. *Emerging Markets Finance & Trade,* 43(4), 24-45.

Muga, L. and Santamaria, R. (2007b). The stock market crisis and momentum. Some evidence for the Spanish stock market during the 1990s. *Applied Financial Economics,* 17(6), 469-486.

Muga, L. and Santamaría, R. (2009). Momentum, market states and investor behavior. *Empirical Economics,* 37(1), 105-130.

Mun, J. C., Kish, R. J. and Vasconcellos, G. M. (2001). The contrarian investment strategy: additional evidence. *Applied Financial Economics,* 11(6), 619-640.

Mun, J. C., Vasconcellos, G. M. and Kish, R. (1999). Tests of the Contrarian Investment Strategy Evidence from the French and German stock markets. *International Review of Financial Analysis,* 8(3), 215-234.

Mun, J. C., Vasconcellos, G. M. and Kish, R. (2000). The Contrarian/Overreaction Hypothesis: An analysis of the US and Canadian stock markets. *Global Finance Journal,* 11(1-2), 53-72.

National Bureau of Economic Research (2013). *US Business Cycle Expansions and Contractions*. [Online]. Available at: http://www.nber.org/ [Accessed 02/10/2013].

Naughton, T., Truong, C. and Veeraraghavan, M. (2008). Momentum strategies and stock returns: Chinese evidence. *Pacific-Basin Finance Journal,* 16(4), 476-492.

Newey, W. and Kenneth, D. A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica,* 55(3), 703.

Nijman, T., Swinkels, L. and Verbeek, M. (2004). Do countries or industries explain momentum in Europe? *Journal of Empirical Finance,* 11(4), 461-481.

O'Donnell, D. J. and Baur, D. G. (2009). Momentum in the Irish stock market. *Applied Economics Letters,* 16(11), 1133-1138.

Odean, T. (1998). Are Investors Reluctant to Realize Their Losses? *The Journal of Finance,* 53(5), 1775-1798.

Officer, R. R. (1972). The distribution of stock returns. *Journal of the american statistical association,* 67(340), 807-812.

Olejnik, S. and Algina, J. (2000). Measures of effect size for comparative studies: Applications, interpretations, and limitations. *Contemporary Educational Psychology,* 25(3), 241-286.

Onayev, Z. and Savickas, R. (2004). The Effect of Ex Ante Price on Momentum Profits. *The Journal of Behavioral Finance,* 5(1), 8-22.

Pan, L., Tang, Y. and Xu, J. (2013). Weekly momentum by return interval ranking. *Pacific-Basin Finance Journal,* 21(1), 1191-1208.

Parmler, J. and González, A. (2007). Is Momentum Due to Data-snooping? *European Journal of Finance,* 13(4), 301-318.

Pendery, D. (2009). Three Top Economists Agree 2009 Worst Financial Crisis Since Great Depression; Risks Increase if Right Steps are Not Taken. *Business Wire*.

Pollin, R. and Heintz, J. (2011). *Transaction Costs, Trading Elasticities and the Revenue Potential of Financial Transaction Taxes for the United States*. University of Massachusetts, Amherst: Political Economy Research Institute.

Power, D. M., Lonie, A. and Lonie, R. (1991). The over-reaction effect—some UK evidence. *The British Accounting Review,* 23(2), 149-170.

PricewaterhouseCoopers (PwC) (2012). *Worldwide Tax Summaries*. London: PwC.

Rao, P. and Griliches, Z. (1969). Small-sample properties of several two-stage regression methods in the context of auto-correlated errors. *Journal of the American Statistical Association,* 64(325), 253-272.

Reinganum, M. R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics,* 9(1), 19-46.

Reinhart, C. M. and Rogoff, K. S. (2011). The Forgotten History of Domestic Debt*. *The Economic Journal,* 121(552), 319-350.

Reisen, H. and Von Maltzan, J. (1999). Boom and bust and sovereign ratings. *International Finance,* 2(2), 273-293.

Richardson, M. and Smith, T. (1993). A test for multivariate normality in stock returns. *Journal of Business*, 295-321.

Rosenberg, B. and Houglet, M. (1974). Error rates in CRSP and Compustat data bases and their implications. *The Journal of Finance,* 29(4), 1303-1310.

Rouwenhorst, K. G. (1998). International Momentum Strategies. *Journal of Finance,* 53(1), 267-284.

Rouwenhorst, K. G. (1999). Local Return Factors and Turnover in Emerging Stock Markets. *The Journal of Finance,* 54(4), 1439-1464.

Ruxton, G. D. (2006). The unequal variance t-test is an underused alternative to Student's t-test and the Mann–Whitney U test. *Behavioral Ecology,* 17(4), 688-690.

Ryan, P. and Curtin, R. (2006). Profitability of Price Momentum Strategies Surprising Evidence from Pacific-Basin Countries. *The Journal of Investing,* 15(4), 38-45.

Ryan, P. and Overmeyer, I. (2003). The Profitability of Momentum Strategies Based on the Release of Firms' Quarterly Results: Evidence from the Constituents of the DAX 30. *Irish Journal of Management,* 24(2), 68-78.

Ryan, P. and Overmeyer, I. (2004). Profitability of Price Momentum Strategies. *Journal of Investing,* 13(2), 55-62.

S&P Dow Jones Indexes (2011). *Dow Jones Indexes Country Classification System*. [Online]. Available at: http://www.djindexes.com/ [Accessed 01/03/2013].

Sadka, R. (2003). Momentum, Liquidity Risk, and Limits to Arbitrage. *NATIONAL Bureau of Economic Research,* 2(1), 1-59.

Samuelson, P. A. (1964). Theoretical notes on trade problems. *The Review of Economics and Statistics,* 46(2), 145-154.

Samuelson, P. A. (1994). Facets of Balassa-Samuelson Thirty Years Later*. *Review of International Economics,* 2(3), 201-226.

Satterthwaite, F. (1946). An Approximate Distribution of Estimates of Variance Components. *Biometrics,* 2(6), 110-114.

Schatzberg, J. D. and Reiber, R. R. (1992). Extreme Negative Information and the Market Adjustment Process: The Case of Corporate Bankruptcy. *Quarterly Journal of Business and Economics,* 31(2), 3-21.

Schiereck, D., De Bondt, W. and Weber, M. (1999). Contrarian and Momentum Strategies in Germany. *Financial Analysts Journal,* 55(6), 104.

Schmidt, F. L. (1992). What do data really mean? Research findings, meta-analysis, and cumulative knowledge in psychology. *American psychologist,* 47(10), 1173.

Schröder, M. (2000). *The New Capital Markets in Central and Eastern Europe. Final Report*. Mannheim, Germany: Centre for European Economic Research.

Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance,* 1, 939-974.

Scowcroft, A. and Sefton, J. (2005). Understanding Momentum. *Financial Analysts Journal,* 61(2), 64-82.

Sehgal, S. and Balakrishnan, I. (2002). Contrarian and Momentum Strategies in the Indian Capital Market. *Vikalpa,* 27(1), 13-19.

Sehgal, S. and Balakrishnan, I. (2004). Momentum Profits, Portfolio Characteristics and Asset Pricing Models. *Decision,* 31(2), 49-77.

Sercu, P., Vandebroek, M. and Vinaimont, T. (2008). Thin-Trading Effects in Beta: Bias v. Estimation Error. *Journal of Business Finance & Accounting,* 35(9-10), 1196-1219.

Shambaugh, J. C., Reis, R. and Rey, H. (2012). The Euro's Three Crises [with Comments and Discussion]. *Brookings Papers on Economic Activity,* 2012(1), 157-231.

Shefrin, H. and Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *Journal of Finance,* 40(3), 777-790.

Shleifer, A. and Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance,* 52(1), 35-55.

Shumway, T. (1997). The Delisting Bias in CRSP Data. *The Journal of Finance,* 52(1), 327-340.

Siganos, A. (2007). Momentum returns and size of winner and loser portfolios. *Applied Financial Economics,* 17(9), 701-708.

Siganos, A. and Chelley-Steeley, P. (2006). Momentum profits following bull and bear markets. *Journal of Asset Management,* 6(5), 381-388.

Solnik, B. H. (1974). Why not diversify internationally rather than domestically? *Financial Analysts Journal*, 48-54.

Stafford, P. (2012). Plus Markets to close after sale failure. *The Financial Times,* May.

Standard and Poor's (2012). *Standard & Poor's Ratings Definitions*. [Online]. Available at: https://www.globalcreditportal.com/ [Accessed 10/01/2012].

Standard and Poor's (1994). Sovereign Rating Criteria. *Emerging Markets,* October, 124-127.

Statman, M. (1987). How many stocks make a diversified portfolio? *Journal of Financial and Quantitative Analysis*, 353-363.

Stock, J. H. and Watson, M. W. (2003). Has the business cycle changed and why? In: *NBER Macroeconomics Annual 2002*. Vol. 17. MIT press, pp. 159-230.

Surmacz, W. (2013). Na początku była gildia. *Forbes*, May.

Swinkels, L. (2002). International Industry Momentum. *Journal of Asset Management,* 3(2), 124-141.

Tax Foundation (2012a). *U.S. Federal Individual Income Tax Rates History, 1862-2013*. [Online]. Available at: http://taxfoundation.org/ [Accessed 10/01/2012].

Tax Foundation (2012b). *State Individual Income Tax Rates, 2000-2013*. [Online]. Available at: http://taxfoundation.org/ [Accessed 10/01/2012].

Taylor, B. (1969). Investment: Art, Science or what? *Lloyds bank*, 91: 10-21.

The NASDAQ OMX Group (2012). *NASDAQ OMX Corporate Timeline*. [Online]. Available at: http://www.nasdaqomx.com/ [Accessed 10/02/2012].

Thompson, B. (2004). The “significance” crisis in psychology and education. *The Journal of Socio-Economics,* 33(5), 607-613.

Thomson Reuters (2011). *Fact Book 2011*. New York: Thomson Reuters.

Thomson Reuters (2013). *Risk free interest rates*. [Online]. Available at: http://extranet.datastream.com/ [Accessed 15/05/2013].

Tomz, M. (2007). *Reputation and International Cooperation, Sovereign Debt Across Three Centuries*. Princeton: Princeton University Press.

Trading Economics (2012). *Credit ratings*. [Online]. Available at: http://www.tradingeconomics.com/ [Accessed 10/01/2012].

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science,* 185(4157), 1124-1131.

US Securities and Exchange Commission (2013). *Penny Stock Rules*. [Online]. Available at: http://www.sec.gov/ [Accessed 15/05/2013].

Van Dijk, M. A. (2011). Is size dead? A review of the size effect in equity returns. *Journal of Banking & Finance,* 35(12), 3263-3274.

Van Dijk, R. and Huibers, F. (2002). European Price Momentum and Analyst Behavior. *Financial Analysts Journal,* 58(2), 96.

Vermaelen, T. and Verstringe, M. (1986). Do Belgians Overreact? *Working Paper (Catholic University of Louvain, Belgium)*.

Wai, U.T. and Patrick, H.T. (1973). Stock and Bond issues and Capital Markets in Less Developed Countries. *International Monetary Fund Staff Papers*, 20(2): 253-305.

Wallace, T. D. and Silver, J. L. (1988). *Econometrics: an introduction*. Reading, Massachusetts: Addison-Wesley.

Wang, C. (2004). Relative strength strategies in China's stock market: 1994–2000. *Pacific-Basin Finance Journal,* 12(2), 159-177.

Wang, C. and Chin, S. (2004). Profitability of return and volume-based investment strategies in China's stock market. *Pacific-Basin Finance Journal,* 12(5), 541-564.

Wang, J., Burton, B. M. and Power, D. M. (2004). Analysis of the overreaction effect in the Chinese stock market. *Applied Economics Letters,* 11(7), 437-442.

Wang, J. and Wu, Y. (2011). Risk adjustment and momentum sources. *Journal of Banking & Finance,* 35(6), 1427-1435.

Warsaw Stock Exchange (2012). *History*. [Online]. Available at: http://www.gpw.pl/ [Accessed 10/01/2012].

Weimin, L., Strong, N. and Xinzhong, X. (1999). The Profitability of Momentum Investing. *Journal of Business Finance & Accounting,* 26(9/10), 1043-1091.

Wilkinson, L. (1999). Statistical methods in psychology journals: guidelines and explanations. *American psychologist,* 54(8), 594.

Wu, Y. (2011). Momentum trading, mean reversal and overreaction in Chinese stock market. *Review of Quantitative Finance and Accounting,* 37(3), 301-323.

Xiang, J., He, J. and Cao, M. (2002). Continuous overreaction, insiders trading activities and momentum strategies. *Journal of Multinational Financial Management,* 12(4–5), 429-449.

Xfi Centre (2013). *Fama-French and Momentum Factors, Portfolios and other Benchmark Portfolio Data.* [Online]. Available at: http://business-school.exeter.ac.uk/research/areas/centres/xfi/ [Accessed 02/10/2013].

Yao, Y. (2012). Momentum, contrarian, and the January seasonality. *Journal of Banking & Finance,* 36(10), 2757-2769.

Zarowin, P. (1989). Short-Run Market Overreaction: Size and Seasonality Effects. *Journal of Portfolio Management,* 15(3), 26-29.

Zarowin, P. (1990). Size, Seasonality, and Stock Market Overreaction. *Journal of Financial & Quantitative Analysis,* 25(1), 113-125.

Zhou, H., Geppert, J. and Kong, D. (2010). An Anatomy of Trading Strategies: Evidence from China. *Emerging Markets Finance and Trade,* 46(2), 66-79.

Zhou, Z.-G. (2010). The high-volume return premium: evidence from the Chinese stock market. *Review of Quantitative Finance and Accounting,* 35(3), 295-313.