Attributing the returns of different hedge fund strategies under changing market conditions

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Abstract

The purpose of this thesis is to contribute to theoretical knowledge and help investors, fund administrators, financial regulators and database vendors. Its chapters examine hedge fund performance attribution and fund persistence under changing market conditions, and issues of hedge fund index engineering, using a rigorously constructed unified database (U.S. dataset, from 1990 to 2014).

The core of my modelling approach is a custom piece-wise parsimonious multifactor model with predefined and non-defined structural breaks, flexible enough to capture differences in asset and portfolio allocations. This is implemented on a strategy, fundamental, and a mixed level. Concerning funds' persistence, I use several parametric and non-parametric techniques whereas I develop a framework with mixed trading strategies for investors' conditional high returns. I examine the classification problem of hedge funds by implementing several classification techniques used by database vendors, on the same dataset.

The findings are robust, showing that during stressful market conditions most hedge fund strategies do not provide significant alphas to investors as fund managers are more concerned about minimizing their systematic risk and there is a switch from equity to commodity asset classes. Directional strategies have more common exposures than non-directional strategies under all market conditions. Falling stock markets are harsher than recessions for hedge funds. Moreover, during stressful conditions, small funds suffer more than large funds, young funds outperform old ones and funds that do not impose restrictions (and survive) outperform funds with no lockups. There are cases where funds can deliver significant negative alpha to investors conditional on stressful market conditions. In general, stressful market conditions have a negative impact on all types of funds' persistence whereas my zero investment "synthetic" trading strategy can bring conditional high returns to investors. Furthermore, I found that the differences between index vendors are mainly due to the use of different selection criteria and different datasets.

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Declaration of Authorship

This thesis is the result of the research that I have produced as a PhD student at the University of York, The York Management School, from 2012 to 2016. I declare that I am the sole author of this work having developed the original ideas, prepared the data, carried out the empirical analysis, written the thesis, and the paper drafts. The appropriate credit has been given where reference has been made to the work of others.

Parts of earlier versions of chapters two, three, four, five and six have been published at the Social Science Research Network as papers and most of them are under review at journals. A version of the Part 2 of the chapter two has been published in the International Review of Financial Analysis. In addition most parts of this research have been presented in the University of York, CEGBI/CSWL (Centre for Evolution and Global Business and Institutions – Centre for the Study of Working Lives) conferences (06/2013, 07/2014, 07/2015), to the White Rose Doctoral conferences (08/2013, 07/2014, 07/2016), to BAFA (British Accounting and Finance) conferences (04/2014, 09/2015) and to the 3rd Young Finance Scholar's Conference by the University of Sussex (06/2016).

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1 Chapter: Introduction

This chapter begins with an introduction about the nature of the hedge fund and its difference from other traditional investments, and the current state of the hedge fund industry. Then it deals with the background of the problems that the hedge fund literature is associated with and are examined in this PhD thesis. It proceeds by identifying the gaps, why these are important and the motivation behind this study. Then it clearly states the research objectives and the research questions that this thesis deals with. In the research design and theoretical framework section, it briefly informs the reader about the methodologies and techniques used in order to deal with the research questions. Afterwards, it informs the reader about this PhD thesis structure and closes with a short conclusion.

1.1 Introduction

1.1.1 The nature of hedge funds

The term hedge fund means a usually aggressive portfolio of investments that can engage in a broader range of trading and investments activities than other conventional funds. It uses state-of the art investment strategies in markets using leverage, derivatives, short and/or long positions internationally and domestically with a target to generate high returns. This may be absolute returns or returns above a certain market benchmark. In legal terms, hedge funds are usually constructed as private investment partnerships that are available to a limited number of investors requiring a very large initial minimum investment. The investors are typically high wealth individuals, and institutions such as pension funds, life insurance companies, university endowments and foundations. Today, most hedge funds usually have four different groups of service providers (in-house or usually firms). These are a lawyer, a prime broker, an audit accounting firm, and very often an administrator.

Hedge funds have a private nature and all the other characteristics derive from it (Lhabitant, 2004). As the general public has no access to this pool, regulators regard this pool as not a traditional investment vehicle such as mutual funds, portfolio stocks, bonds or cash, so there is no need to regulate them nor any need for disclosure. Hedge fund managers are not obliged to disclose their underlying investment practices and there is no obligation to conform to the requirements of registered investment companies. Moreover, the manager may pursue a wide range of financial instruments and any type of investment strategy even if this include short selling, derivatives, leverage, real-estate, non-listed or illiquid securities. Low liquid placements mean that the financial products are difficult to liquidate or sell in a reasonable time interval with available pricing.

1.1.2 Differences with traditional investments

Hedge funds differ from traditional investment vehicles such mutual funds in terms, first, of transparency as they are not bound by regulation by the U.S. Securities and Exchange Commission (SEC) and they also are not bound by limitations concerning permitted instruments and portfolio make-up. Secondly, hedge funds, contrary to mutual funds, are flexible to design and implement every financial instrument or strategy that is appropriate to achieve their goals (usually high absolute returns). Third, there is a difference in the customer target group. As it is already mentioned, hedge funds are for accredited only investors, contrary to mutual funds that are for the general public and being advertised. Fourth, is the compensation structure; whereas hedge funds' total fees consist of a management fee plus an incentive fee, in mutual funds there is a management fee only equal to a fixed percentage of assets. In the hedge fund industry the typical management fee is between 1% and 2% whereas the incentive fee is around twenty percent on returns. Fifth, hedge funds typically have a higher attrition rate than mutual funds as presented by many studies (e.g. Baba and Goko, 2009; Xu, Liu, and Loviscek, 2011, Getmansky, 2012). Sixth, due to volunteer reporting and the lack of transparency there are different kind of biases such as survivorship, backfill, sample selection from database vendors, that have been examined by many authors (e.g. Fung and Hsieh, 1997, Liang, 2001) hence the researcher should handle them properly by minimizing them.

1.1.3 The current state of the industry

Despite the fact that hedge funds gained mainstream popularity from the mid '90s and onwards, they have been in existence for almost 70 years. A hedge fund was developed and first used in 1949 by Alfred Winslow Jones. He is credited with initiating the first hedge fund partnership. As of the third quarter 2015 hedge funds count for more than $2.7 trillion ($2.9 according to the HFR) not including $0.5 trillion for funds of funds and $334 billion for CTAs (commodity trading advisors). The number of hedge funds is currently more than 10,000 globally and almost 70% are U.S. funds. During the early 2000 there was a substantial growth in the industry, reaching its peak before the financial crisis in 2008. However, after the 2008-2009 losses, the significant growth in assets continued. Concerning returns, from late 1999 to 2015(Q3) the average investor could have earned between 3.1 and 4.4 times her initial capital (please see chapter 2 for a detail discussion).

As of the first half of 2016, important issues are the hedge fund performance as hedge fund managers try to dig themselves out from problems resulting from the devaluation in China, the global regulatory environment that fund managers are expecting to confront, and achieving size and scale as it seems that firms need to offer multiple products to investors in order to grow. Opportunities for growth and innovation could be pension plans and direct lending to business as banks have pulled back on the lending in the wake of the financial crisis. Disruptions for the hedge fund industry could be the various geopolitical issues, the merging of hedge funds resulting in fewer but larger players in the hedge fund industry, the cost and transparency pressures, the governance and stress-testing or risk management issues (Deloitte U.S., Hedge Fund Trends, 2016).

After a brief discussion about hedge funds, this introductory chapter deals with the background of the problems that the hedge fund literature is associated with and are examined in this PhD thesis. I proceed by identifying the gaps, why these are important and my motivation behind this study. Then I clearly state my research objectives and research questions that I deal in this thesis. In the research design and theoretical framework section, I briefly inform the reader about the methodologies and techniques that I used in order to deal with my research questions. Afterwards, I inform the reader about this PhD thesis structure.

1.2 Background of the problem

1.2.1 The return generating process

One aspect of hedge funds that the literature deals with is the return generating process of hedge funds. Early studies (such as Sharpe, 1992) tried to explain hedge funds in a linear framework. However, these studies are more appropriate for long only funds giving more weight to the asset categories or where the fund manager trades. They provided a static representation of hedge fund performance attribution. Afterwards, there was a development toward non-linear models that tried to explain hedge funds' performance as option portfolios (e.g. Fung and Hsieh, 2004; Agarwal and Naik, 2004). There are also studies that showed that the so called market neutral strategies are not really neutral for investors (Duarte, Longstaff, and Yu, 2007). Although these studies following the down-up approach are important, nevertheless they do not capture the dynamic nature of the exposures that change over time. There are other studies that follow the up-down approach such as Bali, Brown and Caglayan (2011, 2014), Avramov, Barras, and Kosowski (2013), Racicot and Theoret (2016) or Namvar, Phillips, Pukthuanthong, and Rau (2016) that tried to explain hedge fund performance attribution through time. There is also another group of studies following the up-down approach that addressed different methodological issues and tried to identify structural breaks in hedge fund returns. These studies confirmed earlier studies that hedge funds have nonlinear returns and exposures and these are changing over time (for more details about the up-down, down-up, and alternative approaches, please see chapter 2).

All the previous studies are important for performance attribution, however, there are important issues that constitute problems for the investors and have not examined accordingly. First, regarding the macroeconomic environment, the current knowledge is fragmented (focusing on only one crisis or economic event) hence cannot be generalized (e.g. the behaviour for stressful conditions). Second, there is no direct link between market conditions and fund performance as some studies (e.g. Bollen and Whaley, 2009; Jawadi and Khanniche, 2012) focus on the internal change of funds' exposures, and the macro variables used by other authors (e.g. Avramov et.al., 2013 or Bali et.al., 2014) or the macro uncertainly represented by specific variables (e.g. Racicot, and Theoret, 2016) do not necessarily represent the different states of the economy (there is a specific definition by the NBER and ECRI about business cycles – please see chapter 3). Thus, investors still have not get a clear picture concerning hedge fund behaviour in relation to market conditions. Third, the *market condition* is presented in the current literature in different ways (e.g. uncertainly, down market regimes, financial crisis) and there is no distinction and comparison between them. Fourth, the single models used corresponding to all hedge fund strategies or market conditions are over-simplistic and do not efficiently capture the exposures and the excess returns delivered to investors. Fifth, many models containing commodities contain one general commodity factor that insufficiently captures individual commodities as they have different behaviour over time.

1.2.2 Cross-Sectional differences

Concerning hedge fund performance and fund specific characteristics (fundamental level), despite the contradictory results, the majority of the studies (e.g. Schneeweis, Kazemi, and Martin, 2002; Hedges, 2003; Harri and Brorsen, 2004; Ammann and Moerth, 2005; Meredith, 2007; Joenvaara, Kosowski, and Tolonen, 2012) found that there is a negative relationship between fund performance and size. There are also studies (e.g. e.g. Howell, 2001; Amenc and Maertellini, 2003; Meredith, 2007; Frumkin and Vandegrift, 2009) showing that there is a negative relationship between age and fund performance. Concerning the lockup periods studies showed that there is a positive relationship with hedge fund performance (Aragon, 2007; Joenavaara, Kosowski, and Tolonen, 2012). All the previous studies are important for understanding hedge fund behaviour; however, investors are still confused with hedge fund complexity as these associations are investigated on fundamental-only or strategy-only levels, without also examining the relationship between them and the conditional changes over time. There is no a holistic approach between performance, and elements such as fundamental factors, strategies, and market conditions. Also, the issues mentioned in the previous paragraph (e.g. focusing on one only crisis or economic event, over-simplistic models for all hedge funds or under all changing conditions) are still valid, when examining hedge fund at the fundamental or mixed level.

1.2.3 Performance persistence

A large part of the hedge fund literature examines hedge fund performance persistence and there is strong evidence that there is at least short term performance persistence (e.g. Agarwal and Naik, 2000a; Harri, and Brosen, 2004; Eling, 2009; Joenvaara, Kosowiski, and Tolonen, 2012; Hentati-Kaffel and Peretti, 2015). Nevertheless, there are studies (e.g. Jagannathan, Malakhov, and Novikov, 2010; Ammann, Huber, and Schumid, 2013) that challenge the above studies showing that there is long term persistence which can be over a year. All the previous studies are valuable however there are two issues that cause problems for investors and constitute a gap in the literature. First, there is a lack of clear definition and distinction between different kinds of persistence. Most studies deal with the fund persistence within its group such as whether top (bottom) performer funds continue to be top (bottom) performers. However, there are other aspects of persistence such as the smoothness (how constant are raw or risk-adjusted returns), and the persistence of out or over performance against a specific benchmark that need to be addressed. Second, previous studies do not consider persistence with regard to different market conditions thus investors are ignorant about this matter. In addition, there is no study helping investors how to deal with these persistence issues so as to gain higher returns.

1.2.4 Classification issues

Another issue is that in the hedge fund industry there is no a universal classification scheme for hedge fund strategies. Most authors have used predefined classification schemes from the database vendors as "consumers". Also, some authors grouped hedge funds into broader styles or categories. The issue is that, none of those who used the predefined classification schemes focused on the vendors' classification process. There is little or no examination in the extant literature of the issues arising from the various vendors' different hedge fund classification processes, and more specific the examination of the quantitative techniques used by these vendors. Hence, in the literature there is a significant gap regarding hedge fund index construction methods and how this can have an impact on hedge funds' performance evaluation. On the other hand, investors struggle to find the appropriate benchmarks to assess their portfolios, and little is known about the differences in indices that they use. It is not clear whether the differences in hedge fund indices are due to the different datasets that private database vendor's use or due to their different classification techniques.

1.3 Motivation and significance

1.3.1 Motivation

Based on the above background of the problems, my motivation for this PhD thesis is to contribute to the existed theoretical knowledge by covering the gaps and assisting investors in their investment decision process. I apply a holistic approach focusing on the "big" picture so as to generalize having results that can help investors in a practical way. My motivation also is to help fund administrators by applying more flexible fee policies in fund managers' performance. Another motivation is to have a research with impact on financial regulator policies and on database vendors regarding index benchmarking practices. Last but not least, there is a big problem with the data in the hedge fund industry and I noticed that in the literature there is no integrated guidance about data assurance quality. Therefore, I followed a strict and transparent approach in data management (e.g. database merging and cleaning processes) that can be considered as a benchmark and can be followed by other authors, as well.

1.3.2 Significance of the study

Overall, this study is significant because it covers gaps in the literature that are important for researchers and investors. I justify this by discussing the significance of my study for each chapter separately, so as to crystallize it to the reader in a better way.

Before this study, there were specific gaps in the literature having to do with the lack of generalization, the absence of a direct link between market conditions and fund performance, the absence of a distinction and comparison between different “kinds” of market conditions, the use of one only commodity factor, and the over-simplistic models (all these analyzed in the previous section). All these issues that I take into consideration in this PhD thesis, created confusion for investors thus not having a clear and big picture about the behaviour of hedge funds. There was no study following a holistic approach that confronted the above issues so as to be a guide to investors or researchers when examining hedge funds. The first empirical chapter in this study is important as it helps resolve these issues that investors struggle with.

The second empirical chapter deals with fund performance at the fundamental (fund characteristics) and mixed level (strategies and fund characteristics together). Thus, beyond dealing with the above issues described before (e.g. generalization, absence of a direct link between market conditions and performance etc.) it also covers other important gaps regarding the cross-sectional differences in hedge funds (for that reason I use an extra dataset covering assets under management, and redemption restrictions forming several portfolios of funds with different strategies and fund specific characteristics). More specific, before this study the existing studies examined hedge fund performance at a strategy only or at the fundamental only level. There was no study examining funds at a mixed or fundamental only level under changing market conditions. All these issues that I take into consideration in this study, created ignorance to investors not having a deep knowledge of funds’ performance taking into consideration all these interactions. The investor was not conscious of hidden dangers e.g. paying a fee for a negative alpha for specific funds conditional on stressful market conditions as he/she was taking for granted that hedge funds always provide superior returns to investors. In other words, there was an illusion or myth about hedge fund performance.

The third empirical chapter deals with hedge fund persistence. The persistence was another issue that was problematic for investors as till now there was not a clear definition and distinction between different kinds of persistence. This is essential as most investors in their capital allocation process rely on past performance. However, which kind of persistence? There was an obscure issue. Moreover, there was no examination of persistence during changing market conditions as this is dynamic (as I found and describe in the third empirical chapter). Hence, investors one more time were in the darkness. In order to resolve these issues I used several parametric and non-parametric tests. Another important thing that was missing and it is addressed in this PhD thesis is the investigation of how investors can exploit the persistence and form trading strategies for higher returns. Hence, having that into consideration I created a framework for mixed trading strategies that investors can use for conditional high returns.

Another significance of this study is the examination in the final empirical chapter of the classification issues of hedge funds as, unfortunately, there is not a universal classification scheme for hedge fund strategies. In this thesis I use the strategies disclosure by fund managers, however there are studies that simply use hedge fund indices that depends on vendors' index construction techniques without any further investigation of potential side effects. It was a surprise to me that there has been not statistical work dealing with the different classification methods of hedge funds in a practical way. Until now, investors and most of the authors used the existing classification of hedge funds by the database vendors as it is (just as "consumers"), without investigating why different database vendor indices are different even when they represent the same hedge fund strategy. Identifying and using the appropriate benchmark indices is a difficult task and can have a significant impact on the asset or portfolio allocation process of the investors. This study deals with these important issues and shed light on the index construction methodologies and in particular on the classification processes.

1.4 Objectives – research questions

This doctoral thesis has as a prime purpose to understand and explain the attribution of returns of different hedge fund strategies under changing market conditions, using the longest period to date, from 1990 to 2014[1]. In other words, to examine the return generating process of the hedge fund strategies under changing market conditions. The first objective is to examine what the impact is of multiple business cycles and different market conditions on hedge fund strategies under a holistic approach, focusing on the North America region due to the use of three full U.S. business cycles. Beyond this, the North American hedge fund industry represents more than $1.9 trillion of assets under management corresponding to almost 72% of worldwide total (Preqin Global Hedge Fund Report, 2014). I use the terms *multiple business cycles* and *market conditions* so as to examine hedge fund behavior in a more comprehensive way and not just isolating one or two economic periods or financial crisis events. I make the distinction between *business cycles* and different *market conditions* so as to shed light on the difference between them in hedge fund strategies, assisting investors in their decision process. By using a *piece-wise parsimonious* model (see empirical chapter 1), I focused on hedge funds that invest primarily in the North America region due to my use of three full U.S. business cycles.

The second objective of this study is an extension of the first objective where I examine hedge funds' performance at fund fundamental (hedge fund characteristics such as size, age, and redemption restrictions) and mixed level (strategy and fundamental levels together). This is important as there is an interaction between these levels taking into consideration changing market conditions, as well. The third objective is to examine hedge fund performance persistence in different aspects and more specifically persistence in terms of the smoothness of returns, the persistence against the market benchmark, and the persistence within each strategy. I also examine how investors can utilize the differences in persistence in hedge fund strategies so as to gain higher returns. The fourth objective is to examine the differences between hedge fund indices from different database vendors even though they are supposed to represent the same strategy. On the same dataset, I apply specific classification techniques used by database

[1] When selecting hedge fund databases I had strict specification criteria such as those concerned with pre-1994 data as the majority of the databases for commercial use came into existence early/mid 1990s. Contrary to other studies, this dataset contains pre-1994 dead funds so as not to have the type of survivorship bias. However, in the findings I have additional robustness checks that excluded the prior 1994 period so as to verify my results.

vendors so as to examine whether the differences in hedge fund indices are a result of the different classifications or the different datasets used by the vendors.

Based on the above, my research questions are:

1. *How and what is the impact of the (multiple) business cycles and different market conditions on hedge fund strategies in terms of performance (alphas and exposures)?*

2. How and what is the impact of the (multiple) business cycles and different market conditions on hedge funds at the fundamental and mixed level in terms of performance (alphas and exposures)?

3. What is the impact of multiple business cycles and different market conditions on hedge fund performance persistence at a strategy level and how investors can exploit the persistence?

4. Why there are such large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy?

1.5 Research design - methodology

My research methodology converges to the positivist realm as being purely quantitative. I follow a deductive approach as I start with the implicit hypothesis that hedge funds have different behaviour within different market conditions and business cycles and also there are some fundamental factors that contribute to the alpha creation of hedge funds. Also the exposures are constantly changing and vary between hedge fund strategies. In this thesis I examine and test all these issues with data analysis using appropriate methods and techniques, discussed later. I use secondary data in this study and I used a mono-method (quantitative) approach due to the use of only one method collection (secondary data from databases) exploiting several quantitative techniques in my analysis. Concerning the time horizons I deal mostly with time-series as I involve the time dimension when analyzing "one entity per round' (e.g. hedge fund strategy).

Similar to the most recent studies (e.g. O'Doherty, Savin, and Tiwari, 2015; Racicot and Theoret, 2016; Namvar, Phillips, Pukthuanthong, and Rau, 2016) I examine hedge funds' performance in a non-linear framework. The core of my modelling approach is a custom piece-wise parsimonious multi-factor model with predefined and non-defined structural breaks. The predefined structural breaks are the U.S. business cycles whereas the non-defined are computed through a Markov switching process. This proposed parsimonious model is flexible enough to capture differences in portfolio and asset allocation of hedge funds as it uses a technique (stepwise regression) to capture the most suitable factors per each fund group (e.g. strategy) within each specific time period.

In the second empirical chapter, I include also the portfolio approach by forming groups of hedge funds at a strategy and fundamental level, as well. In the third empirical chapter, I use several parametric and non-parametric tests so as to examine hedge fund performance persistence at different aspects and in many cases I use more than one test so as to have even more robust results. I also developed a framework about mixed trading strategies that investors can exploit for higher returns conditional on changing market conditions. In the last empirical chapter (hedge fund indexing) I used several classification techniques similar to that used by popular database vendors to investigate the differences between hedge fund indices. In this thesis I used robustness checks (e.g. examining simpler models, out-of-sample tests, excluding the first four years of data etc.) so as to verify the results.

Last but not least, as the database merging and cleaning processes are not trivial tasks I provide the reader with the algorithms and processes that used so as to have the best possible data quality. Contrary to many other authors I followed a transparent approach when dealing and preparing the data for the further analysis. In addition, I managed issues that may affect the data quality (e.g. outliers, consecutive zeros in the dataset) with a special care which are disclosed in this study so as to ensure the best possible transparency in the data management processes.

1.6 The thesis structure

The rest of this doctoral thesis is organized in chapters (papers) regarding the four research questions that are discussed above. Every chapter has its own structure with an introduction, methodology, empirical analysis, and conclusion section. The next chapter (chapter 2) which is the literature review chapter, examines hedge funds' return generating process (part 1- first paper), performance persistence, and hedge fund returns and funds' characteristics (part 2 – second paper). In the next four chapters I mostly cover the gaps identified in the literature review. More specifically, the third chapter examines the first research question (funds' performance at strategy level), the fourth chapter examines the second research question (funds' performance at fundamental and mixed level), the fifth chapter examines the third research question (persistence and mixed trading strategies), and the sixth chapter examines the last research question (hedge fund indexing). Finally, the last chapter (chapter 7) presents the conclusions.

1.7 Conclusion

This doctoral thesis examines gaps in the hedge fund literature that constitute problems for investors and researchers. These problems are related with the hedge fund return generating process, the cross-sectional differences in hedge funds, the performance persistence, and the classification issues of the hedge fund industry. Overall this thesis is significant because it covers gaps in the literature having to do primarily with the lack of generalization, the absence of a direct link between market conditions and fund performance, the absence of a distinction and comparison between different "kinds" of market conditions, the use of one only commodity factor, and the over-simplistic models (all these analyzed in the previous section). My motivation is to contribute to the existed theoretical knowledge by covering the gaps and assisting investors in their investment decision process.

I apply a holistic approach focusing on the "big" picture so as to get results that can help investors, researchers and financial regulators in a practical way. Hence, researchers are familiar with different aspects of hedge fund behaviour under changing market conditions and they can exploit the avenues for further research that are revealed; investors know what to expect from hedge funds with different strategies and different characteristics thus helping them in their investment decision process; fund administrators and financial regulators can apply more flexible fee policies or have a better understanding of the hedge fund industry in case there is a need for a closer monitoring or a change in the legal framework.

2 Chapter: Literature review

This literature review chapter consists of two parts (papers): the first part (a version of this paper is published at the International Review of Financial Analysis journal) deals with the hedge fund return generating process and the second (a version of this paper is under re-review at the Global Finance Journal) deals with hedge fund performance persistence, including the relationship between fund characteristics and performance.

The first part surveys articles covering how hedge funds returns are explained, using largely non-linear multifactor models that examine the non-linear pay-offs and exposures of hedge funds. It provides an integrated view of the implicit factor and statistical factor models that are largely able to explain the hedge fund return-generating process. Their evolution through time is presented by discussing pioneering studies that made a significant contribution to knowledge, and also recent innovative studies that examine hedge funds exposures using advanced econometric methods. This is the first review that analyses very recent studies that explain a large part of hedge fund variation. It concludes by presenting some gaps for future research.

The second part surveys articles on hedge funds' performance persistence and fundamental factors from the mid-1990s to the present. For performance persistence, some pioneering studies are presented that contradict previous findings that hedge funds' performance is a short term matter. Recent innovative studies are discussed that examine the size, age, performance fees and other factors to give a 360° view of hedge funds' performance attribution. Small funds, younger funds and funds with high performance fees all outperform the opposite. Long lockup period funds tend to outperform short lockups and domiciled funds tend to outperform offshore funds. All these factors should be taken into consideration to optimize investment results. This review is important because it is the first survey of recent innovative and challenging studies into hedge funds' performance attribution.

2.1 Introduction – First part

A large and growing body of literature has investigated hedge fund performance attribution through the use of implicit or statistical factor models (e.g. Akay, Senyuz, and Yoldas, 2013; O'Doherty, Savin, and Tiwari, 2015, Racicot and Theoret, 2016). Investors want to know what is behind hedge fund return variation and what to expect from different hedge fund strategies or funds with different styles. Furthermore, it is essential for investors to be familiar with the principles that enable them to understand hedge fund performance behaviour. Although there is a large volume of published studies describing the role of factors or exposures of hedge funds in delivering high excess return to investors, nevertheless, there is no survey that summarizes and discusses the results, thus leading to uniform conclusions. This issue creates confusion to investors who do not have a clear picture or a holistic interpretation the dynamics of hedge fund performance attribution.

Therefore, the present study closes an important gap. The aim of this study is to survey the literature and investigate the hedge fund return generating process within implicit or statistical factor models. This is the first survey and synthesis of older literature to yield a historical perspective, along with surveying in more detail recent innovative studies to depict advances in hedge fund performance attribution[2]. Hence, readers will have an integrated view and a deeper understanding of hedge funds. The findings both facilitate hedge fund investors and untangle opportunities for further research, as I present later.

The main conclusions are that early studies (e.g. Sharpe, 1992), through the use of Principal Component Analysis and Common Factor Analysis (which is the most common statistical approach) dealt mainly with linear factor models giving weight to the asset categories or where the fund manager trades. They depicted a static representation of hedge fund performance attribution. Then, there was a development toward non-linear models that tried to explain hedge funds' performance as option portfolios (e.g. Fung and Hsieh, 2004; Agarwal and Naik, 2004). Nevertheless, in later years there have been several studies (e.g. Patton and Ramadorai, 2013; Bali, Brown and Caglayan, 2014; O'Doherty, Savin, and Tiwari, 2015) using more advanced models regarding hedge fund exposures. They confirmed previous studies that hedge funds have nonlinear returns in relation to the market return but they moved further and showed how these nonlinear exposures change over time according to financial conditions. Different strategies frequently have different exposures. However, there are a few exposures that are valid for virtually every hedge fund strategy (equity market, volatility, liquidity). Furthermore, systematic and more specific macroeconomic risk has a significant role in explaining hedge fund performance for nearly all strategies. Higher moment factors provide extra explanatory power to the models.

[2] Although older literature is known, it is important to include some key studies so as to integrate and analyse with newer studies.

This paper makes a number of important contributions to the understanding of the hedge fund literature. First, it covers a significant gap by presenting a survey that summarizes and discusses studies examining hedge fund performance attribution within statistical factors and exposures. Moreover, it demonstrates a historical perspective by combining earlier and more recent innovative studies, with their strengths and weaknesses. Therefore, the reader is able to look at the dynamic nature of the literature explaining hedge fund returns. This study assist investors in their asset allocation process in two ways; it facilitates the deeper understanding of what is behind hedge fund return variation and it also enables them to know what to foresee from funds with different strategies or fund styles. Last but not least, this study has identified some gaps for future research. An example is the absence of a unified framework that takes into consideration the comprehensive macroeconomic environment along with the internal structure of the hedge fund industry in explaining returns, or identifying the proportion of alpha affected by each of the underlying factors.

In the part one, section 2.2 depicts different general approaches in measuring the performance of all hedge fund strategies[3]. Section 2.3 briefly reviews earlier linear studies. Section 2.4 reviews in detail the most recent nonlinear models within the down-up, up-down, and alternative modeling approaches, as I describe later. The final section 2.5 presents and summarizes the key conclusions and reveal some gaps that should be addressed in future research.

2.2 Model categories

This section presents two general categories of models which are the absolute pricing models and the relative value models. Then there is a focus on two different statistical approaches: Principal Component Analysis and Common Factor Analysis.

Generally speaking, asset pricing models are divided into two main categories: (*i*) absolute pricing models and (*ii*) relative value models (Lhabitant, 2004 and 2007). The first category consists of fundamental equilibrium models and consumption-based models in combination with many macro-economic models. They use asset pricing theory and price each asset individually taking into consideration its exposures. They give an economic interpretation of *why* prices are what they are and *why* exposures are

[3] The four named models cover all hedge fund strategies and refer to the category of relative price models.

what they are. In addition they are supposed to *predict* price changes due to economic structure changes. The second category of asset pricing models explores the *evidence* of the *different* asset pricing rather than trying to fit an explanation of the financial markets. They price each asset by taking into consideration the prices of some other assets that are extraneous. In other words, they provide a plain illustration of *how* the financial world works. A typical well known example is the Black-Scholes (1973) formula that computes an option price in regard to its underlying asset price, disregarding whether that asset is fairly priced by the market. The factor models that I mention belong to the category of relative price models. They price or evaluate hedge funds in regard to the market or any other risk factors. They do not concentrate on what induces the primitive factors, the market or factor risk premium, or the risk exposures accepted by the fund managers.

The majority of factor (or relative price) models use a two-stage approach: At the beginning, they hypothesize that hedge funds returns are specific functions of macro-economic and micro-economic factors (variables). Second, they test those initial assumptions and assess the sensitivity of hedge funds returns to those assumptions. Factor models determine the relationships between a large number of variables (for instance fund returns) and describe these relationships in terms of their common underlying dimensions, so called 'factors'. Hence, there is the advantage of dimensionality reduction because it sums up the information that is contained in a large number of original values (hedge funds returns) into a smaller set of factors with a minimum loss of information. In other words, via factor models the covariance matrix (correlation or covariance among the returns of all hedge finds) can be simplified.

Amenc, Sfeir and Martellini (2002) report four types of factor models. These are: (1) *Explicit macro factors*: These are macro-economic variables that are calculated either as predictive variables or adopted ex-post to measure market sensitivities in relation to some macroeconomic parameters. (2) *Explicit index factor model*: In these models each factor is investable and represents some index or fund available as an ETF (Exchange Trading Funds) or futures contract. (3) *Explicit micro factor models*: These microeconomic parameters (or variables) that refer to fund-specific features are estimated and forecast in a comparable manner as the explicit factor models. (4) *Implicit factor models*: These implicit factors are mainly derived through Principal Component Analysis (PCA) or Common Factor Analysis (CFA) and are regarded as a merely statistical approach. An analogous classification is suggested by Connor (1995) with the use of three types of factor models that are available for examining asset returns, named as: *Macroeconomic factor models, Fundamental factor models* and *Statistical factor models*.

In this part of the literature review I deal with statistical or implicit factor models. Regarding those factor models there are two widely-used methodologies that are used to distinguish the underlying factors: (*i*) *Principal Component Analysis (PCA)* and (*ii*) *Common Factor Analysis (CFA)*. I explain and analyse those two methodologies and studies with regard to hedge funds.

2.2.1 Principal components analysis

The PCA methodology was first described by Pearson (1901). Implicit factors are obtained via this approach. The purpose is to explain the return series of observed variables via a smaller group of non-observed implicit variables. Those implicit factors are extracted from the time series of returns. In other words, the main objective of PCA is to explain the behaviour of a number of correlated variables using a smaller number of uncorrelated and unobserved implied variables or implicit factors called *principal components*.

Fung and Hsieh (1997) used PCA to extract implicit factors in order to provide a quantitative classification of hedge funds based on returns alone. They took into consideration the location (market) as well the strategy (investment style) followed by managers. The returns are supposed to be correlated to each other even though they might not be linearly correlated to the returns of asset markets. They used a database (1991-1995) from Paradigm LDC and from TASS Management. They found that five principal components jointly accounted for 43% of the return variance of hedge funds. They assigned concise names to these components: (1) Trend-following strategies on diversified markets such as managed futures and CTAs (Commodity Trading Advisors), (2) Global/macro funds, (3) Long/short equity funds, (4) Funds with trend-following strategies specialized in major currencies, (5) Distressed securities funds.

Later, Amenc, Martellini and Faff (2003) used PCA in creating a passive hedge fund index or index of indices. Their method was a natural generalization of the equally weighted portfolio of indices. Using PCA they created a portfolio of indices with appropriate weights so that the combination of indices captured the largest possible amount of information contained in the data (time-series returns) of those indices. The first component was a candidate for a pure style index. This component caught a large percentage of cross-sectional variation due to the fact that those competing indices tend to be highly positively correlated. They proved mathematically that an index of indices is always more representative than any competing index upon which it is based. Furthermore, an index of indices is consistently less biased than the average of the set of indices it is derived from.

Additional authors who used PCA are Christiansen, Madsen and Christiansen (2003) so as to identify the minimum number of components needed to describe the returns of hedge funds from the CISDM database (1999-2002). They found that there were five components, and by comparing these with the qualitative self-reported classifications of hedge funds they identified five different strategies that could explain greater than 60% of hedge fund return variation (Opportunistic/Sector, Event Driven, Global Macro, Value and Market Neutral Arbitrage). It is evident from the above papers that using four to five components is sufficient to explain a large part of hedge fund returns.

2.2.2 Common factor analysis

The second statistical approach that is used more often in the literature is the *Common Factor Analysis (CFA)*. Its goal is identical to PCA, which is to transform a number of correlated variables into a smaller number (dimensionality reduction) of uncorrelated variables, that is, factors. Nevertheless, there is a great difference with PCA. Here, the underlying factors are *observable* and *clearly stated* by the researcher carrying out explanatory and/or confirmatory analysis. They are not just implied by the data. As with PCA, the number of factors should be as small as feasible in order to have the advantages of dimensionality reduction. However, the researcher is making a trade-off between the dimensionality reduction and the accuracy she wants to maintain.

It is very common in factor analysis to choose factors on an *ad hoc* basis. The basic principle is to pick up variables that are considered most probably to influence asset returns. A researcher should take into consideration quantitative and qualitative approaches in order to decide which factors to use. Furthermore, a researcher should look for evidence from the empirical asset pricing literature. For many years researchers looked for factors[4] that explained and influenced the cross-sections of expected returns.

Certain models that are extensions of the basic CAPM model have heavily influenced hedge funds models. These are Fama and French (1993), using the size and book to price ratio and Carhart (1997) that included the momentum as a fourth factor. Other more recent models are Fung and Hsieh's (2004) seven factor model, or Capocci's (2007) fourteen factor model. In the following two sections I present some earlier and some more recent studies using implicit factor models that are useful to reveal hedge funds exposures and explain their returns. A branch of the CFA approach is Asset-Based Style (ABS) factors, where the factors are constructed by trading in the appropriate securities within the underlying conventional assets (e.g. bonds or equities) that mimic the returns of hedge funds (please see section 2.4.1).

Last but not least, one important application of factor models is hedge fund replication. There is a distinction between traded factors (e.g. market and size factors) and non-traded factors (e.g. volatility or liquidity), the latter of which are not readily tradeable. Investors may therefore encounter problems in their replication. In general, the same issues arise in the context of non-linear models where some of them do not allow for easy replication of hedge funds.

2.3 Linear factor models

In this section I briefly discuss some linear multi-factor models that are considered to be key studies in the hedge fund literature. It is known that linear multi-factors models are based on the general linear equation model (Ross, 1976). In addition to the market factor (Sharpe, 1964) the most popular is the Fama and French (1993) model with the SMB (small minus large) and HML (high minus low book to market ratio) factors. Carhart (1997) was the first who used the momentum factor (Jegadeesh and Titman, 1993) as the fourth factor – a zero investment portfolio that is long in past winners and short in past losers. His model is an extension of the Fama and French factor model. All these previous factors are extensively used in the hedge fund academic literature.

[4] These include, for example, market value or equity capitalization size proposed by Banz (1981) and Reinganum (1981), and earnings-to-price ratio proposed by Basu (1983). Other examples are leverage, mentioned by Bhandari (1988) and stock liquidity as mentioned by Amihud (2002).

I first consider style analysis-trading factors so as to introduce the reader gently to further linear and non-linear models. Therefore, I start from Sharpe (1992). Sharpe used an asset class factor model implementing style analysis as a substantial complement to other methodologies designed to assist investors achieve their targets in a cost-effective manner. He used a model composed of twelve asset classes to analyse the performance of funds between 1985 and 1989. The twelve asset classes were: (1) T-bills, (2) Intermediate-term Govt. Bonds, (3) Long-term Govt. Bonds, (4) Corporate Bonds, (5) Mortgage-Related Securities, (6) Large Cap Value Stocks, (7) Large Cap Growth Stocks, (8) Medium Cap Stocks, (9) Small Cap Stocks (10) Non-U.S. Bonds, (11) European Stocks and (12) Japanese Stocks. The variation of fund returns in any specific period could be associated with the combined effects of their exposures to these asset classes and the realized returns on these classes. Those investors' exposures to asset classes were a function of, first, the proportion of the investor's portfolio invested in the various funds and second the exposures of each given fund to the asset classes. The exposures of a fund to wider asset classes depended on two elements: the amount of money that the fund had invested in various securities and the exposures of the securities to the asset class.

Sharpe's (1992) style analysis can be used to appraise the behaviour of a fund manager's exposures to asset classes over a specific time period. Moreover it can be used to measure a fund manager's relative performance, in other words the value added by her skills (alpha). A passive hedge fund manager provides investors with an investment style whereas an active hedge fund manager provides both *style* and *selection*. Thus the terms *active* and *passive* management can be defined. An investor may choose a set of asset classes that is superior to the performance of the 'standard' static mix and fulfils the requirement for higher fees. As a result, fund selection return according to Sharpe (1992) is denoted as the difference between the fund's return and that of a passive mix with the same style. Once the styles of an investor's funds have been estimated it is possible to estimate the effective asset mix. The effective asset mix reflects the style of the investor's overall portfolio.

The model for explaining the results of traditional mixed funds (composed of equities and bonds) first introduced by Sharpe (1992) is limited to funds that pursue a long-only strategy. However, hedge funds are much more flexible and can also use short selling and leveraging. These trading strategies of hedge funds lead to option-like structures that are not covered by the basic Sharpe model or other similar models. Confronting that problem, Fung and Hsieh's (1997) study is presented in section 2.4.1 dealing with non-linear factor models.

Schneeweis and Spurgin (1998) used factors designed to capture the trading opportunities available to CTAs or hedge funds as a means of forecasting return performance. They used the databases of HFR, EACM, MAR and Barclays from 1990 to 1995. They considered the following factors to examine the returns to active management of hedge funds, CTAs and mutual funds: (1) a natural return to owning financial and real assets, (2) the use of both short and long positions, (3) the exploitation of the indices' intermonth volatility and (4) the exploitation of market inefficiencies that result in temporary trends in prices. These factors were able to significantly explain the differences in investment returns within each investment grouping. Using multivariate regressions they showed that CTA returns are positively related to commodity market trends. Hedge funds were related to the returns of the index which they were investing whereas they offer higher returns than CTAs for any given level of risk.

A few years later, Capocci and Hubner (2004) examined hedge funds' behaviour from 1984 to 2000 (HFR, MAR) using various asset pricing models. Those included an extended form of Carhart's (1997) model, combined with the Fama and French (1998) and Agarwal and Naik (2000) models plus one more factor that takes into consideration the fact that hedge funds may invest in Emerging Markets. According to the authors, that combined model better explained variations of hedge funds over time than other studies, especially for Event Driven, U.S Opportunities, Global Macro, Equity non-hedge and Sector Funds. The performance analysis showed that one quarter of individual hedge funds delivered significant positive excess returns. The majority of them preferred to invest in smaller stocks and also invest in emerging markets bonds. Nine out of twelve strategies offered significantly positive returns. Most Event Driven, Market Neutral and US Opportunistic funds prefer stocks with high book-to-market ratios.

To sum up, there are several studies (e.g. Sharpe, 1992; Capocci and Hubner, 2004) that examined hedge fund performance under a linear framework. However, linear models are more suitable for traditional mixed funds (investing in equity and bonds). Moreover they cannot capture the time variation of funds' exposures. Some of these issues addressed with non-linear factor models that are presented in the following section[5]. For reader's convenience the above studies are listed in Table 1.

[5] The return of any portfolio is a linear average of the returns of its assets. However, the definition of a (non-) linear model is not an easy task because the term linear can be interpreted into different ways. First, it may be the linearity in variables, although if the independent variable appears with a power 2 then it can be interpreted as a non-linear function. Second, it may be the linearity in parameters, although it may or may not be linear in the independent variable(s), thus being a linear (in the parameters) regression model. Third, it may be the case that the linearity between the dependant and independent variables changes over time. A model with structural breaks can be regarded (as a whole) as a non-linear model.

Table 1 Performance Attribution – Linear Studies

This Table presents the main characteristics and findings of the linear studies of hedge fund performance attribution. Abbreviations: CTA: Commodity Trading Advisors, EACM: Evaluation Associates Capital Market, HFR: Hedge Fund Research, MAR: Managed Account Reports. Some databases (e.g. Lipper and TASS, MAR and CISDM) have been merged.

Study	Sample	Methodology	Findings
Capocci and Hubner (2004)	HFR, MAR, 1988-1995	Regression based and portfolio construction	One quarter of individual hedge funds deliver significant positive excess returns. The majority of them invest in smaller stocks and emerging market bonds having also exposure to the US bond market. Nine out of twelve strategies deliver significant positive returns. Most Event Driven, Market Neutral, and US Opportunistic funds prefer stocks with high book-to-market ratios
Scheneeweis and Spurgin (1998)	HFR, EACM, MAR, Barclays, 1990-1995	Regression based	CTA returns are positively related to commodities and currency movements whereas hedge fund returns are related to the index returns invested. Hedge funds systematically offer higher returns than either mutual funds or CTAs for any given level of risk
Sharpe (1992)	C. Jarrett & Company, Inc., 1985-1989	Regression based, portfolio construction	Focus on traditional mixed funds (composed of equities and bonds). Fund returns depend on their exposures to the investable assets and their realized returns. Exposures to assets classes are a function of the proportion of the investor's portfolio invested in various funds and exposures of each given fund to the asset classes

2.4 Non linear factor models

Beyond the linear factor models that were used for explaining hedge fund returns during the earlier years there is a development toward non-linear models. These try to capture exposures and the non-linear payoffs of hedge fund returns in relation to their risk or market returns. In general, there are two different approaches: down-up (or indirect) and up-down (or direct). The former starts with the underlying assets (e.g. stocks or bonds) to find the sources of hedge funds' returns. It involves replicating hedge fund portfolios by trading in the correspondent securities. These trading constructed factors are defined as asset-based style (ABS) factors (Fund and Hsieh, 2002a). The latter approach starts with identifying the sources of hedge fund returns and relates pre-specified risk factors for hedge fund performance attribution. It uses additional factors that better explain hedge fund returns. I also present a third approach (an extension of the up-down) that deals with methodological issues and tries to identify funds' structural breaks. For the reader's convenience the studies of the above three approaches are presented in Tables 2, 3, 4.

2.4.1 Down-Up approach

2.4.1.1 Option portfolios and trend followers

In this sub-section, I begin with Fung and Hsieh (1997) who provided a useful characterization of the type of option strategy that one should expect when analysing hedge fund returns. Then I proceed with the Fung and Hsieh (2001) study which showed how to model hedge funds returns by concentrating on the 'trend-following' strategy. Examining futures and option futures, they demonstrated empirically that the returns of trend-following funds resemble lookback straddle returns[6]. Fung and Hsieh (2002a) extended their 2001 study to construct asset-based style factors. They demonstrated a model that could predict the returns behaviour of trend following strategies during certain market conditions. Fung and Hsieh (2004) was another extension of their previous work in 2001 and 2002a on asset-based style (ABS) factors. It proposed a model of hedge funds returns that is comparable to models depending on arbitrage pricing theory with dynamic risk coefficients. Huber and Kaiser (2004)

[6] A lookback straddle is an option strategy that is a combination of a lookback call plus a lookback put (options that are traded in Over-The-Counter markets). The first component grants the holder the right but not the obligation to buy an asset at the lowest price identified during the lifetime of the option. The second component grants the holder the right but not the obligation to sell an asset at the highest price observed during the lifetime of the option.

confirmed Fung and Hsieh (1997, 2001) that CTAs have a payoff profile similar to a long straddle[7].

The authors Fung and Hsieh (1997) raised the issue of considering hedge funds as option portfolios. Their study is an extension of Sharpe's (1992) style analysis as beyond the "location" component or factor of returns (which tell us the asset categories or where the manager trades using a static buy and hold policy) they added two other components: 'Trading strategy factors' (the way the manager trades, denoting the type of dynamic strategy) and the 'leverage factor' (a scaling factor, the quantity that is invested and regarded as a component of the return). In order to quantify their statement (modelling hedge funds as option portfolios) and identify the location and trading strategy factors, the authors used a relatively simple method that is equivalent to non-parametric regression. They compared the performance returns of hedge funds strategies versus U.S. equities (S&P 500) in five different economic conditions (from worst to best). As suspected the short-only strategy had no option-like feature and behaved almost exactly the opposite of equities. The CTA strategy had a return profile close to a straddle on equities. The global macro strategy performed like a short put on the S&P 500 and had an approximately linear profile with regard to the USD/JPY exchange rate. Finally, the distressed securities and risk arbitrage strategies also behaved like short puts on the S&P 500. Ultimately, Fung and Hsieh (1997) provided a convenient characterization of the type of option strategy that one should anticipate when dealing with funds' returns, as hedge fund strategies are highly dynamic (e.g. using derivatives, short-selling etc.). Moreover, their study showed that there are five dominant strategies[8] in hedge funds having lower correlations with standard asset returns and mutual fund returns.

A few years later, Fung and Hsieh (2001) showed a way to model hedge funds returns by concentrating on the well-known 'trend-following' strategy. They examined futures and option futures from the Futures Industry Institute (FII), The Chicago Mercantile Exchange (CME) and Datastream. They used a general methodology for understanding hedge fund risk by modelling a specific trading strategy which is widely referred as "trend following" within the industry. They demonstrated empirically that the returns of trend-following funds resemble lookback straddle returns. They explored hedge funds

[7] A long straddle is a combination of a long call and a long put with the same strike price.
[8] These are: Systems/Opportunistic, Global/Macro, Value, Systems/Trend Following, and Distressed.

returns through modelling the differences between trend-following and market-timing as trading strategies.

Given the market prices in any specific time period, the optimal pay-out of any trend-following strategy should be equal to the one that bought at the lowest price and sold at the highest price. It was for this reason that Fung and Hsieh (2001) suggested using a lookback straddle. Indeed, the lookback straddle is of specific interest due to its close connection to the return profiles of trend-following hedge funds. The majority of CTAs or managed futures funds are in fact 'trend-followers' (or primitive trading strategies). The payoff of a perfect market timer who may take long only positions should be very similar to the payoff from holding a call option. However, if the flawless market timer may take long or short positions, this would correspond to a perfect trend follower who could 'buy low and sell high'. This is equivalent to the payoff of a lookback straddle. Therefore, the lookback straddle can be regarded as a primitive trading strategy exploited by market timers.

Fung and Hsieh (2001) showed that a lookback straddle is better fitted to capture the principle of trend following strategies than simple standard asset benchmarks. Trend-following funds have a systematic risk that cannot be captured by linear-factor models applied to standard asset benchmarks. Also, trend-followers or portfolios of lookback straddles can reduce the volatility of a typical bond and stock portfolio during severe market downturns. However, it is important to mention that it is not possible to have a unique benchmark that can be used to model the performance of every trend follower. That is because there are significant dissimilarities in trading strategies among trend-following funds.

Extending their 2001 study, Fung and Hsieh (2002a) used previously-developed models to build asset-based style factors. They demonstrated a model that can predict the returns behavior of trend following strategies during certain periods and particularly during stressful market conditions such as those of September 2001. In this study the authors added almost four years of data (1998 to 2001) since their publication of 2001. Hence, they provided out-of-sample validation for their finding that trend followers have returns characteristics that mimic the payout of a lookback option on traditional assets. They showed that it is beneficial to model hedge funds strategies using asset-based style factors. Hedge fund directional strategies can be modelled with "long only" asset-based style factors and the “directional component” represents more than 50 percent of the hedge fund return variation.

Fung and Hsieh’s 2004 study was an extension of their previous 2001 and 2002 papers on asset-based style (ABS) factors. It proposed a model of hedge fund returns that is comparable to models based on arbitrage pricing theory, with dynamic risk coefficients. They examined data from HFR and TASS databases for 1998 to 2002 and identified seven ABS factors to create hedge fund benchmarks that capture hedge funds’ common risk factors. The seven ABS factors were two equity factors (market and size), two fixed income factors (change in bond yield and change in credit spread yield), and three trend-following factors (lookback straddles on bonds, commodities, and currencies). Using funds of funds as a proxy for hedge fund portfolios these factors were able to explain up to 80 percent (as represented by the R-squared and depending on which time period they used) of monthly return variations. Regarding the average hedge fund portfolio (using as proxy the HFR fund of funds index), they found that it had systematic exposures to directional equity and interest rates odds (bets), but they also had exposures to long equity and credit events. The authors also used the Kalman Filtering technique with a set of exogenous market events (e.g. LTCM, 09/11) for result verification. There are more studies that are based on the same initial ABS-creation mechanism, describing other strategies. For example, Mitchel and Pulvino (2001), Fund and Hsieh (2002a) and Fung and Hsieh (2000c) developed factors for risk arbitrage, convergence traders and long-short equity funds, respectively.

The final paper that it is covered in this section on non-linear models is Huber and Kaiser (2004). They supported Fung and Hsieh (1997, 2001) in that, because hedge funds trade in a flexible way, their strategies lead to option-like structures that cannot be covered by the classic Sharpe model. They explained how these option-like structures come about. Thus hedge funds and CTAs using certain trading strategies generate returns similar to options. In particular, the structures of CTAs have a payoff profile similar to a long straddle. In their research, the authors presented an investigation of the risk factors affecting the nine Standard & Poor’s Hedge Fund Indices. Daily data about hedge funds indices were available from 1998 to 2003. The highest return was achieved by the Equity Long/Short basket (23.6% p.a.) followed by Convertible Arbitrage (21.8%) and Managed Futures (19.2%). The poorest performers were Fixed Income Arbitrage (3.9%) and Merger Arbitrage (6.9%). The authors used the classical Sharpe model equation using several factors F_k. The empirical section of their study explained the risk factors of the Standard & Poor's Hedge Fund Indices taking the option-like futures into account. For instance merger arbitrage had a significant determinant similar to a short put on the S&P index, and managed futures, a long straddle on the S&P 500 index.

2.4.1.2 Option-Based buy and hold strategies

This sub-section presents the other line of research originating from Agarwal and Naik (2000), who suggested a general asset factor model consisting of excess returns on passive option-based strategies and on buy-and-hold strategies. In a later study (2004) they focused on the systematic risk exposures of hedge funds practicing buy-and-hold and option-based strategies. A more recent discussed study is from Duarte, Longstaff, and Yu (2007) that focused on fixed-income strategies showing that "market neutral" strategies imposed substantial risk exposures on investors.

Agarwal and Naik (2000) suggested a general asset factor model consisting of excess returns on passive option-based strategies and on buy-and-hold strategies. Despite the fact that many hedge funds implement dynamic strategies, they found that a small number of simple option writing/buying strategies were sufficient to explain a large part of the variation in hedge fund returns over time. Using the Hedge Fund Research Database from 1990 to 1998 (hedge fund indices), they evaluated the performance of hedge funds that adopted different strategies (especially Event Driven and Relative Value Arbitrage) using a general asset class factor model composed of excess return on Location (buy-and-hold) and on Trading Strategy (option writing/buying) factors.

Agarwal and Naik presented four main findings: first their model composed of Trading Strategy factors and Location factors was able to interpret a significant amount (up to 93%) of hedge funds' returns over time. Second, non-directional strategies displayed more significant loadings on Trading Strategy factors whereas directional strategies displayed significant loadings on Location factors. They found that in the early 1990s 38% of hedge funds added significant value (excess return or alpha) compared to 28% of hedge funds that added value in the late 1990s. Last but not least, leveraged funds did not consistently perform better or worse than funds that did not use leverage.

Likewise, in 2004 the same authors examined the systematic risk exposures of hedge funds practicing buy-and-hold and option-based strategies. They used data from HFR and TASS (hedge fund indices, 1990-2000). They found that a large number of equity-oriented hedge funds strategies had payoffs similar to a short position in a put option on the market index. This was in alignment with findings from other studies such Awargal and Naik (2000) and Fund and Hsieh (1997) concerning the payoff style of some hedge funds strategies. They found that a short position in a put option on the market index brought a significant left-tail risk that was not captured sufficiently in the mean-variance framework. Hence, they used a mean-conditional value-at-risk framework and they demonstrated the degree to which the mean-variance framework underestimated the tail risk, also showing that the last decade is not representative of long term hedge fund performance.

In order to identify the linear and non-linear risks of a wide range of hedge funds strategies they used buy-and-hold and option-based risk factors. They followed a three-step approach: first they considered the loading coefficients (betas) using the returns of standard asset classes and options on them as factors. Then they constructed replicating portfolios that best explained the in-sample variation in hedge funds returns. Finally they examined how well those replicating portfolios caught the out-of sample performance of hedge funds. They conducted an analysis not only at the index level, but also at the individual hedge fund level. As well as their characterization of a nonlinear risk-return relationship between portfolio return and its risk when examining hedge funds, Agarwal and Naik (2004) found that hedge funds exhibited significant exposures to Fama and French's (1993) three-factor model and Carhart's (1997) momentum factor.

A more recent study using the ABS approach was from Duarte, Longstaff, and Yu (2007) that examined the return and risk characteristics of fixed-income strategies using the CSFB/Tremont and HFR databases from 1994-2004. Implementing isotonic regression and linear-kernel regressions, they found all five strategies exhibited positive excess returns. Some strategies such as yield curve arbitrage, mortgage arbitrage and capital structure arbitrage presented significant positive alphas (even after taking fees into consideration) as they required the most "intellectual capital" to implement. They also found that, with the exception of the volatility arbitrage strategy, the returns had positive skewness. Moreover, several so called "market-neutral" arbitrage strategies imposed substantial risk exposures such as equity and bond market factors on investors. However, they found little evidence that these strategies exposed investors to substantial downside risk.

All the studies that have been covered in this sub-section have been non-linear models that tried to explain hedge funds' performance as option portfolios. Fung and Hsieh (1997) provided a useful characterization of the type of option strategy that one should expect when analyzing hedge funds returns. Fung and Hsieh (2001, 2002a) demonstrated empirically that returns of trend-following strategies resemble lookback straddle returns. The same authors in 2004 presented the seven factor model that was able to capture the common risk ABS factors in hedge funds. Huber and Kaiser (2004) verified Fung and Hsieh (1997, 2001)'s results. They also showed that hedge funds (especially those using a convergence strategy) also have option-like return structures. Agarwal and Naik (2000 and 2004) suggested a factor model based on passive option-based strategies and buy-and-hold strategies to benchmark the performance of hedge funds. Their findings were consistent with Fung and Hsieh (1997) concerning the payoff style of some hedge fund strategies. Duarte, Longstaff and Yu (2007) found that the so-called market neutral strategies were not so neutral for investors and some fixed income strategies required the most "intellectual capital" to implement.

Although these studies are important to conceptually explain hedge funds returns using non-linear models, there is a weakness as those perspectives may not help investors in a practical way to choose and evaluate hedge funds. This is because, first, these exposures are not static and change very often (see section 2.4.3) and, second, these factors are not for an investor easy to replicate. Moreover, some strategies (such as global macro or multi strategy) are not well defined, hence they are difficult to replicate. I discuss this issue further in section 2.4.3.

Table 2. Performance Attribution – Non-linear Studies

This Table presents the main characteristics and findings of the nonlinear studies (down-up approach) of hedge fund performance attribution. Abbreviations: CSFB/Tremont: Credit Suisse First Boston, CME: Chicago Mercantile Exchange, FII: Futures Industry Institute, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services, PCA: Principal Component Analysis. Some databases (e.g. Lipper and TASS, MAR and CISDM) have been merged.

Study	Sample	Approach/Methodology	Findings
Agarwal and Naik (2000)	HFR, 1990-1998	Down-Up/Regression based, portfolio construction	Trading strategy and location factors are able to interpret a significant amount (up to 90%) of hedge fund returns. Non-directional strategies present more significant loadings on trading strategy factors. Directional strategies present significant loadings on location factors. Only 35% of the hedge funds have added significant excess returns to investors. Funds that use leverage do not necessarily perform better or worse than funds that do not use leverage
Agarwal and Naik (2004)	HFR, TASS, 1990-2000	Down -Up/Regression based, portfolio construction	Hedge fund strategies have payoffs similar to a short position in a put option on the market index and significant exposures to the size, value, and momentum factors. A short position in a put option on the market index delivers a significant left-tailed risk that is not captured sufficiently in the mean variance framework. The expected tail losses of mean-variance optimal portfolios can be underestimated and the performance during the last decade is not representative of hedge fund long-term performance
Duarte, Longstaff, and Yu (2007)	CSFB/Tremont, HFR, 1994-2004	Down -Up/Isotonic regression, Linear-Kernel regression	In general, fixed income arbitrage strategies deliver positive excess returns which are positively skewed. However, they expose investors to substantial levels of market risk. After adjusting for equity and bond factors, the Swap spread arbitrage and the Volatility Arbitrage strategies deliver insignificant alphas. In contrast, some "intellectual capital" intensive strategies such as Yield curve arbitrage, Mortgage arbitrage or Capital structure arbitrage produce significant alphas (even after taking fees into consideration)
Fund and Hsieh (1997)	Morningstar, 1991-1995	Down -Up/Regression based, portfolio construction, PCA	There are certain types of option strategies corresponding to specific strategies. There are five dominant strategies: Systems/Opportunistic, Global/Macro, Value, Systems/Trend Following, and Distressed. Beyond the “location” component of return they focus on “how the manager trades” and leverage. Dynamic trading strategies can improve the performance of a traditional stock-bond portfolio without substantially increasing its risk
Fung and Hsieh (2001)	FII, CME, Datastream, 1989-1997	Down -Up/Regression and portfolio based	Trend-following fund returns resemble lookback straddle returns. Trend followers or portfolios of lookback straddles can reduce the volatility of a typical bond and stock portfolio during severe market conditions. Trend-following funds do have systematic risk, although this risk cannot be observed in the context of a linear model applied to standard asset benchmarks. In addition, during stressful market conditions trend-following funds can reduce the volatility of a typical stock and bond portfolio
Fung and Hsieh (2002a)	FII, CME, Datastream, 1989-2001	Down -Up/Regression and portfolio based	Trend followers mimic the pay-out of a lookback option on traditional assets. It is beneficial to use asset-based style factors for modelling hedge funds. Hedge fund directional strategies can be modelled with “long only” asset-based style factors (e.g. conventional indices). The “directional component ” can represent more than 50% of the hedge fund return variation

Table 2. Performance Attribution – Non-linear Studies (continued)

Fung and Hsieh (2004)	HFR, TASS, 1998-2002	Down-Up/Regression based, PCA, and Kalman filter	The proposed model of hedge funds returns is similar to arbitrage pricing theory models with dynamic risk coefficients explaining up to 80 % of monthly returns variation. Their seven ABS risk factors are found in 37% of HFR hedge funds and 57% of those in the TASS database
Huber and Kaiser (2004)	S&P Hedge Fund Indices, 1998-2003	Down-Up/Regression based, portfolio construction	Hedge funds and CTAs using certain trading strategies generate returns similar to options. The structures of CTAs have a payment profile similar to a long straddle. The Merger arbitrage strategy can be determined with a short put option on the S&P 500 index whereas the Managed futures strategy can be determined by a long straddle in the S&P 500 index

2.4.2 Up-Down approach

This sub-section deals with up-down approaches that in general use additional factors that better explain hedge fund returns and also statistical techniques refining these risk factors within the multi-factor models. Later studies use more advanced econometric techniques. I begin with two studies of Patton (2009) and Bali, Brown, and Caglayan (2012) that have examined hedge funds' claim of market neutrality. Given the evidence that hedge funds contain systematic risk I proceed further to studies that attribute hedge fund performance to various risks.

2.4.2.1 Market neutrality

An in-depth study of the dependence between hedge fund returns and the S&P 500 index was carried out by Patton (2009) using the HFR and TASS databases from 1993 to 2003. He proposed five new neutrality concepts: mean neutrality, variance neutrality, value-at-risk neutrality, tail neutrality, and complete neutrality. The neutrality tests showed that about one quarter of funds in the market neutral category were significantly non-neutral. For other fund styles the proportions of non-neutral funds are from 50% for fund of funds to 85% for equity non-hedge. However, market neutral style funds were more neutral to market returns than other categories such as equity hedge, non-equity hedge, or event driven funds. Overall, even for market neutral funds there was significant and positive dependence between hedge fund returns and market returns.

A closely related study to the above came from Bali, Brown, Caglayan (2012) who examined how much the market risk, residual risk and tail risk justified the cross-sectional dispersion in hedge fund returns, using the Lipper/TASS database from 1994 to 2010. The authors separated the total risk into systematic and fund-specific or residual risk components. Using cross-sectional regressions, univariate and bivariate portfolio analysis they found that systematic risk was more powerful than residual risk in predicting the cross-sectional variation in hedge funds even after taking into consideration various fund characteristics (e.g. fees, size and age). Furthermore, funds within the highest systematic risk quintile generated on average 6% higher annual returns than funds within the lowest systematic risk quintile. These results remained when using risk-adjusted returns as well. In addition the relationship between residual risk and future fund returns was insignificant.

2.4.2.2 Dealing with systematic risk

As has been mentioned, given that hedge fund strategies are not as neutral as they claim (at least for the so-called market neutral strategies), there are studies that have examined the systematic risk that hedge funds impose on investors due to the market and the general macroeconomic environment that funds operate within. Ibbotson, Chen and Zhu (2011) examined hedge funds' alphas, betas and costs in a common framework. They used the TASS database and the sampling period was from 1995 to 2009. Fees were based on median fees - normally a 20 percent incentive fee and 1.5 percent management fee. Using regressions against the S&P 500, U.S. intermediate-term government bond returns and U.S Treasury bills, they broke down average hedge funds annual returns of 11.3% into alpha (3.0%), beta (4.7%) and costs (fees, 3.43%). Their results showed that alphas were positive even during the financial crisis in 2008. The only exception was in 1998. A typical fund manager could add value in both bear and bull markets and their betas were in general reduced during bear markets. For example, during the technology bubble collapse fund managers underweighted equities in their portfolios.

A comparable study is from Bali, Brown and Caglayan (2011) who examined how hedge funds' exposures to various financial and macroeconomic factors could justify the cross-sectional variations in hedge fund returns. They used the Lipper/TASS database from 1994 to 2008. Their most important finding was that there is a positive relation between hedge fund exposure to default risk premium and hedge fund future returns. This could be interpreted as meaning that risk premia on risky assets are negatively correlated with present economic activity. For example, investors demand higher expected returns in recessions and lower expected returns in booms when holding risky assets. In a recession period, the default risk spread is high, so hedge funds with higher exposure to the default premium are expected to give higher returns. They also found that hedge funds with lower exposure to inflation derived higher returns in the future. This has to do with uncertainty. As inflation rises, there is uncertainty in the economy (as investors have changing expectations) and they expect to observe a decline not only in hedge fund values but also in other financial instruments. When inflation is stable and uncertainty is low then investors expect those hedge funds and other financial instruments to have attractive returns. Overall, non-directional strategies (such as Fixed Income Arbitrage and Convertible Arbitrage) had lower variation and spreads in their exposures (beta factors) than directional strategies such as Global Macro and Emerging Markets.

Extending their 2011 work, Bali, Brown, and Caglayan (2014) proposed custom measures of macroeconomic risk that could be regarded as measures of economic activity, using the Lipper TASS database from 1994 to 2012. The macroeconomic variables that the authors used were the default spread, term spread, short-term interest rates changes, aggregate dividend yield, equity market index, inflation rate, unemployment rate, and the growth rate of real gross domestic product per capital. By using cross sectional regressions and portfolio analysis, they showed that uncertainty betas can describe a significant proportion of cross section return differences between hedge funds (two exceptions were unemployment and short-term interest rate changes). More specifically, funds in the highest uncertainty index beta quintile delivered 0.80% to 0.90% higher monthly returns and alphas compared to funds in the lowest uncertainty index beta quintile. Moreover, the macroeconomic risk was a more powerful determinant of hedge fund returns than other commonly used financial risk factors (e.g. market returns, size, high minus low and momentum). In addition, through the use of principal components analysis, the authors constructed an aggregate or broad index of macroeconomic risk where the first principal component explained about 62% of the corresponding hedge fund return variance. Moreover, directional strategies had direct exposure to the underlying macroeconomic risk factors and non-directional strategies did not have significant macro-timing ability.

Analogous to that study but emphasizing forecasting more was the study by Avramov, Barras, and Kosowski (2013). They developed a unified methodological framework to assess both in-sample and out-of-sample hedge fund returns predictability based on macroeconomic variables, using the Barclayhedge, TASS, HFR, CISDM, and MSCI databases from 1994 to 2008. Beginning from in-sample analysis, approximately 63% of the sample funds had expected returns that changed according to business conditions. They used five macro variables (default spread, dividend yield, VIX index, net aggregate flows in the hedge fund industry) and found that returns predictability was widespread across different hedge fund strategies, consistent with economic intuition A conditional (singe-predictor) strategy that forecast each macro variable (and selecting the top decile of funds with the highest return mean) was able to deliver superior performance. By diversifying across forecasts, the combination strategy is more sufficient when return forecasts are not sufficiently accurate, thus avoiding a poor fund selection.

Racicot, and Theoret (2016) using strategy indices from the Greenwich Alternative Investment database from 1995 to 2012 examined the behaviour of the cross-sectional dispersions of hedge funds' returns, market betas and alphas during times of macroeconomic uncertainty. In their model they used the three Fama and French (1993) factors and the Fung and Hsieh (1997, 2001, 2004) lookback factors. Macroeconomic uncertainty was included by relying on the conditional variances of six macro and financial variables (growth on industrial production, interest rate, inflation, market return, growth of consumer credit, and the term spread). Using the Kalman filter technique they found that hedge fund market beta reduces with macro uncertainty. This makes their strategies more homogeneous, resulting in a contribution to the increased systematic risk of the financial system. The dispersion of hedge funds returns and alphas increases during times of rising macroeconomic uncertainty.

Relevant to the above study is one from Namvar, Phillips, Pukthuanthong, and Rau (2016) who used the CISDM and TASS Lipper databases from 1996 to 2010. Using Fung and Hsieh's (2004) factors in their model with PCA, time-series and panel regressions they examined the prevalence and the determinants of the systematic risk management (SRM) skill of fund managers and its consequence on funds' performance over time. They used the spread between the AA and BB corporate bond index yield to define the strong, medium and weak market state. They found that during weak market states skilled fund managers maintain low systematic risk via active adjustments to return factor loadings even though they provide low excess return. In strong market states, skilled fund managers provide incremental higher alpha than low skill managers through superior asset selection ability. More experienced or more educated fund managers present higher SRM skill, Moreover, SRM is lower for managers who manage fund with distress indicators (e.g. low investor flows or poor performance).

2.4.2.3 Higher moment risk and refined factors

This sub-section presents some studies that try to explain hedge fund performance attribution based on higher moment risk. For example, Agarwal, Arisoy and Naik (2016), using the Eurekahedge, HFR, Lipper TASS and Morningstar databases from 2006 to 2012 investigated whether uncertainty about volatility of the market portfolio could explain the performance of hedge funds, both in the cross-section and over time. They measured uncertainty about volatility of the market portfolio using the volatility of the aggregate volatility (VOV) of equity market returns. They constructed an investable version of this measure by calculating monthly returns on lookback straddles on the VIX index. They found that there was negative relationship between VOV exposures and hedge fund risk adjusted returns; however, this was not homogenous across all hedge fund strategies. They also found that the VIX negative exposure was a significant determinant of hedge funds returns at the general index level, at different strategy levels, and at the individual level as well. Strategies with less negative VOV betas outperformed strategies with more negative VOV betas during banking crisis period. Conversely, strategies with more negative VOV betas delivered superior returns when the uncertainty in the market was less. Also funds' VOV betas had a significant ability to predict excess returns one month ahead.

Related to the above study was one from Hubner, Lambert and Papageorgiou (2015), who modelled hedge fund returns on a conditional asset pricing model using the information content of market skewness and kurtosis. They used the HFR database from 1996 to 2009. They described the dynamics of the equity hedge, event-driven, relative value and fund of funds styles and in their model considered the location, trading and higher-moment factors. Within this framework they investigated the effect of the implied moments retrieved from the US equity markets and more specifically from the option-implied higher moments. The implied skewness and kurtosis of index portfolios increased the model's explanatory power and reduced the specification error for the majority of strategies. Market Neutral, Relative Value and Fund of Funds change their market exposure during financial crises. The authors recognized that an extension of their framework to other market types and locations would provide extra explanatory power to their model.

There are studies that use high frequency econometrics or refined statistical methods to choose the appropriate factors. For instance, Patton and Ramadorai (2013) proposed a new performance evaluation method that was based on Ferson and Schadt's (1996) model (a customized conditional model for mutual funds incorporating lagged information variables). That model was able to capture higher-frequency variations in hedge funds' exposures. They used the HFR, CISDM, TASS, Morningstar and Barclays databases and the sample period was from 1994 to 2009. In their factor model that included a simulation process, they used daily hedge fund (index) returns in relation to monthly hedge fund (individual) returns. They observed similar parameter estimates across the two sampling frequencies. Furthermore, hedge funds exposures varied across and within months. Moreover, they discovered patterns where the exposure variation was higher early in the month (immediately after the reporting date) and then got progressively lower until the reporting date. In addition, they found changes in portfolio allocations (weights) (that ultimately led to exposure changing) rather than changes in exposures to different asset classes and also a tendency to cut positions in response to significant market events (such as sharp changes in market returns or volatility). The authors' results showed that hedge funds, contrary to mutual funds, responded very quickly, were very flexible and adapted to any market triggers.

Brown (2012) proposed a specific framework for hedge fund return and risk attribution. He used the HFN and HFR databases and the sample period was from 1997 to 2010. In order to better estimate hedge funds fees, betas and alphas he suggested a framework that monthly returns be drawn from the following influences: fees (management and incentive fees) and four simple systematic risk factors. Those were volatility, leverage and two other more traditional factors such as equities, credit, interest rates, or commodities. For most fund strategies, volatility is the most important source of systematic risk. Brown applied stepwise regressions to various style or aggregate indices because of the need to customize performance benchmarks to different styles. He found that many hedge fund styles carried significant exposures to traditional systematic risk factors such as equities, interest rates or credit. Due to the fact that incentive fees are computed on total returns, there is a potential that abnormal returns attributed to those systematic exposures may overwhelm hedge fund alpha. Thus, fund managers may get paid for simple passive market exposures. Those problems of charging incentive fees on simple market exposures extend to most hedge fund styles and therefore constitute a barrier to their efficient usage.

Lastly, Slavutskaya (2013) improved the out-of-sample accuracy of linear factor models by combining cross-sectional and time-series information (panel data methods) for groups of hedge funds with similar investment strategies. She used the TASS, HFR, CISDM, and Alvest databases from 1994-2009. She suggested that current factor models are over-parameterized which results in unstable estimates. The "shrinkage" estimate, which is the trade-off between the individual estimates and the common mean estimate (the average risk exposure of a particular hedge fund style) provided a more accurate estimate. More specifically, she found that the root mean squared monthly error in panel data models was 10-15% smaller than in linear regressions, and the rate of decrease was significant. Nevertheless, she pointed out that the use of cross-sectional beta estimates assumed that all funds had the same risk exposures for a given time.

2.4.2.4 Holdings/SEC filings

A study that focused on the funds' security holdings and stock-picking was that of Chung, Fung, and Patel (2015). They examined whether hedge funds deliver consistent superior performance by focusing long-equity holdings. They used four databases: GOEF, CRSP, data from French's website, and that of Orissa Group from 1997 to 2006. By focusing on the characteristics of returns associated with long-equity picks of hedge funds and other institutional investors, they showed that hedge funds presented stock-picking superiority on their loading on the market risk factor compared to other institutional investors across three different market eras: bubble, deflation, and recovery. Moreover, high information acquisition (high churn rate) and active portfolio management (high active share) appeared to be necessities for the superior returns of hedge funds relative to other institutional investors.

Related to the above study is the paper by Agarwal, Jiang, Tang and Yang (2013) who examined the "confidential holdings" from hedge funds which are amendments to Form 13F (SEC's requirement of quarterly holdings report for funds with over $100 million in qualifying assets), using the SEC's EDGAR database (1999-2007). The authors incorporated and compared confidential holdings' performance to original holdings' performance of fund managers' portfolios providing a clear picture of the stock-picking ability of hedge funds. They showed that confidential treatment provides an incentive for active portfolio managers and also relieves fund managers from having to reveal their private information before reaping the full benefits of their investments. Funds managing large risky portfolios with nonconventional strategies (e.g. higher idiosyncratic risk) pursue confidentiality frequently and confidential holdings exhibit superior performance from 2 to 12 months. Although the conventional 13F databases which ignore confidential holdings may be biased, this bias is small when considering aggregate institutional holdings in public companies. However this is a significant omission when analyzing position changes of individual institutions or in response to certain events.

The above studies using additional factors and statistical techniques examined in detail systematic risk and performance, and the way they change according to financial conditions or holdings. However, more work is needed look at the time variation of hedge fund performance attribution. This is an issue that can better be captured with the identification of the structural breaks within the underlying models, as presented in the section 2.4.3.

Table 3. Performance Attribution – Non-linear Studies

This Table presents the main characteristics and findings of the nonlinear studies (up-down approach) of hedge fund performance attribution. Abbreviations: CISDM: Centre for International and Securities Markets, CRSP: Centre from Research in Security Prices, GOEF: Global Equity Ownership Feed of Thomson Financial, HFN: Evestment Com (database), HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services, MSCI: Morgan Stanley Capital International, VOV: Volatility of the aggregate volatility. Some databases (e.g. Lipper and TASS, MAR and CISDM) have been merged.

Study	Sample	Approach/Methodolog	Findings
Agarwal, Arisoy, and Naik (2016)	Eurekahedge, HFR, Lipper TASS, and Morningstar, 2006-2012	Up-Down/Regression based, portfolio construction	Hedge funds have a significant negative VOV (volatility of aggregate volatility) exposure especially during financial crises. Funds' VOV betas have a significant ability to predict excess returns one month ahead. Funds with low VOV betas outperform funds with higher VOV betas during the financial crisis period. Strategies with more negative VOV betas deliver superior returns when uncertainty in the market is less
Agarwal, Jiang, Tang, and Yang (2013)	SEC's EDGCAR database, 1999-2007	Up- Down /Probit-Tobit model, logistic regression, portfolio construction	There is evidence of managerial skill in stock picking. Funds running large risky portfolios with nonconventional strategies pursue confidentiality frequently and confidential holdings exhibit superior performance up to 12 months. Confidential treatment provides an incentive for active portfolio managers, whereas it relieves fund managers from having to reveal their private information, not having exploited the full benefits yet
Patton (2009)	HFR, TASS, 1993-2003	Up- Down /Regression based, bootstrap methods	About one quarter of funds in the market neutral category are significantly non-neutral. For other fund styles the proportions of non-neutral funds are from 50% for fund of funds to 85% for equity non-hedge style. Market neutral style funds are more neutral to market returns than other categories such as equity hedge, non-equity hedge, or event driven funds
Avramov, Barras, and Kosowski (2013)	Barclayhedge, TASS, HFR, CISDM, MSCI, 1994-2008	Up-Down/Regression based, portfolio construction	Approximately 63% of the sample funds have expected returns that change according to business conditions. Out-of-sample, a simple strategy that combines the fund's return forecasts obtained from individual investors produces superior performance. A conditional (singe-predictor) strategy that forecasts each macro variable (and selecting the top decile of funds with the highest return mean) is able to deliver superior performance. Another option is to diversify and use the average forecast from each predictor that avoids a poor fund selection when there is no accuracy in the return forecasting
Bali, Brown and Caglayan (2011)	Lipper/TASS, 1994-2008	Up-Down/Cross-sectional regressions, quintile portfolios	There is a positive relationship between default risk premium and hedge fund future return. More specifically, funds with higher exposure to the default risk premium in the previous month deliver higher returns in the following month. Hedge funds with lower exposure to inflation deliver higher returns in the future. In particular, funds with lower exposure to inflation in the previous month deliver higher returns in the following month
Bali, Brown and Caglayan (2012)	Lipper/TASS, 1994 to 2010	Up-Down/Cross-sectional regressions, portfolio analysis	Systematic risk is more powerful than residual risk in predicting the cross-sectional variation in hedge funds even after controlling for various fund characteristics (e.g. age, size and fees) and risk factors. Funds within the highest systematic risk quintile generate 6% more average annual return compared to funds within the lowest risk quintile. The relationship between residual risk and future fund returns is insignificant

Table 3. Performance Attribution – Non-linear Studies (continued)

Bali, Brown and Caglayan (2014)	Lipper TASS, 1994-2012	Up-Down/Cross-sectional regressions, portfolio analysis, PCA	There is a positive and significant relationship between uncertainty beta and hedge fund returns even when taking into consideration fund characteristics and risk factors. Macroeconomic risk is a better determinant of hedge fund returns than common financial risk factors. Directional strategies have a high exposure to the underlying macroeconomic risk factors. Non-directional funds and mutual funds do not have significant macro-timing ability
Brown (2012)	HFN and HFR, 1997-2010	Up- Down/Stepwise regressions	For most hedge fund strategies, volatility is an important source of systematic risk. Volatility measures based on equity market returns are more robust than volatility measures based on commodity market or fixed income. Many hedge fund styles carry significant exposures to traditional systematic risk factors such as equities, interest rates or credit. There is some evidence that fees may overwhelm hedge fund alpha
Chung, Fung, and Patel (2015)	GOEF, CRSP, French's website, Orissa Group, 1997-2006	Up- Down/Regression based, cross-sectional regressions	Hedge funds present stock-picking superiority for their loading on the market risk factor compared to other institutional investors across three different market eras: bubble, deflation, and recovery. A high churn rate and a high active share appear to be necessities for superior hedge fund returns. In addition, hedge funds load negatively on an illiquidity factor compared to other institutional investors. The robust superiority of hedge funds aligns with the use of active information acquisition (high churn rate) and active portfolio management (high active share)
Hubner, Lambert and Papageorgiou (2015)	HFR, 1996-2009	Up- Down/Higher moment regression based	The implied skewness and kurtosis of index portfolios increase models' explanatory power and reduce the specification error for the majority of hedge fund strategies. Market neutral, Relative value, and Fund of funds styles change their market exposure during financial crises. If fund managers use the volatility, skewness, and kurtosis implied by US options as tools for anticipating market movements then they should adjust their market exposure according to these movements
Ibbotson, Chen and Zhu (2011)	TASS, 1995-2009	Up- Down/Regression based	Hedge funds have positive alphas even during the 2008 financial crisis. Their exposures are generally reduced during bear markets. During the technology bubble collapse, fund managers on average underweighted equities in their portfolios
Namvar, Phillips, Pukthuanthong, and Rau (2016)	CISDM and TASS Lipper, 1996-2010	Up- Down/PCA, time-series, panel regression	During weak market states skilled fund managers maintain low systematic risk via active adjustments to return factor loadings even providing with low excess return. In strong market states, skilled fund managers provide incremental higher alpha than low skilled managers through superior asset selection ability. Over a two-year period, only 30% of funds remain in the same risk quintile. Systematic risk management skill is higher for better educated fund managers and lower for fund managers who manage funds with poor performance, low investor flows, and greater performance volatility
Patton and Ramadorai (2013)	HFR, CISDM, TASS, Morningstar and Barclay, 1994-2009	Up- Down/Dynamic high frequency econometrics	Hedge fund risk exposures change across and within months. Exposure variation is higher early in the month and then gets progressively lower until the reporting date. There are changes to portfolio allocations and to exposures in different asset classes, however changes in portfolio allocations are the main drivers of the funds' risk exposure variation. Also, hedge funds update their positions at a higher frequency than mutual funds

Table 3. Performance Attribution – Non-linear Studies (continued)

Racicot and Theoret (2016)	Greenwich Alternative Investment, 1995-2012	Up-Down/Kalman filter, time-series and cross-sectional regressions	The macroeconomic uncertainty is relied on conditional variances of six macro and financial variables (growth on industrial production, interest rate, inflation, market return, growth of consumer credit, and the term spread). Hedge funds' market beta reduces with macro uncertainty. This makes their strategies more homogeneous, resulting in a contribution to increased systematic risk in the financial system. The dispersion of hedge funds returns and alphas increases during times of rising macroeconomic uncertainty
Slavutskaya (2013)	TASS, HFR, CISDM, Altvest, 1994-2009	Up- Down/Cross-sectional and time-series regressions	By combining cross-sectional and time-series information there is an improvement in the out-of-sample accuracy of the linear factor model. The root mean squared prediction error in panel data models is significantly smaller (10%-15%) than linear regressions. The "naïve shrinkage" beta estimates correspond to weighted averages of individual fund and mean strategy betas

2.4.3 Alternative approach

This section presents studies that have addressed different methodological issues and tried to identify structural breaks in hedge fund returns. These studies focus on model uncertainty and its different behaviour when describing hedge fund returns. As with the up-down approach, these studies also tend to use more advanced econometric techniques.

I begin with Bollen and Whaley (2009) who used the CISDM database from 1994 to 2005. They ran an optimal change-point regression model that allowed risk exposures to change-switch (although they implemented it using just one change-point) and a stochastic beta model that used an autoregressive process for risk exposures. In order to select the most appropriate subset of available factors they first selected a subset of factors that maximized the explanatory power of a constant parametric regression by using the Bayesian Information Criterion. The change-point regression model performed better overall compared to the stochastic beta model, showing that approximately 40% of the hedge funds in their sample presented a significant shift in risk exposures. Moreover, for live funds, switches tend to take place early in the fund's life, whereas switcher funds tend to outperform non-switchers funds. Overall, time-varying risk exposures presented better estimates of funds' alphas and could make better hedge fund returns predictions.

Giannikis and Vrontos (2011) used the HFR database from 1990 to 2009 to examine the nonlinear risk exposures of hedge funds to various risk factors. Their analysis revealed that different strategies exhibited non-linear relationships to different risk factors and that a threshold regression model incorporating a Bayesian approach improved the ability to appraise hedge fund performance. They used the Bayesian approach to identify the relevant risk factors (instead of stepwise regression or performing other statistical criteria) and at the same time detect possible thresholds in the model. The Bayesian methodology solved two problems of the regression models: first, the uncertainty of the set of the risk factors and, second, the number and the values of the appropriate thresholds. This was a probabilistic approach incorporating prior information – inferences appropriate to the underlying datasets. Finally, different hedge fund strategies presented different timing abilities.

One more recent innovative study was from Jawadi and Khanniche (2012). They used the CSFB/Tremont database (hedge fund indices) over the period 1994 to 2009. They examined the adjustment dynamics of hedge fund returns and their exposures in a non-linear framework, and more specifically the smooth transition regression method. They found that the dynamics of hedge funds returns realized significant asymmetry and nonlinearity in relation to the market return, showing that they changed and differed asymmetrically with respect to different financial conditions. Furthermore, hedge funds exposures varied over time depending on the strategy and regime. They advocated the superiority of nonlinear models to capture the evolution of hedge funds exposures, especially during periods of financial crisis.

In the same year, Billio, Getmansky and Pelizzon (2012) examined hedge funds exposures using regime-switching beta models on data from the Credit Suisse/Tremont database from 1994-2009 (hedge fund indices). They noticed that hedge funds had non-linear exposures not only to the equity market risk factor, but also to the liquidity risk factor, volatility, credit, term spreads and commodities. Also, hedge funds changed their exposures when dealing with up, down, or tranquil regimes. Furthermore, they found that the S&P 500, Credit Spread, Small-Large and VIX (measure of volatility in S&P 500 index options – Chicago Board Options Exchange) were common hedge fund factors, especially in a falling market. The estimated exposures were unaffected even when authors de-smoothed the returns.

Related to the above study was one from Akay, Senyuz and Yoldas (2013) who examined hedge fund industry contagion and time variation in risk adjusted return (alpha), using the Dow Jones Credit Suisse Hedge Fund Indices database from 1994 to 2010. They used a Markov regime switching model and found three regimes that could capture hedge fund returns dynamics: the first was the crash state with large negative mean and extreme volatility, the second regime was a low mean and high volatility state, and the third regime was a high mean state with minimal volatility. They also found evidence for a decline in risk adjusted returns for most investment strategies especially after the stock market crash in 2000. Moreover, they found that co-movement in hedge funds returns, after counting for common risk factors, was not only restricted to times of extreme financial turbulence. Last but not least, they linked the probability of observing the crash state to liquidity proxies and panic, measured by the VIX index and found that both played a significant role in leading to contagion.

A final study is from O'Doherty, Savin, and Tiwari (2015), using the Lipper TASS database from 1994 to 2011, implementing a pooled benchmark model by combining (with different weights) five linear models: five equity factors, three fixed income and commodity factors, three global factors, the five Fung and Hsieh (2001) trend following factors, and the four Agarwal and Naik (2004) option-based factors. Their optimal pool was based on the score log which was a measure of the conditional performance of a factor model, regarding its ability to track the monthly return for a given hedge fund. The authors verified that the above factors of the models capture hedge funds' exposures; in addition, their optimal pooled benchmark mitigated the (benchmark) error of these factor-based attribution models. Also the model pooling approach had more predictive power for failures among the funds in their sample than other performance attribution models.

To sum up, several non-linear studies that follow the down-up approach have examined hedge fund performance as a non-linear payoff of hedge fund returns in relation to market returns. However this replication is not easily understood or implemented by investors. Moreover, there are some hedge fund strategies (such as multi-strategy and global macro) that are less well-defined, thus making their return replication through security trading a challenge. On the contrary, studies that follow the up-down and especially the alternative approach have as a strength higher flexibility in explaining hedge fund performance attribution. They supported previous studies that hedge funds have nonlinear returns and exposures and they studied how these nonlinear exposures change over time, explaining hedge funds' behaviour. In addition, different strategies usually have different exposures although there are a few exposures that are valid for nearly every hedge fund strategy (e.g. equity market, volatility).

Table 4. Performance Attribution – Non-linear Studies

This Table presents the main characteristics and findings of the nonlinear studies (alternative approach) of hedge fund performance attribution. Abbreviations: CISDM: Centre for International and Securities Markets, CSFB: Credit Suisse First Boston, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services. Some databases (e.g. Lipper and TASS, MAR and CISDM) have been merged.

Study	Sample	Approach/Methodology	Findings
Akay, Senyuz, and Yoldas (2013)	Dow Jones Credit Suisse Hedge Fund Indices, 1994-2010	Alternative/Markov regime switching model	There are three regimes that describe hedge fund returns. When accounting for common risk factors, there is hedge fund return co-movement across different time periods. When considering common risk factors, the co-movement in hedge fund returns is not limited to periods of extreme financial turmoil. The TED spread (margin requirement on the S&P 500 contract) and the VIX index play a significant role in leading to contagion in hedge fund returns
Billio, Getmansky and Pelizzon (2012)	CSBF/Tremont, 1994-2009	Alternative/Regime switching models	Beyond market exposure, hedge funds have non-linear exposures to liquidity, volatility, credit, term spread, and commodities. Hedge funds change their exposures when dealing with different regimes. Hedge fund exposures depend on whether the equity market is in the up, down or tranquil regime
Bollen, and Whaley (2009)	CISDM, 1994-2005	Alternative/Optimal change-point regression	Through change-point regression (allowing for a single shift in parameters for each fund), there are significant changes in risk factor parameters in about 40% of the sample hedge funds. For live funds, switches tend to occur early in the fund's life whereas switcher funds tend to outperform non-switcher funds
Giannikis and Vrontos (2011)	HFR, 1990-2009	Alternative/Threshold regression with Bayesian approach	Different hedge fund strategies exhibit non-linear relations to different risk factors. A Bayesian approach improves hedge fund performance appraisal. Different hedge fund strategies exhibit different timing abilities
Jawadi and Khanniche (2012)	CSFB/Tremont, 1994-2009	Alternative/Smooth transition regression	Hedge funds returns change and differ asymmetrically during different financial conditions. Hedge fund exposures vary over time according to strategy and regime. Also, the relationship between hedge fund returns and risk factors varies over time and depends on regimes (e.g. expansion, crisis)
O'Doherty, Savin, and Tiwari (2015)	Lipper/TASS, 1994-2011	Alternative/Pooled benchmark model approach, portfolio construction	By using the pooled benchmark approach, there is a reduction in the (benchmark) error of the factor-based attribution models. The model pooling approach has more predictive power for failures among sample funds than other performance attribution models

2.5 Conclusion – First part

This part has demonstrated how hedge funds returns can be explained using implicit or statistical factor models. It has presented a combination of older literature to give a historical perspective and recent papers to reveal advances in those topics. This review is important because is the first that presents and analyses very recent studies that explain a large part of the hedge fund return generating process, showing and discussing how the research has evolved.

Principal Component Analysis and Common Factor Analysis are the two widely-used statistical approaches that are used to distinguish the factors underlying hedge fund returns and these are presented in detail. Concerning the CFA, which is more common in the literature, early studies dealt mostly with linear factor models. Then there was a consiserable amount of work done in a movement toward non-linear models that tried to explain hedge funds' performance as option portfolios. Non-linear studies may follow a down-up, an up-down, or alternative approach (that is an extension of the up-down approach). Recently, there have been several studies using more advanced models regarding hedge fund exposures that have contributed a great deal to hedge fund knowledge. They confirmed previous studies that hedge funds have nonlinear returns in terms of market returns, and they studied how these nonlinear exposures change over time according to financial conditions. Different strategies usually have different exposures. However there are a few exposures that are valid for nearly every hedge fund strategy (e.g. equity market, volatility, liquidity). Macroeconomic risk has a significant role in hedge fund performance for nearly all strategies. Moreover, higher moment factors can provide extra explanatory power to the models, and hedge fund managers in general show superior stock-picking ability than other institutional investors.

In this review I have presented and analyzed studies that try to explain hedge funds returns using implicit statistical factors. It is crucial for an investor or researcher to understand how hedge funds exposures change over time, taking into consideration their styles as well as the economic environment in which they operate. That environment is very dynamic, thus the researcher should incorporate those external variables into her model for more robust and reliable results. It is also helpful to understand the evolution and advances in hedge fund implicit factors so as to better evaluate hedge funds or at least know what to expect from different hedge fund strategies or fund styles. I believe that this study adds value to investors and uncover opportunities for further research, presented later.

A limitation of this study is that I do not consider other aspects of hedge funds, for instance, specific characteristics (e.g. fundamental factors such as size, lockup periods etc.) that affect fund performance, fund performance persistence[9] or qualitative performance criteria (e.g. fund investment policies, management experience); this is because this study specializes in the return generating mechanism of hedge funds within implicit or statistical factor models. Another limitation is that there are differences in studies due to industry heterogeneity and authors use different sample periods, datasets, and methodologies. However, this is a common issue faced by other authors. Even with this limitation, there are some consistent trends and conclusions that can be helpful to investors.

Possible directions for future research include, first, the external macroeconomic environment that hedge funds operate and, second, the internal structure of the hedge fund industry. Concerning the former, there is a need for a general comprehensive framework that includes the impact of economic policies (e.g. monetary and fiscal) on hedge funds' performance or examining the impact of different market conditions in a holistic approach not isolating one or two only stressful economic events. However, this depends on hedge fund data availability for the earlier years. Concerning the later, there is a need to examine the return generating mechanism within the hedge fund market microstructure. For example, the way that the working processes in the hedge fund industry relate to transaction costs, quotes, volumes, prices and trading behavior needs to be considered. Those elements have an impact on hedge fund exposures and returns.

2.6 Introduction- Second part

In the hedge fund literature there are many studies dealing with performance persistence[10] along with other studies that investigate the relationship between fund returns and fund specific characteristics such size, age and fees[11]. Although these studies use different databases and time periods, they can nevertheless provide a useful guide to investors. Investors expect performance to be stable over time and that some

[9] I provide a relevant survey in another paper, Stafylas, Anderson, and Uddin (2016).
[10] For example Ammann, Huber and Schimid (2013) and Hentati-Kaffel and Peretti (2015).
[11] E.g. Frumkin and Vandegrift (2009); Joenvaara, Kosowski and Tolonen (2012); Bae and Yi (2012).

fund managers outperform their peers. Also funds may show an association between their returns and characteristics such as size, age, fees or other fundamental factors. Until now, there has been no survey summarizing all the results and there is no uniform conclusion on these issues, thus creating confusion for investors. Consequently, the present study closes an important gap. The aim of this paper, is to survey the literature and investigate hedge fund performance in terms of (*i*) return persistence and (*ii*) the relation of fund returns to fund characteristics (fundamental factors) such as size, age, fees and other factors (e.g. lockup and domicile factors as explained in section five). This is the first survey and synthesis of older literature to provide a historical perspective, together with information from recent innovative studies to delineate advances in performance persistence and the attributes of individual hedge funds. The findings both assist hedge fund investors and unravel opportunities for further research, as I describe later. Despite the difference in studies, there are some consistent trends and patterns that reveal useful aspects about hedge fund behaviour in terms of performance persistence and the relation between performance and fund characteristics.

The main conclusions are that early studies (e.g. Agarwal and Naik, 2000a, Bares, Gibson and Gyger, 2003) showed that there is short term persistence (less than a year). Moreover, there is evidence that some non-directional strategies (e.g. e.g. Convertible Arbitrage or Merger Arbitrage strategies) present more persistence than directional strategies (e.g. Long Only or Short Bias strategies). The difference in persistence is mainly related to the type of strategy each fund follows. However, some later studies (e.g. Kosowski, Naik and Teo, 2007; Jagannathan, Malakhov and Novikov, 2010; Amman, Huber and Schmid, 2013) have challenged the above studies and showed that there is persistence beyond one year and possibly up to five years. Concerning the fundamental factors and fund returns, most studies show that there is a negative relationship between fund size and performance. Regarding the age factor there is a clear negative relationship between age and performance. There is also a positive relationship between incentive fees and fund performance. Funds imposing lockups outperform funds that do not impose lockups and on-shore funds outperform off-shore registered funds.

This study makes a number of important contributions to the understanding of the literature. First of all, I close a gap by presenting a survey that summarizes all the results concerning hedge fund return persistence and the relation between fund characteristics and fund returns. In addition, I present a historical perspective by combining older and newer, innovative studies. Thus the reader is able to observe the dynamic nature of the literature in explaining fund return persistence and fund returns according to the underlying fundamental factors. This study helps investors in their asset allocation process as it enables them, firstly, to assign the appropriate weight (according to their needs) in fund selection based on their past returns. Secondly, it enables them to know what to expect from funds with different characteristics. Last but not least, I have identified some gaps for future research such as the absence of a unified framework that examines fundamental factors-attributes on hedge fund performance and their interactions.

In this part 2, Section 2.7 provides a necessarily brief overview of the hedge fund industry. Section 2.8 describes the different categories of models for hedge fund returns. Section 2.9 surveys the literature on hedge funds' performance persistence and section 2.10 covers the literature that seeks to explain hedge fund returns using their characteristics. In these two parts I review all these issues and then discuss some logical observations about the underlying studies. In the final section 2.12 (overall conclusion) I present and summarize the key conclusions and reveal some gaps that should be covered in future research.

2.7 The hedge fund industry

This section briefly introduces the reader to the hedge fund industry, as an extensive analysis would be outside the scope of this paper. It first looks at some issues to do with the nature of hedge funds and their different characteristics in relation to more traditional investments. It then presents the composition and growth of the hedge fund industry in terms of assets under management and returns.

2.7.1 An idiosyncratic industry

Hedge funds are private in nature and all the characteristics of the hedge fund industry derive from this. These investment vehicles are not accessed by the general public and are largely unregulated by the SEC. Therefore fund managers are not obliged to disclose information to investors and authorities as other conventional investments (e.g. mutual funds) are. Consequently, there is no transparency and as far as the compensation structure is concerned, hedge funds rely mostly on incentive fees. On average, fund managers receive a one percent annual management fee on AUM (assets under management) and 20 percent annually on any profits. Most funds use a bonus incentive fee (called the "high-water mark").

Fund managers are able to exploit a wide range of "toolkits" such as buying and selling using a cash account, buying on margin, short selling and securities lending, leverage (borrowing) and derivatives. A cash account is the simplest and most common form of transaction because there is no further commitment, as such transactions do not involve any loan or require any collateral.

The hedge fund industry is very competitive and demanding as it focuses on providing accredited investors with the best possible performance. There are many categories and strategies of hedge funds depending on their investment style/strategy and/or region that invest in. Unfortunately, there is no universal classification scheme for hedge funds. In the literature there are several classification schemes (e.g. Tran, 2006; Kosowski, Naik and Teo, 2007 or Bali, Brown and Caglayan, 2011) or those provided by the various private database vendors. A hedge fund may have many structures (e.g. Limited Liability Company or Partnership, Onshore or Offshore) and require many service providers to operate.

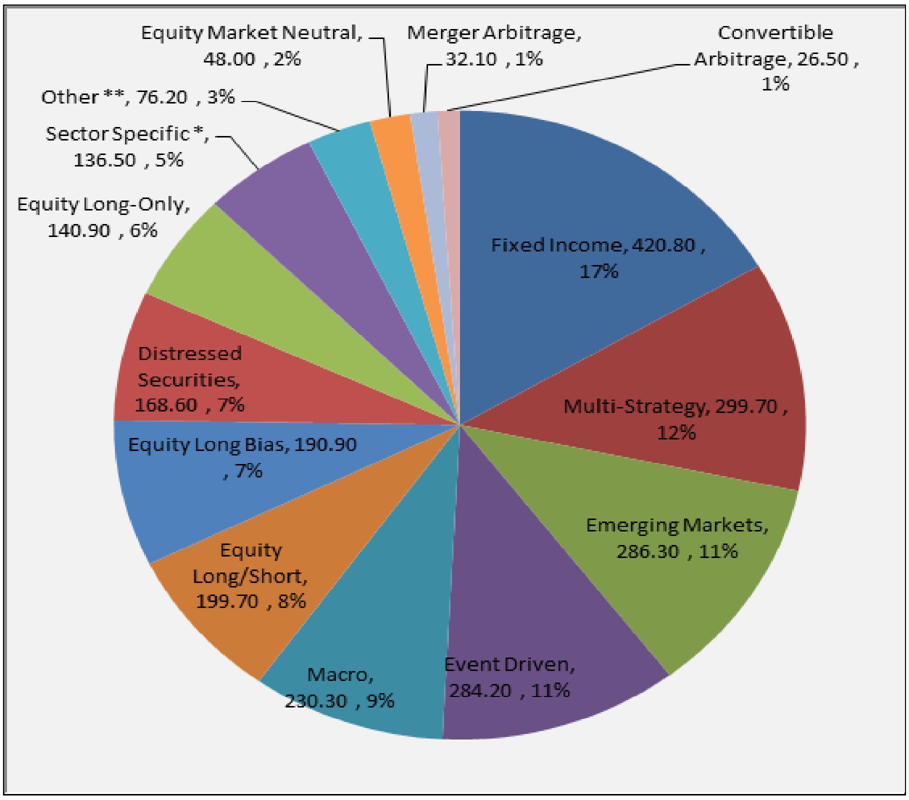
The hedge fund industry is complex by its nature and investors cannot easily cope with this when evaluating hedge funds unless they have specialized knowledge and access to specific information. Hedge funds do not provide full information disclosure (not only about the fund itself but sometimes about the fund management team, as well) and there are many benchmark indices in the market, thus making investors' decision processes even more difficult. However, one aspect that investors try to rely on in their asset allocation process is fund performance persistence and the relation between fund returns and fund characteristics. Hence, this survey summarizes all the results concerning hedge fund return persistence and the relation between fund characteristics and fund returns, which should be particularly useful for investors trying to choose between hedge funds.

2.7.2 Industry growth in assets under management

The decade to 2015 has seen considerable growth in the hedge fund industry. Except for 2008 and 2011 all the other years were profitable. As of 2015Q2 total assets under management for hedge funds were more than $2.7 trillion. This figure does not include

Fund of Funds and Commodity Trading Advisors (CTAs) that account for approximately $500 billion and $330 billion respectively. Figure 1 provides some numbers for assets under management (AUM) as of 2015Q2. It can been seen that four strategies (Fixed Income, Multi-Strategy, Emerging Markets and Event Driven) account for 51 percent of the total AUM. On the contrary, the four least popular strategies (Convertible Arbitrage, Merger Arbitrage, Equity Market Neutral and Other) account for only seven percent of the total AUM. As it will be shown in section four, some non-directional strategies (e.g. Convertible Arbitrage, Merger Arbitrage, Relative Value or Event Driven) and Emerging Market strategies demonstrate more persistence than aggressively directional strategies (e.g. Global Macro, Long Short, Long Only or Short Bias strategies).

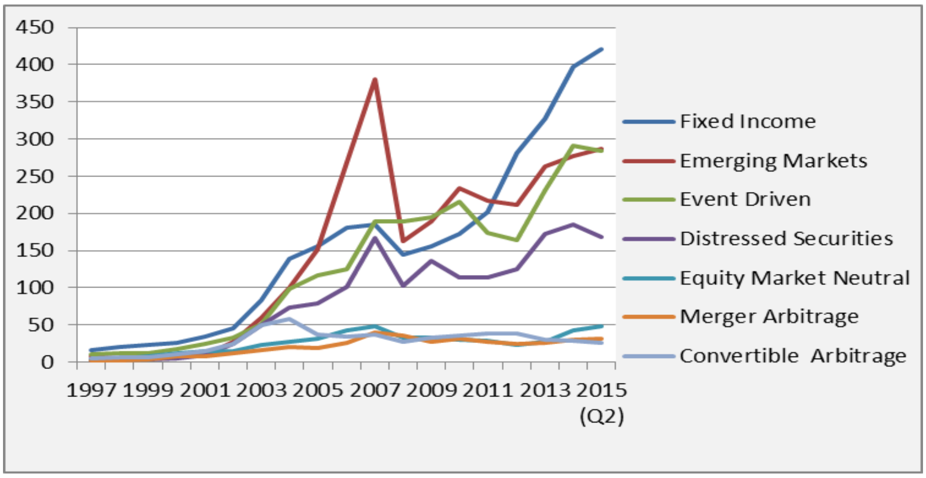
Figure 1. Assets Under Management (USD Billions)



Assets allocated per strategy (source: BarclayHedge, 2015)

Currently the number of hedge funds is more than 10,000 globally. The growth in the hedge fund industry is due to the appreciation of assets and new money entering the industry. Figure 2 presents the historical growth of the assets for non-directional strategies. During the early 2000s there was substantial growth in the industry, reaching its peak before the financial crisis in 2008. After the 2008-9 losses the significant growth in assets continues.

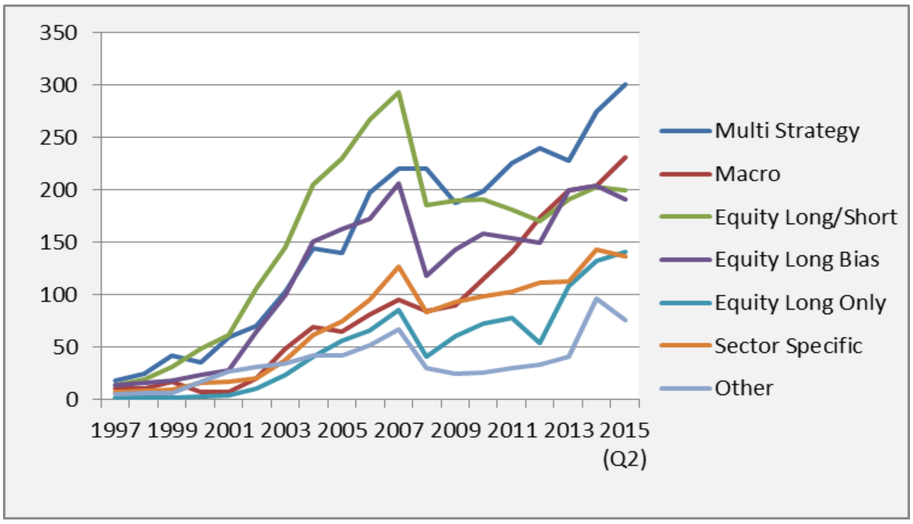
Figure 2. Hedge Fund Industry AUM – Non Directional Strategies



Non-directional strategies Assets Under Management (source: BarclayHedge, 2015)

Figure 3 presents the historical growth in assets for directional strategies. During the early 2000s there was substantial growth in the industry (more than in non-directional strategies) that reaching its peak before the financial crisis in 2008. Again, the 2008-9 losses have largely been made up (or more) by 2015.

Figure 3. Hedge Fund Industry AUM – Directional Strategies

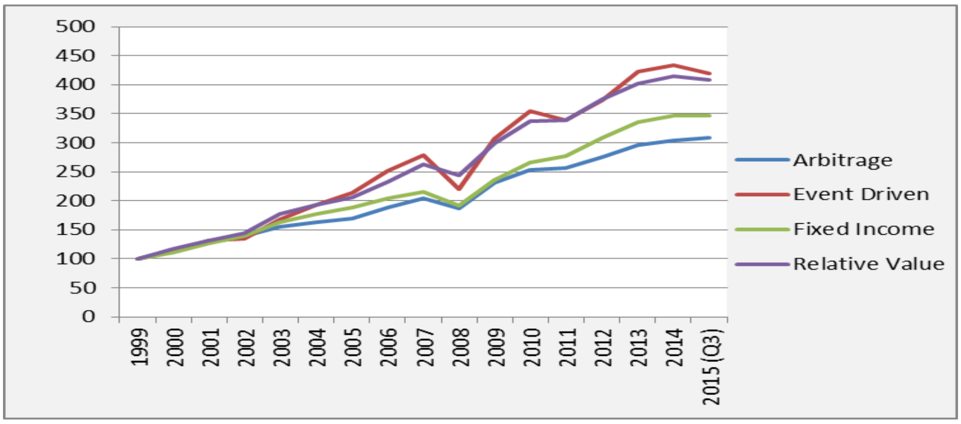


Directional strategies Assets Under Management (source: BarclayHedge, 2015)

2.7.2.1 Returns

Figure 4 presents accumulated returns for indicative non-directional strategies. (In general, figures in this section provide indicative-only information on the hedge fund industry as an extensive representation and analysis would be out of the scope of this paper.) From late 1999 to 2015(Q3) the average investor could have earned between 3.1 and 4.2 times her initial capital. The indices were moving upwards for the whole period except for 2008 (financial crisis) and 2011 (Eurozone crisis). This reduction in returns coincides with the reduction in AUM, particular in 2008.

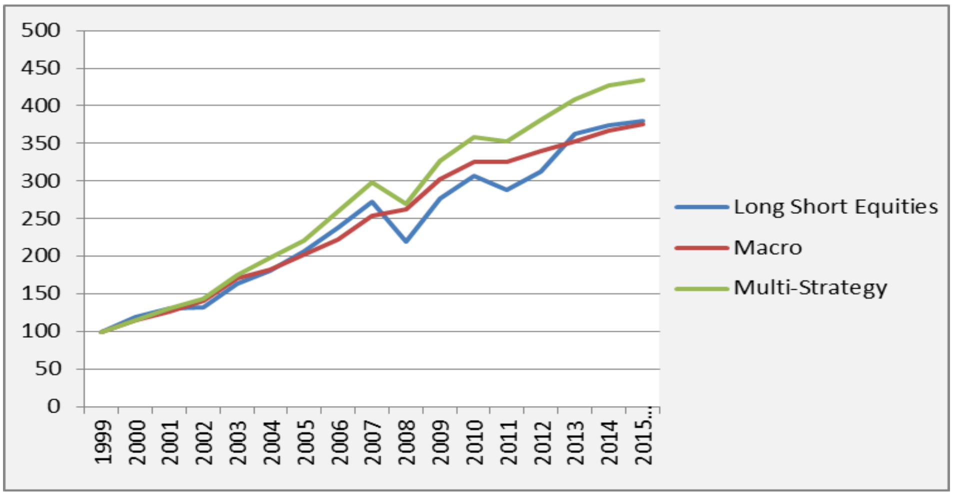
Figure 4. Hedge Fund Industry Returns – Non-Directional Strategies



Strategy Indices, Base=100 (Dec 99) (source: Eurekahedge, 2015)

Finally, Figure 5 presents accumulated returns for indicative directional strategies. From late 1999 to 2015(Q3) the average investor could have earned between 3.8 and 4.4 times her initial capital. These returns are higher than those of non-directional strategies because directional strategies are usually more aggressive, having higher volatility than non-directional strategies. As for non-directional strategies, the indices were moving upwards for the whole period except for 2008 and 2011.

Figure 5. Hedge Fund Industry Returns- Directional Strategies



Composite Index, Base=100 (Dec 99) (source: Eurekahedge, 2015)

2.8 Categorising models of hedge fund returns

This section provides a general overview of the various types of hedge fund models that are applied to all hedge funds. Each type of model represents a different approach to measuring the performance of all hedge fund strategies. In general, asset pricing models are divided in two main categories (Lhabitant, 2004): (*i*) absolute pricing models and (*ii*) relative value models. The first category includes fundamental equilibrium models and consumption-based models in conjunction with many macro-economic models. All the models that I mention in this section refer to the category of relative price models which price or evaluate hedge funds relative to market or any other risk factors.

The reader is reminded that Amenc, Sfeir and Martellini (2003) recorded four categories of factor models. These are: (1) *Explicit macro factors*, (2) *Explicit index factor model*: (3) *Explicit micro factor models* (I discuss this perspective in this part). (4) *Implicit factor models* through the use of Principal Component Analysis (PCA) or Common Factor Analysis (CFA). A similar classification is proposed by Connor (1995) with three categories of factor models that are available for examining asset returns. These are: *Macroeconomic factor models*, *Fundamental factor models* and *Statistical factor models*.

Regarding the statistical or implicit factor models there are two widely-used methodologies that are used to identify the underlying factors: (i) *Principal Component Analysis (PCA)* and (ii) *Common Factor Analysis*. PCA was invented by Pearson (1901). The purpose is to justify the return series of observed variables via a smaller group of non-observed implicit variables or principal components. The second methodology, common factor analysis, is similar to PCA in that it transforms a number of correlated variables into a smaller number (dimensionality reduction) of uncorrelated variables, that is, factors. However, there is a great difference with PCA. Here, the selected factors are observable and clearly decided by a combination of confirmatory and/or explanatory analysis. They are not just implied by the data. As with PCA the number of factors should be kept as small as feasible in order to have the advantages of dimensionality reduction.

Explicit micro-factor models are selected factors that refer to fund specific features, such as size, age, fund manager tenure and performance fees. As I discuss below (section five), there are many studies that deal with that issue (for more details on category models please see section 2.2).

2.9 Performance persistence

Performance persistence is one perspective by which an investor evaluates hedge funds. Other perspectives include hedge funds biases that are inherent from various databases, hedge funds as portfolio diversifiers and hedge funds' survivability. Other authors have tried to explain and evaluate hedge funds using risk-adjusted returns and volatility, and also multi-factor models (that they are mentioned earlier) showing their low or negative correlation with market indices. This section reviews studies that cover performance persistence.

2.9.1 Evaluating performance persistence

The term 'Performance Persistence' is used to denote how steady hedge funds' performance is. In other words, how constantly hedge funds perform in a positive or negative manner. Performance persistence is usually measured in the short term (less than or equal to a year) and long term (more than a year).

There are many studies concerned with hedge fund performance persistence and some of them are presented. Most pre-2007 findings argued that there is short term performance persistence (from one to three months). At most persistence lasts up to one year. However, beyond this there appears to be no persistence. Also some strategies appear to be more consistent than others. This is intuitive especially for non-directional strategies. However, during the last five years some studies, using more advanced econometric methods, have found that there is long term performance persistence. In some cases the performance persistence reaches up to five years. Below there is an analysis and critique of the relevant studies in detail. They are examined short-term persistence in returns, long-term persistence and then how researchers or investors can best exploit what is known. Table 5 shows the relevant studies.

Table 5. Performance Persistence

This Table presents the main characteristics and results of the studies on hedge fund performance persistence. Abbreviations: CISDM: Centre for International and Securities Markets, GMM: Generalized Method of Moments, GR: Generalized Runs Tests, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services, MSCI: Morgan Stanley Capital International, SDI: Strategy Distinctiveness Index. Some databases (e.g. Lipper and TASS) have been merged.

Study	Sample	Methodology	Results
Agarwal, V. and Naik, N. (2000a)	HFR, 1982-1998	Regression, chi square, cross product ratio, Kolmogorov Smirnov	Persistence at quarterly horizon
Agarwal, V. and Naik, N. (2000b)	HFR, 1995-1998	Regression, cross product ratio	Persistence at quarterly horizon
Ammann, M. Huber, O. and Schmid, M. (2013)	Lipper/TASS and CISDM, 1994-2008	Panel probit regression	Persistence up to three years
Bae. K.H. and Yi, J. (2012)	TASS, 1994-2008	Probit regression, comparison of rankings	Persistence at least yearly
Bares, P.A., Gibson, R. and Gyger, S. (2003)	FRM, 1992-2000	Regression, benomial representation, comparison of rankings	Persistence up to three months
Brown, S. and Goetzmann, W. (2003)	TASS, 1989-1999	Regression	Persistence at less than a year
Capocci, D. (2009)	HFR, MAR, TASS, Barclays, 1995-2002	Regression, comparison of rankings	Persistence at less than a year
Capocci, D. and Hubner, G. (2004)	HFR and MAR, 1984-2000	Regression, comparison of rankings	Persistence at less than a year
Eling, M. (2009)	CISDM, 1996-2005	Regression, chi square, cross product ratio, Spearman, Kolmogorov Smirnov	Persistence up to six months
Harri, A. and Brorsen, B. (2004)	LaPorte Asset Allocation, 1977-1998	Regression, Spearman	Persistence up to four months
Hentaki-Kaffel, R. and Peretti, P. (2015)	HFR, 2000-2012	Regression, GR tests	Persistence less than a year
Jagannathan, R., Malakhov, A. and Novikov, D. (2010)	HFR, 1996-2005	Regression-GMM	Persistence over three years
Joenvaara, J., Kosowski, R. and Tolonen, P. (2012)	BarclayHedge, EurekaHedge, HFR, Morningstar and TASS, 1994-2011	Contingency table, regressions, comparison of rankings	Persistence up to one year
Koh, F., Koh, W. and Teo, M. (2003)	Eurekahedge and AsiaHedge, 1999-2003	Cross product ratio, chi square, Kolmogorov Smirnov	Persistence up to quarter
Kosowski, R., Naik, N. and Teo, M. (2007)	TASS, HFR, CISDM and MSCI, 1990-2002	Bayesian approach, bootstrap approach, regression	Persistence over a year
Park, J., Staum, J. (1998)	TASS, 1986-1997	Chi square, Spearman	Persistence at yearly horizon
Wang, A. and Zheng, L. (2008)	TASS, 1994-2007	Regression, SDI	Persistence up to five years

2.9.1.1 *Short-Term persistence*

In their early study Park and Staum (1998) examined hedge fund performance persistence using the TASS database from 1986 to 1997. They used regressions taking into consideration non-adjusted returns for the risk-free rate. More specifically they used the ratio α/σ where α is the return in excess of an index benchmark and σ the standard deviation of the fund. They found that there is performance persistence for a year. That element could give some indication of future performance. However, the strength of the persistence seemed to vary substantially from year to year. Similar results were also found for CTAs (Commodity Trading Advisors).

In their research, Agarwal and Naik (2000a) investigated the extent of pre-and post-fee hedge funds persistence from 1982 to 1998 using the Hedge Fund Research database. They used a multi-period framework and the traditional two-period framework. Within the former there is less likelihood that the observed persistence will be by chance. They also measured whether the persistence is sensitive due to returns measured over quarters (short term) or over years (long term). Finally, they investigated whether fees affect the degree of persistence observed among hedge funds.

Regarding their methodology, they used regression-based (parametric) and table-based (non-parametric) methods. In the first approach, they regressed alphas (appraisal ratios) during the current period against those of the previous period. A positive slope coefficient meant that a hedge fund that performed well in the previous period, performed well also in the given period. For the second methodology they constructed a contingency table of winners and losers. In this table, a hedge fund was considered a winner if the alpha of that fund was higher than the median alpha of all the hedge funds that follow a comparable strategy, in that specific period. Otherwise that hedge fund was a loser. The techniques were a cross-product ratio/CRP and Chi-square statistic.

Agarwal and Naik (2000a) found a substantial amount of persistence at the quarterly horizon. This characteristic weakened as they moved to yearly returns. Hence, hedge fund persistence is mainly short term in nature. The persistence did not appear to be related to the type of strategy followed by the hedge fund. The degree of persistence realized in a multi-period framework was significantly smaller than that realized based on the traditional two-period framework. Moreover, the multi-period framework had almost no persistence when examined in relation to yearly returns. Short term persistence was not affected by the imputation of performance fees.

In the same year, Agarwal and Naik (2000b) using the HFR database from 1995 to 1998 examined hedge fund persistence using parametric and non-parametric methods. More specifically, they used similar approaches in their (2000a) study such as regression-based (appraisal ratios) and contingency-table-methods of winners and losers with the cross-product-ratio/CPR statistic. They had similar results to their previous study, showing that there is persistence mainly at a quarterly horizon in various hedge fund strategies: fund losers continue to be losers instead of winners continuing to be winners.

Similarly, Bares, Gibson and Gyger (2003) examined the performance persistence of hedge funds across short and long term investment horizons using the Financial Risk Management (FRM) database from 1992 to 2000. They relied on non-parametric tests. They regarded a fund as a winner a fund if its performance was above average for a given period and the opposite for a loser. They found that the Specialist Credit and Relative Value strategies were the most persistent strategies (they contained the highest percentage of managers who were consistently outperforming their median peers). This is different from Agarwal and Naik (2000a) who found that persistence did not pertain to any type of strategy. Nevertheless, that persistence disappeared rapidly as the time horizon extended. The authors also analysed the duration of performance persistence. They observed significant short term (one to three months) persistence.

In the same year, an interesting study from Koh, Koh and Teo (2003) examined Asian hedge funds regarding their style, fund characteristics and persistence. They used the databases of EurekaHedge Advisors Pte Ltd (now Eurekahedge) and HedgeFund Intelligence (hereafter AsiaHedge). The data sample was from 1999 to 2003. Using two-period and multi-period tests (Kolmogorov-Smirnov statistic), they found that Asian hedge funds' returns persisted more vigorously at monthly periods to quarterly periods. That persistence diminished considerably after lengthening the measurement time interval beyond a quarter did not seem to be because of the charging of fees.

Harri and Brorsen (2004) used data from 1977 to 1998 provided by LaPorte Asset Allocation. They examined hedge fund persistence and the relation between fund size and performance. They identified seven styles of hedge fund strategy: global, global macro, sector, market neutral, short sales, event driven and long only. Also, there were two categories of Fund of Funds (FoF): U.S. and offshore FoF. The authors used three alternative methodologies: (*i*) a regression between current returns and past returns, (*ii*) a style analysis resembling Sharpe (1992) and Fung and Hsieh (1997) and (*iii*) a sample test using Spearman rank correlation. They found an indication of short-term performance persistence for almost all styles apart from short sales. However, the performance persistence was small. There was a need for a large number of observations and rigorous techniques were necessary to detect it despite the fact that they used data covered a long period of time and used three alternative methodologies. Their results were very similar to those of Agarwal and Naik (2000a) who similarly found some performance persistence in hedge funds except from short-sales strategies. The styles that showed the largest persistence were market neutral and the two FoF styles (U.S and offshore FoFs). Global, global macro and event driven also showed some performance persistence. Agarwal and Naik (2000a) also discovered that some hedge fund styles exhibited greater performance persistence than others.

In the same vein, one study considering a long period of hedge funds returns was by Capocci and Hubner (2004). They examined hedge fund performance using the HFR and MAR databases from 1984 to 2000. They found (using 10 and 14-factor regression models) that the top performer funds followed momentum strategies whereas the bottom performers followed contrarian strategies (and significantly invested in emerging markets bonds, unlike top performers). Also, there was no performance persistence for the best and worst performing hedge funds. By contrast, there was performance persistence in the middle quintile of funds. In addition, funds that experienced average returns often bought high book-to-market stocks. Conversely, those funds that were the best and worst performers were in favour of low book-to-market stocks. Concerning strategies, they found that two of them systematically out-performed markets: Global Macro and Market Neutral, which out-performed the market for 1994 to 2000. However, there was a concern about the statistical reliability of return observations for the period from 1984 to 1993 due to survivorship and instant history biases (there is lack of data for funds that were dissolved prior to 1994 in the databases).

Extending his previous study (Capocci and Hubner, 2004) and using the same methodology but adding two more databases (TASS and Barclays), Capocci (2009) considered criteria that enable hedge funds to outperform equities and bond indices over bull and bear markets. The period was 1995-2002 (that contained the peak of the

NASDAQ composite index). The evaluations used include the returns, the volatility, the Sharpe score, the alpha, the beta, the skewness and the kurtosis. He found that hedge funds with stable returns and low volatility and/or low exposure to the market were able to significantly outperform the market indices in a consistent way under all market conditions.

In the same year, another very important study of performance persistence was from Eling (2009). He reviewed a number of studies into hedge funds’ performance persistence. Jointly evaluating these results showed him that there was hedge fund persistence for short time periods of up to six months. However, the longer the time period, the lower the significance of hedge fund performance persistence. Eling additionally presented an empirical study of hedge funds’ performance persistence.

Eling used data from CISDM and six different methodologies (cross-product ratio test (CPR), chi-square test (CS), rank information coefficient (RIC), Spearman rank correlation (SRC), cross-sectional regression (CSR) and Kolmogorov-Smirnov test (KS)). The data sample was from 1996 to 2005. He considered 18 hedge fund strategy groups with six time horizons: monthly, bimonthly, quarterly, half-yearly, yearly and two-yearly. He also considered six performance measures (raw returns, Sharpe ratio, two versions of alpha and the two associated appraisal ratios).

Most of the tests showed high levels of persistence for horizons of up to six months. The persistence levels weakened slightly as the time horizon was extended beyond six months. However it is important to mention that the level of persistence varied widely depending on the methodology. Eling confirmed the conclusions of Agarwal and Naik (2000a) that the level of performance persistence realized in a multi-period framework is substantially smaller than that noticed in a two-period framework.

Eling found differences in performance for different hedge fund strategies. The Convertible Arbitrage and Emerging Markets strategies had very high levels of persistence. In contrast, strategies such as Equity Long Only had smaller levels of significance. Furthermore, Merger Arbitrage and Sector strategies preserved their high levels of significance across time horizons, contrary to all the other strategies where the significance level decreased as Eling extended the time horizon. Eling concluded that hedge funds’ performance persistence is related to the specific style of fund management (he found that 20% of the cross-sectional variability of funds' returns can be attributed to the style management).

Concerning the performance measures and their relation with performance persistence, Eling found that there are small differences in the levels of significance among these different performance measures. The persistence significance levels weakened as he extended the horizon. However, the appraisal ratios keep a very stable level of significance. It appears that the level of hedge fund performance persistence is not associated with the choice of performance measure.

An important study that first challenged all the above studies is from Kosowski, Naik and Teo (2007). They used four databases: TASS, HFR, CISDM and MSCI. The sample period was from 1990 to 2002. Exploiting a bootstrap procedure, they found that the best hedge fund performance cannot be justified by chance. Furthermore, there is hedge fund performance persistence at annual horizons. In addition, using Bayesian measures they overcame the negative issue of the short sample period (many of the top funds have very short return histories so produced alphas overestimate the performance of top funds and underestimate the performance of the bottom funds). Kosowski *et al*. argued that early researchers imprecisely measured performance and relied too much on the frequency probability of returns in short periods. That is, they focused too much how returns behaved in short time periods.

The authors took into consideration other explanations of the persistence results (persistence in fees or short-term serial correlation in returns), but found evidence of inconsistency in these justifications. For example the evidence for persistence is weaker for hedge funds with high inflows. Last but not least, hedge fund performance persistence is stronger for some hedge funds strategies such as Long/Short Equity, Directional Traders, Relative Value and Fund of Funds.

A recent comprehensive study with similar results to Kosowski *et al*. (2007) is from Joenvaara, Kosowski and Tolonen (2012) that used five databases from 1994 to 2011. The databases were BarclayHedge, EurekaHedge, HFR, Morningstar and TASS. They considered three periods: quarterly, semi-annual and annual. They found marginally significant performance persistence at annual horizons. In detail, small funds showed persistence even at an annual horizon, whereas short-term persistence was difficult to exploit due to share restrictions (lockup, notice and redemption periods). Larger funds' persistence is much weaker. They emphasized the effects of database differences and biases in hedge funds' average performance persistence and cross-sectional relationships between funds' characteristics and risk-adjusted returns. They documented that hedge fund performance, persistence and cross-sectional differences are sensitive to the choice of database. Also, performance persistence is sensitive to share restrictions, fund size, rebalancing frequency and weighting schema.

Hentati-Kaffel and Peretti (2015) used the HFR database from 2000 to 2012 to analyse the statistical properties of hedge fund returns in terms of randomness. They used the generalized runs test which allows checking for the null of randomness (i.e. no persistence), against a broad and undefined alternative including structural breaks or first and second-order dependence. They found that less than 50 percent of the sample was based on independent, identically distributed random variables but that this behaviour depended on the strategy. Under their new framework which deal with randomness and the persistence of hedge fund returns, greater persistence allowed some strategies (e.g. Relative Value or Event Driven) to be clustered better than other funds (e.g. Equity Hedge and Macro Strategies).

To sum up, the overall view is that short term persistence exists (Agarwal and Naik, 2000a; Bares *et al.*, 2003) but it seems that non-directional strategies show persistence more clearly (Bares *et al.*, 2003; Eling, 2009). More details concerning the nature of this short-term persistence are still emerging, for example there is differential persistence between different strategies (Harri and Brorsen, 2004; Eling, 2009) and between different fund characteristics such as size (Joenvaara, Kosowski and Tolonen, 2012).

2.9.1.2 Long–Term persistence

An innovative study came from Wang and Zheng (2008) who first introduced the 'Strategy Distinctiveness Index' (SDI). They examined the TASS database from 1994-2007 using regression analysis (with the Fung and Hsieh 7-factor model, the Carhart model and Fama-MacBeth analysis). The SDI index is a measure of a hedge fund's distinctiveness and is based on historical return data. They found a substantial cross-sectional variation in SDI and a strong persistence in fund SDI for up to five years. Their results also showed that, on average, higher SDI is linked with better performance. Furthermore, their results showed that smaller funds, younger funds and funds containing higher incentive fees display higher SDI. Ultimately, there is evidence that the SDI index is an indicator of the fund manager's innovation and could be used by investors.

A recent study that is related closely to the previous study is from Ammann, Huber and Schmid (2013). They examined hedge fund performance over time horizons between 6 to 36 months, using the Lipper/TASS and CISDM databases from 1994 to 2008. They used the probit regression method to distinguish the fund characteristics that significantly affect hedge funds' performance persistence. They also used two-way sorted portfolios (depending on past performance and fund characteristics). In this model the dependent value can only take two values (i.e. persistent or non-persistent HF performance) and the purpose is to estimate the probability that an observation with particular characteristics (i.e. size, age, leverage) will fall into a specific category. They found that there is alpha persistence for up to three years. The persistence in raw returns was substantial for two years although statistically significant only over a six-month period. Ammann *et al*. also examined fund characteristics such as: fund size, age, flows, the length of the notice and the redemption period, management and intensive fees, leverage, a pseudo variable for whether the fund is closed to new investments, and a pseudo variable for whether the fund manager is personally invested in the fund. An additional variable was used: 'Strategy Distinctiveness Index' (SDI). This index was first introduced by Wang and Zheng (2008) and measures the extent to which a fund's strategy differentiates from the strategies of peer funds. Ammann *et al.* showed that all these characteristics are significantly associated with performance persistence but the SDI index has the ability to systematically enhance performance persistence up to a two-year horizon. However, the high score SDI are indications linked with lower returns in the crisis of 2008. This means that these funds took larger risks during the crisis and delivered lower returns.

An important study that also challenged the results regarding short term persistence was from Jagannathan, Malakhov and Novikov (2010). They measured performance persistence using hedge fund style benchmarks using Getmansky, Lo and Makarov (2004) methodology and the HFR database from 1996 to 2005. They developed a method for evaluating hedge funds' performance based on an appropriately-constructed peer group, taking into consideration the fact that hedge funds strategies have option-like features and serial correlation (or autocorrelation) in their returns due to investments in illiquid assets. They also took into consideration the backfill bias and illiquid assets (e.g. the chance that a hedge fund may be liquidated or closed and exit the data set). Jagannathan *et al*. found evidence of hedge fund performance persistence over a three-year horizon, particularly among the top performing funds. However, they found little evidence of persistence among bottom performing funds. Furthermore, they argued that the estimation period of performance persistence should be at least three years. This is because many hedge funds have issues that are related to illiquidity such as lockup, redemption and notice periods.

An additional perspective on the above studies was given by the pioneering study (in terms of using in-out flow restrictions) of Bae and Yi (2012), which used the TASS database from 1994 to 2008. Like Ammann *et al*. (who also examined fund characteristics such as size and age) they examined the impact of flow restrictions on hedge funds' performance persistence. They used non-parametric methods (based on a contingency table) and parametric methods (based on regression). They found that flow restrictions resulted in superior performance persistence in hedge funds. In detail, they found that not only money *outflow restrictions* such as redemption notice period, payout period and lock period, but also *inflow restrictions* such as minimum investment amount, close-ended funds (those that do not issue or redeem shares) and closing to individual investors were positively associated with winner persistence. However, between outflow and inflow restrictions, the first was considered a more important factor than the second. Managerial incentives also had a positive relation to winner persistence.

To sum up, the above innovative strategies (in terms of econometric methods) showed that there is long-term returns persistence in hedge funds. As for short-term persistence, the details depend on individual fund characteristics. More specifically, Wang and Zheng (2008) found long term persistence that depends on different fund styles/innovation strategies. This is similar to Ammann, Huber and Schmid (2013) who also found long term persistence that is affected by strategy/style innovation and fund specific characteristics (e.g. size, inflows/outflows and fees). Likewise, Jagannathan, Makakhov and Norvikov (2010) found long term persistence especially for top performing funds. Bae and Yi (2012) found long term performance persistence for funds that impose flow restrictions, with outflows being the more important factor.

2.9.1.3 Exploiting performance persistence

An initial conclusion to draw from the above studies is that the different methodologies are one of the major reasons for the different results found in the hedge fund literature. Moreover, different databases and different time horizons play an important role. Several studies such as Joenvaara, Kosowski and Tolonen (2012) have examined results from four or more different databases. Another issue that certainly does not facilitate comparisons is the different time periods that various studies examine. Most pre-2007 findings indicate that there is some persistence but it is mainly in the short run (for instance one to three months). Nevertheless, if this length of time is extended then there appears to be no persistence. Also, Agarwal and Naik (2000b) suggested that performance persistence appears to be driven more by losers continuing to be losers rather than winners persisting being winners. This is contrary to Capocci and Hubner (2004) that there is performance persistence in the middle quintile funds. Another important element is that some strategies appear to be more consistent than others (Eling, 2009; Brown and Goetzmann, 2003; Harri and Brorsen, 2004). This is a point that is intuitively logical, especially for non-directional strategies.

However, during the last five years there have been a few innovative studies (Kosowski *et al*., 2007; Jagannathan *et al*., 2010; Wang and Zheng, 2008) that used more advanced econometric methods (e.g. a Bayesian approach or a probit regression approach) and converged on the same opinion: there is persistence in hedge fund performance beyond one year and possibly up to five years. It is evident that with the use of more advanced econometric tools, along with the introduction of other innovative parameters (e.g. Strategy Distinctiveness Index - SDI), they were able to produce results that cannot be achieved by older methods and definitions. As an example, the Bayesian method is an approach to stock (or fund) assessment that facilitates taking fuller account of the uncertainties related to models and parameter values. On the contrary, the majority of other methods are based on maximum likelihood (or least squares) estimation involving fixed values of parameters that may have an important influence in the outcome about which there is a considerable uncertainty. One of the major benefits of the Bayesian approach is the ability to incorporate prior information (from historical data or expert knowledge) about the underlying parameters of the model.

Furthermore, an important aspect is fund characteristics (e.g. Amman *et al*., 2010). For example, young and emerging funds realized strong performance persistence. Also, funds not open to new investments are more likely to be persistent winners. In addition, some strategies such as Emerging Markets, Equity Market Neutral, Event Driven and Managed Futures exhibit alpha persistence over a twelve month horizon. In general it is intuitive that non-directional strategies have more persistence rather than aggressively directional strategies with higher volatility. Also, Bae and Yi (2012) found that flow restrictions resulted in superior performance persistence in hedge funds. However outflow restrictions were considered a more important factor that the inflow restrictions.

There are also two important elements that a researcher or a practitioner should consider. First, short term performance persistence is affected by the smoothing of returns and by liquidity restrictions (e.g. lockups periods) that hedge funds impose on investors. The former can distort the results because of returns manipulation by the fund manager. The latter has great impact because the fund manager has to re-balance her portfolio’s net positions, especially in the case of redemptions. There are many studies (e.g. Bollen and Pool, 2006; Eling, 2009) that deal with that issue. These are presented in the next section.

2.9.2 Concerns about performance persistence

2.9.2.1 Managing prices

The term *smoothing returns* mean the mitigation of the unexpected returns (surprise) either upwards either downwards. It is exploited (*i*) either by investing in illiquid assets or (*ii*) by managing prices (returns). Concerning (*i*), when fund managers invest in illiquid assets they subjectively evaluate these assets because there are no objective prices in the market. Furthermore when they invest in non-marketable securities in over-counter-markets (OTC) there is again no objective market price for these securities. So in both cases there is either no objective price evaluation, or lagged prices at best. Regarding (*ii*), fund managers are managing prices in a way that is more palatable to investors. It is not easy to do that in marketable securities where there is a known market price. However, this is possible when there is some flexibility on the valuation (exploiting spreads from various brokers) of the asset traded by the funds. Table 6 details the relevant papers.

Table 6. Performance Smoothing

This Table presents the main characteristics and results of the studies on performance smoothing. Abbreviations: CISDM: Centre for International and Securities Markets, CRSP: Centre for Research in Security prices, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services, MSCI: Morgan Stanley Capital International.

Study	Sample	Methodology	Results
Agarwal, V. Daniel, N. and Naik, N. (2011)	CISDM, HFR, MSCI, TASS and Eurekahedge, 1994-2006	Regression	Return manipulation, December spike, timing in reporting earning and losses
Bollen, N. and Pool, V. (2006)	CISDM, 1994-2003	Regression, descriptive comparisons	Return manipulation, conditional serial correlation,
Eling, M. (2009)	CISDM, 1996-2005	Regression, descriptive comparisons	Return manipulation, serial correlation
Getmansky, M., Lo, A. and Makarov, I. (2004)	TASS, 1977-2001	Regression	Return manipulation, serial correlation
Huang, Liechy and Rossi (2009)	CISDM, 1994-2005	Bayesian approach, regression	Return manipulation, serial correlation
Itzhak, B.D., Franzoni, F., Landlier, A. and Moussawi, R. (2013)	TASS, CRSP, Compustat, 2000-2013	Regression, high frequency econometrics	Return manipulation particularly critical reporting dates
Malkiel, B.G. and Saha, A. (2005)	TASS, 1996-2003	Chi square, comparison of rankings	Return manipulation, survivorship and instant history bias affect persistence

Smoothing returns might help to explain the short-term persistence of hedge funds. These non-synchronous pricing problems, either because of stale or managed prices, are an important matter in monthly hedge funds returns that can underestimate hedge funds' risk. Also, they overestimate the delivered alpha within any period (Asness, Krail and Liew, 2001). As a result, funds that act in illiquid markets such as Convertible securities or mortgage-backed securities show high persistence whereas other more liquid funds such as equity markets demonstrate less persistence. Artificial smoothing of hedge fund returns can be observed in the form of serial correlation coming from illiquidity exposures and smoothed returns (see Getmansky, Lo and Makarov, 2004). Likewise, according to Eling (2009) the highest serial correlation (or autocorrelation) is found in illiquid markets. These were Convertible Arbitrage, Relative Value Multi Strategy and Fixed Income Mortgage-backed securities (MBS) and showed high persistence. On the other hand the lowest serial correlation is found in liquid markets. These were in Global Macro, Equity Long Only and Short Bias and showed low levels of persistence. However, Huang, Liechy and Rossi (2009) found that even relatively liquid strategies (such as Equity hedge funds) can have smoothed returns causing an upward bias in excess performance measures and a downward bias in risk measures.

Eling (2009) explored the four factors that could generate artificial performance persistence. These are the use of: first, option-like strategies, second, return smoothing, third, survivorship bias and fourth, backfilling or instant history bias. Concerning the first factor, he examined 250 hedge funds that were using option-like strategies and found that, whatever the time horizon, these strategies had no performance persistence. Concerning the second factor (return smoothing) Eling measured the serial correlation strategy by strategy and found that it is possible to explain the high levels of short-term persistence realized by some strategies (e.g. Convertible Arbitrage).

Concerning the third and fourth factors (survivorship and instant history biases) he found that they can at least partially explain the performance persistence, confirming the findings of other authors (such as Malkiel and Saha, 2005) who examined hedge funds biases and found that they affect funds' performance persistence. In detail, the level of persistence was slightly higher when *only* surviving funds were examined. Living funds tended to have higher returns and lower standard deviations compared to dead funds. On the other hand, dead funds had lower levels of persistence. Even though survivorship bias can have an impact on the level of persistence, it is nevertheless not able to explain the differences among hedge fund strategies.

As far as the backfilled bias is concerned, Eling reproduced the investigation for the level of hedge funds' performance persistence after he had dropped the first 24 months of returns for each hedge fund from the database. He found a lower level of persistence. Thus, it appears that survivorship and backfill bias at least partially explains performance persistence.

2.9.2.2 Other smoothing returns techniques

This sub-section presents some recent studies about smoothing return techniques that can distort performance persistence: conditional correlation and critical reporting dates.

Illustrating conditional correlation, Bollen and Pool (2006) found that if a fund manager distributes true returns but fully reports gains and delays reporting losses, then the reported returns will display conditional serial correlation. They also found evidence that conditional serial correlation is a prominent indicator of fraud because it indicates price management or other illegal activities by fund managers. Hedge funds with conditional serial correlation tended to have greater volatility of fund flows resulting in higher risk. In addition, funds which have been investigated for fraud by the SEC (Security Exchange Commission) are more likely to display conditional serial correlation than other funds. Hence regulators should develop statistical techniques (e.g. filters) to focus on hedge funds with an increased risk of fraud.

An important related study is from Agarwal, Daniel and Naik (2011). They used five databases: CISDM, HFR, MSCI, TASS (now Lipper) and Eurekahedge with a sample period from 1994 to 2006. They found that during December hedge funds returns are significantly higher (December spike) than returns during the rest of the year. This applied to funds that have high incentive fees and more opportunities to artificially increase returns. Thus, hedge funds manage their returns upwards in an opportunistic way so as to have higher fees. Furthermore, they found strong evidence that funds artificially increase their returns in December by underreporting returns earlier in the year. However, there is only weak evidence that hedge funds “borrow” from next year’s (January) returns.

In relation to the above study, Itzhak, Franzoni, Landlier and Moussawi (2013) used the TASS hedge fund database from 2000 to 2013, while they used CRSP and Compustat for daily stocks returns and stock characteristics. They used also the NYSE TAQ (Trade and Quote) intraday trades data to compute the intraday return and volume information. They found that hedge fund managers manipulate stock prices during critical reporting dates. Stocks in the top quartile of hedge fund holdings showed abnormal returns of 0.3% on the last day of the quarter and a reversal of 0.25% on the following day. An analysis of an intraday volume and order imbalance showed that a significant part of the return is earned during the last minute of the trading.

Having discussing the above smoothing related studies, it is clear that it is very difficult to evaluate hedge funds’ performance persistence. Earlier studies showed that the persistence is short term in nature but studies using more advanced quantitative techniques revealed that there is long term persistence even for five years. However there are important issues that have to do with hedge funds’ illiquidity and managing returns. There is a need for more advanced techniques to allow the researcher to manage these problematic issues. The hedge fund industry evolves very quickly and fund managers are able to find ways to maximize their performance in an artificial way, especially in the short term, thus increasing apparent persistence.

Consequently, the researcher or the investor should use more advanced econometric tools using delayed time (lag) variables in order to capture those smoothing techniques. Investors should always be sceptical when dealing with hedge funds' performance persistence. The situation would be much better if *all* hedge funds had independent administrators for their NAV (net asset value) calculations and performance reporting. However, in order to do this there would need to be increased transparency and a stricter regulatory framework for the hedge fund industry.

2.10 Hedge funds returns and characteristics

Having discussed performance persistence, I now continue the review of modelling hedge funds. As presented in part two of this chapter, there are alternative perspectives to explain hedge fund returns. I refer here to the fundamental factor models or explicit factor models (size assets under management, age, fees and liquidity/restrictions) that are able to explain hedge funds returns using individual hedge funds characteristics. Regarding size and performance, the majority of studies conclude that there is a negative relationship, i.e. smaller hedge funds perform better. Age and performance seems to have a positive relationship, i.e. older funds outperform younger ones. Fees and performance also appear to have a positive relationship.

The next subsections analyse and critique the relevant studies for each characteristic (size, age and performance fees). They also briefly cover other micro factors such as lockup periods and fund domicile.

2.10.1 Size

The term 'size' in hedge funds refers to the Assets under Management (AUM). A typical categorization is small (less than \$100 million), medium (between \$100 million and \$500 million) and large (over \$500 million) (Pertrac Corp., 2012). Many scholars deal with the size of the fund and the performance but the findings are contradictory with a slight tendency in favour of small size. I discuss this below in detail, with the papers being listed in Table 7.

Table 7. Performance and Size Factors

This Table presents the main characteristics and results of the studies on performance and the size factors. Abbreviations: CAPCO: Financial Institution, CISDM: Centre for International and Securities Markets, FAV: Favorable Positioning Metric, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services, ZCM/MAR: Zurich Capital Markets.

Study	Sample	Methodology	Results
Agarwal, V., Daniel, N. and Naik, N. (2004)	HFR, TASS and ZCM/MAR, 1994-2000	Regression, comparison of rankings	Small funds outperform large funds
Amenc, N. and Martellini, L. (2003)	CISDM, 1996-2002	Regression, comparison of rankings	Large funds outperform small funds
Ammann, M. and Moerth, P. (2005)	TASS, 1994-2005	Regression, comparison of rankings	Small funds outperform large funds
Getmansky, M. (2012)	TASS, 1994-2002	Regression, Monte Carlo simulations, comparison of rankings	Large funds outperform small funds
Gregoriou, G. and Rouah, F. (2002)	Zurich Hedge Fund and LaPorte, 1994-1999	Correlations, descriptive comparisons	No relationship
Harri, A. and Brorsen, B. (2004)	LaPorte Asset Allocation, 1977-1998	Regression	Small funds outperform large funds
Hedges, J. (2003)	CAPCO, 1995-2002	Descriptive comparison of rankings	Small funds outperform large funds, but mid-size funds perform worst
Joenvaara, J., Kosowski, R. and Tolonen, P. (2012)	BarclayHedge, EurekaHedge, HFR, Morningstar and TASS, 1994-2011	Cross-sectional regression, comparison of rankings	Small funds outperform large funds
Koh, F. Koh, W. and Teo, M. (2003)	Eurekahedge and AsiaHedge, 1999-2003	Cross-sectional regressions	Large funds outperform small funds
Meredith, J. (2007)	HFR, HedgeFund.net, Altvest and Barclays Global HedgeSource, 1996-2006	Comparison of rankings, Monte Carlo simulations	Small funds outperform large funds
Pertrac Corporation (2012)	BarclayHedge, Channel Capital Group, Cogent Investment Research, Eurekahedge, HFR, Lipper, MondoHedge and Morningstar, 1996-2011	Descriptive comparison of rankings	Small funds outperform large funds
Schneeweis, T., Kazemi, H. and Martin, G. (2002)	HFR, 1996-2000	Regression, comparison of rankings	Small funds outperform large funds

2.10.1.1 Small hedge funds outperform

This section present papers demonstrating evidence that there is negative relationship between hedge fund performance and size. Performance measurement is mainly on fund returns, risk and risk-adjusted returns.

Schneeweis, Kazemi and Martin (2002) examined the impact of fund specific factors such as size, age and performance fees on Value, Growth and Small styles using the HFR database (hedge fund indices) from 1996 to 2000. They presented results of fund size compared to fund return, risk and risk adjusted performance. In particular, they computed the correlation between fund size and fund return, risk and risk adjusted returns. In general, smaller funds out-performed larger funds but had a higher risk.

There were further interesting details if the data were disaggregated into sub-strategies. For example, small risk arbitrage funds had higher returns but lower risk. Those results are consistent with smaller asset size funds that benefit the risk arbitrage strategies, unlike large size funds that may lack flexibility. This indicates that high returns may not always come at the expense of higher risk.

Two years later, Harri and Brorsen (2004) (see section 2.9.1 for more information) found similar results. Their results showed a strong negative correlation between hedge fund size and return. This was consistent with the author's assumption that small hedge fund managers benefit from market inefficiencies. The reason for this is that the profit to be made from market inefficiencies is relatively fixed; hence allocating more money to exploit those inefficiencies causes the returns to decrease.

Another case in favour of small funds is the research from Agarwal, Daniel and Naik (2004) that used one comprehensive database culled from three commercial databases: HFR, TASS and ZCM/MAR. The sample period was from 1994 to 2000. They analysed how money inflows are affected by future performance and discovered that larger funds with greater inflows were linked to lower future performance, a consequence that is consistent with decreasing returns to scale.

Similarly to the above, another important study was from Ammann and Moerth (2005) that used data from 1994 to 2005 on the TASS database and examined the influence of fund size on returns, Sharpe ratios and alphas generated from a multi-asset class factor model. Using cross-sectional regression techniques they showed a negative relationship between returns and fund size. However, they found that very small funds underperform on average. One possible explanation of this given by the authors is that very small hedge funds suffer from higher total expense ratios.

Ammann and Moerth (2005) also discovered a negative relationship between standard deviation and fund sizes. In most cases, larger hedge funds tended to have lower volatilities but similar Sharpe ratios. Consequently, very small hedge funds suffered a handicap when competing with medium and larger-sized funds.

Two years later, Meredith (2007) examined the impact of fund age and size on hedge fund performance from 1996 to 2006. He used the Hedge Fund Research, HedgeFund.net, Altvest from InvestorForce and Barclays Global HedgeSource databases. This study is referenced in detail in section 2.10.2 when discussing hedge fund age and performance. Using Monte Carlo simulations, his final conclusion is that if investors want to maximise return then they should search for younger and smaller funds. If they want to maximise capital preservation they should search for larger, older funds.

Except for academic studies there are also some commercial studies on how these micro factors affect hedge fund performance. The Pertrac Corporation (2012) examined the impact of size and age on hedge fund performance from 1996 to 2011. They used fifteen databases from eight different data providers, a number that it is obviously an advantage over other papers. These were: BarclayHedge, Channel Capital Group, Cogent Investment Research, Eurekahedge, Hedge Fund Research, Lipper (A Thomson Reuters Company), MondoHedge and Morningstar.

As far the size factor is concerned, the Pertrac Corporation found that the average small fund outperformed the average mid-sized and large fund for all years except for 2008, 2009 and 2011. However the average large fund outperformed the average small and medium sized fund in the negative performance years of 2008 and 2011. Also, small funds outpaced the mid-size and large funds with regard to the number of months that their returns were above 2%.

Similarly, Joenvaara *et al*. (2012) in their research (please see section 2.9.1.1 for more details) showed that smaller firms and funds outperformed their larger peers.

2.10.1.2 Large hedge funds outperform

Amenc and Martellini (2003) examined the alphas of hedge fund managers and their risks, taking into consideration different models and examining many funds' characteristics (for instance fund size, age, performance and incentive fee). They used the CISDM database from 1996 to 2002.

Concerning the size factor, the authors investigated the effect of a fund's size on performance. For each fund they calculated the average assets over the time period used for that research. Afterwards, they divided the funds into two equally-sized groups. For each class they calculated the average alpha obtained with each method. For all methods the mean alpha for large funds significantly exceeded the mean alpha for small funds. Furthermore, in most of the methods the difference in mean alpha between large and small funds was statistically significant. This demonstrated that, on average, large funds do in fact outperform small funds.

Similarly to the above, Koh, Koh and Teo (2003) examined Asian hedge funds (please see section 2.9.1.1. for more information). They argued that there is evidence that there are economies of scale in the hedge fund industry. Consequently, funds managed by larger holding companies tend to outperform funds managed by smaller ones.

Getmansky (2012) using the TASS database from 1994 to 2002 and regressing between monthly returns on asset size, found a positive but concave relationship between current performance and past asset size. In other words, there are decreasing returns to scale. He found also that there is an optimal asset size for obtaining best returns. Hence, investors should seek to invest in hedge funds that are closest to their optimal size. It is important to mention that the asset size / performance relationship exhibits various forms for different hedge funds strategies. For example the relationship is curved and the optimal size can be obtained for more illiquid strategies such as ‘Emerging markets’ and ‘Convertible arbitrage’. Those hedge funds strategies realize high market impact and are contingent on limited opportunities. On the other hand, Funds of Funds are less affected by negative economies of scale than individual funds.

According to these results Getmansky suggested that fund managers with large assets should decide to close the fund to new investors in preference to suffering a decrease in returns and an increase in the probabilities of liquidation. As far as an investor is concerned, he suggested choosing hedge fund strategies that do not have as asset size greater than the optimum. However, in practice it is difficult for investors to calculate this optimum, unless they have private information.

2.10.1.3 No relationship – Other approaches

Other papers have found no evidence for a size – performance relationship.

Gregoriou and Rouah (2002) used data from 1994 to 1999 exploiting the Zurich Hedge Fund Universe and LaPorte Asset Allocation Systems. They focused on the connection between the size of hedge funds and their performance. The size of the hedge fund was denoted by the total asset amount at the beginning of their calculation period. The authors found no evidence of relationship between the size of the hedge fund (or FoF) and its performance, either unadjusted or adjusted (Sharpe and Traynor ratios).

A year later, an interesting study that provided slightly different results to the majority of authors was from Hedges (2003). He examined the size versus performance issue from 1995 to 2002 using three size-mimicking portfolios of equally weighted monthly returns. He classified hedge funds based on assets under management into three buckets: small, medium and large. Hedges showed that smaller funds outperformed larger funds. However, mid-sized funds performed the worst. This fact suggested the notion of 'mid-life crises' for hedge fund managers as mid – size firms tend to be inefficient in terms of exploiting opportunities and processes to reach optimum performance.

2.10.1.4 Summary

Several papers deal with the size/performance relationship of hedge funds, but there are some contradictory results. Amenc and Martellini (2003) and Koh *et al*. (2003) found that there is a positive correlation. Getmansky (2012) found that there is a positive and concave correlation and suggested that there is an optimal asset size. In contrast, Gregoriou and Rouah (2002) found no evidence of any relationship either for unadjusted or for adjusted returns (Sharpe and Traynor ratios). It is important to mention that Gregoriou and Rouah used the AUM at the inception date of each fund, and not the average that is most commonly used by the other authors. Agarwal *et al*. (2004) have completely opposite results to those of Koh *et al*. (2003), although Koh, Koh and Teo considered only Asian hedge funds. The former found that there is a negative correlation and diseconomies of scale whereas the later found positive correlation and economies of scale. The results may well be different because they use different time periods, databases and different methodologies. Nevertheless, the majority of studies conclude that there is a negative relationship between hedge fund size and performance. These results are in alignment with commercial studies (e.g. Pertrac Corp.) So it can be summarised that there is some negative correlation between size and hedge fund performance. However, for an investor it is one of many factors to consider.

2.10.2 Age

The term 'age' when applied to hedge funds has to do with when the fund was launched, or the time that it was introduced in to the database, or (most commonly) the time it is considered to have existed for, if backfill or instant history bias are eliminated. The majority of scholars come to the conclusion that there is a negative relationship between age and performance, i.e. younger hedge funds outperforms older ones. Table 8 shows the relevant studies on fund age.

Table 8. Performance and Age Factors

This Table presents the main characteristics and results of the studies on performance and the age factors. Abbreviations: CISDM: Centre for International and Securities Markets, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services.

Study	Sample	Methodology	Results
Amenc, N. and Martellini, L. (2003)	CISDM, 1996-2002	Regression, comparison of rankings	Young funds outperform old funds
Frumkin, D. and Vandegrift, D. (2009)	Bloomberg, 2005-2007	Panel regressions	Young funds outperform old funds
Howell, M.J. (2001)	TASS/Tremont, 1994-2000	Comparison of rankings	Young funds outperform old funds
Meredith, J. (2007)	HFR, HedgeFund.net, Altvest and Barclays Global HedgeSource, 1996-2006	Comparison of rankings, Monte Carlo simulations	Young funds outperform old funds
Pertrac Corporation (2012)	BarclayHedge, Channel Capital Group, Cogent Investment Research, Eurekahedge, HFR, Lipper, MondoHedge and Morningstar, 1996-2011	Descriptive comparison of rankings	Young funds outperform old funds
Schneeweis, T., Kazemi, H. and Martin, G. (2002)	HFR, 1996-2000	Regression, comparison of rankings	Old funds outperform young funds

Howell (2001) emphasized the relationship between hedge fund age and performance. His data were from 1994 to 2000 and used the TASS/Tremont database. He defined younger hedge funds as those that had a track record of less than three years. Howell sorted the funds into deciles in regard to their maturity. On the basis of unadjusted returns, the youngest deciles realized 23.2% whereas the median returned 13.4%.

However the percentage was rather overestimated because it did not take into account a potentially higher failure rate. In order to proceed, Howell (2001) adjusted the returns by applying the likelihood of failure to report to the surviving funds. He also adjusted the returns by applying the likelihood of future survival to the survivor's returns by age decile. But the adjusted results were similar to the non-adjusted results: the youngest decile delivered a return of 21.5% whereas the whole sample median showed a return of 13.9%.

It is clear that hedge funds' performance becomes worse with age, even when the risk of failure is taken into consideration. Therefore, the youngest funds appear especially attractive.

Similarly, Amenc and Martellini (2003) (please see section 2.10.1) defined the age as the length of time in operation before the beginning of their study. In order to investigate the impact of a fund's age on its performance they divided the funds into two categories: (*i*) newer funds (age of one or two years) and (*ii*) older funds (age greater than two years). For each category, they computed the average alpha using many different methods.

It is noticeable that for all methodologies they used, the mean alpha for newer funds exceeded the mean alpha for older funds. The range was from 1.16% to 3.66%. Those differences varied in significance across the methodologies. The most significant findings were obtained with the CAPM and Explicit Factor models.

Meredith (2007) (please see section 2.9.1) studied the impact of fund age and size on hedge fund performance: whether smaller, younger hedge funds offer higher performance than larger, older hedge funds. He studied the performance, volatility and risk profiles of different fund groups, using indices compounded from six subsets of hedge fund data (small, medium, large, young, mid-age and old) as well as Monte Carlo simulations. According to his results, if an investor wishes to maximise returns, she should start by aiming for younger and smaller funds. On the other hand, if the investor wishes to maximize capital preservation, she should start seeking larger and older hedge funds. However, the author suggested that an investor should also take into consideration the qualitative aspects of a given fund. It is evident from this study that younger and smaller hedge funds have greater prospects for maximising returns but on the other hand are more risky. Hence the risk-averse investor should search for hedge funds that are less risky and able to preserve capital.

Two years later, Frumkin and Vandegrift (2009) analysed the effects of beta, fund size and age as a consequence of Rule 203 (b) (3)-2. This regulation requires hedge funds to be registered with the SEC, resulting in an increase of the net worth requirement to $1.5 million for accredited investors who are more educated (or ill-educated but rich) providing hedge funds with a more stable asset base. They exploited a fixed-effects panel data model to better perceive the effects of regulation across the entire hedge funds industry from 2005 to 2007 (over nine quarters) using the Bloomberg database. Age had a negative relationship to hedge fund returns. In addition, as a hedge fund's age increases, its managers suffer from style drift, leading to lower returns.

Pertrac Corporation (2012) classified young funds as those that were less than two years old, mid-age those that were between two and four years old and tenured those that were older than four years. They found that the average young fund outperformed both the average mid-age and tenure funds. In addition to that young funds kept a lower volatility profile.

An exception to the above studies was that of Schneeweis, Kazemi and Martin (2002) (please see section 2.10.1) who examined the age / performance relationship using the TASS database because of its wide coverage, with much data on 'dead' funds and comprehensive data coverage from 1991 to 2000. It is intuitive that funds which start in different market environments may have very different track records. The authors computed the 12-month average information ratio for all funds within a specific style that started in the same month. The cyclical variation in information ratios was an indication of possible issues in comparing funds that performed under different market conditions. When the authors disaggregated data into strategies, they found that some strategies (e.g. small risk arbitrage) delivered higher returns and lower risk. To my knowledge, this in the only study that takes into consideration the *same starting month* for funds and shows a positive relationship between age and performance but on the aggregate level.

Summarizing the findings, there is a clear negative relationship between hedge fund age and performance. However, a question that arises is whether indeed there is any point in comparing hedge funds with different lengths of tracks records that started in different market environments. This concern is important because the results of these comparisons are misleading and are not likely to give a real picture of hedge funds' performance. At least, the evaluator should take into consideration the market conditions and make some adjustments to her appraisal regarding hedge funds' performance. Ultimately, examining the above studies, the general conclusion (negative relationship) holds true.

2.10.3 Performance fees

It is commonly known that hedge fund managers charge performance and administration fees to investors. An administration or management fee is the percentage rate of compensation and is very often reported to vendors' databases for each fund. The fee is a fixed percentage (set at the fund's launch) of the assets under management, is calculated monthly and is deducted from the fund's performance reported to the database. The performance fee is a fixed percentage rate on the fund's profits and is payable to the manager, often at the end of each month. Usually performance fees are approximately 20% of profits whereas administration fees are 1%-2% of assets under management. However the important question that arises is whether there is any relationship between performance fees and hedge fund performance. Below, some studies are presented that deal that with that issue. It is concluded that a positive relationship between incentive fees and fund performance exists and the extra returns outweigh the extra costs. This result is rather intuitive and easily explicable as there is alignment between fund managers' interests and investors' interests. Table 9 lists all the studies that research performance fees.

Table 9. Performance and the Fee Factor

This Table presents the main characteristics and results of the studies on performance and the fee factor. Abbreviations: CISDM: Centre for International and Securities Markets, HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services, PCA: Principal Component Analysis.

Study	**Sample**	**Methodology**	**Results**
Ackermann, C., McEnally, R. and Ravenscraft, D. (1999)	HFR, MAR, 1988-1995	Correlations, regressions	Higher fees, higher performance
Amenc, N. and Martellini, L. (2003)	CISDM, 1996-2002	Regression, PCA, comparison of rankings	Higher fees, higher performance
Bae, K.H. and Yi, J. (2012)	TASS, 1994-2008	Probit regression, comparison of rankings	Higher fees, higher performance
Joenvaara, J., Kosowski, R. and Tolonen, P. (2012)	BarclayHedge, EurekaHedge, HFR, Morningstar and TASS, 1994-2011	Cross-sectional regressions, comparison of rankings	Higher fees, higher performance
Koh, F., Koh, W. and Teo, M. (2003)	Eurekahedge and AsiaHedge, 1999-2003	Cross-sectional regressions	No Relationship
Lim, J., Sensoy, B., and Weibach, M. (2016)	TASS, 1995-2010	Bayesian approach, regression based, comparison of rankings	Higher fees-incentives, higher performance
Schneeweis, T., Kazemi, H. and Martin, G. (2002)	HFR, 1996-2000	Regression, comparison of rankings	No Relationship

2.10.3.1 Higher fees, higher performance

Starting the survey, Ackermann, McEnally and Ravenscraft (1999) found that incentive fees were related to high performance using the MAR and HFR databases from 1988 to 1995. This was, they claimed, because of incentive alignment between their interests and investors interests. However performance fees were not able to explain the increased total risk that hedge funds included compared to other 'traditional' investments.

Arguing for a positive relationship between fees and performance, Amenc and Martellini (2003) examined the impact of fees on hedge fund performance. They investigated incentive fees as well as management fees. With respect to incentive fees that are expressed as a percentage of profit, they divided the funds into two categories: those that had incentive fees greater or equal to 20% and those that charged less than 20%. For each category they calculated the average alpha (each with many methods).

For all methodologies the mean alpha for high incentive funds exceeded the mean for low incentive funds. The highest different was 7.72% whereas the lowest was 1.44%. The significance in the differences was high for all the methods except for the implicit factor method, that is, PCA (Principal Component Analysis). The lack of significance in the PCA method suggested a possibility that the fund managers of high-incentive funds may take some risks that were not captured by the other nine methods/models.

When the authors looked at management fees they followed a similar approach. They divided the funds into two groups: those funds that had administration fees greater or equal to 2% and those funds that had administration fees lower than 2%. There was no significant difference at the 5% level between funds with higher or lower administration fees.

A few years later, Joenvaara *et al*. (2012) also found that hedge funds with greater managerial incentives produced superior performance. This is in alignment with Bae and Yi (2012) who found that management fees and managerial fees such as incentive fees or high water mark awards had an influence on winners' persistence.

An extension of the above studies is from Lim, Sensoy, and Weisbach (2016) who examined the direct and indirect incentives of fund managers. More specifically, using the TASS database from 1995 to 2010 they examined a positive relationship between hedge fund performance and fund manager's lifetime income not only directly through incentive fees earned at the time of performance but also indirectly through higher future fees. These future fees come from the increased flows of new investments to the fund and from the increase in the fund's asset base. They found that the indirect fees are notably large for hedge fund managers, accounting for approximately 50% of the expected fund manager lifetime income.

2.10.3.2 No relationship between fees and performance

Other authors have however found no evidence in favour of performance fees.

Schneeweis *et al*. (2002) examined the impact of performance fees (along with other fund specific factors mentioned before) for Value, Growth and Small styles using the HFR database from 1996 to 2000. Their results showed that fees had little effect on performance. For most hedge funds (hedged equity) there was little evidence of the impact of performance fees. Similarly, there was a small effect for lockup affecting overall performance. What was more important was whether the funds belonged to the growth, value, or small firm strategies. Overall, the difference in return (before fees were charged) between the value, growth and small fund hedged equity funds with 20% incentive and those with less than 20% were tiny. Hence, Schneeweis *et al*. could make no conclusion from these results concerning the effects of fees on performance.

Another substantial piece of research was by Koh, Koh and Teo (2003), which explored Asian hedge funds in terms of return persistence, style and fund characteristics (please see section 2.9.9.9 for more details). They also found no evidence to support the idea that hedge funds with higher management or performance fees attained higher returns.

2.10.3.3 Performance fees summary

Most studies show that there is a positive relationship between performance fees and hedge funds' performance. The exceptions are Koh *et al.* (2003) and Schneeweis *et al*. (2002) who found that no conclusion could be drawn as to the effects of fees on performance. Maybe in some very specific situations such as growth equity hedge funds there was a positive relationship but it was small. Ackermann *et al*. (1999) found a positive relationship between incentive fees and performance. Similarly, Amenc and Martellini (2003) found a positive relationship between performance fees and hedge funds' performance. However, it is important to mention that they found no significant differences using the PCA method, which means that high-incentive fund managers may take some risks that are not captured by the other methods. Concerning management fees, they found no significant difference between funds with higher or lower administration fees. Later studies such as Joenvaara *et al*. (2012) and Bae and Yi (2012) also found a positive relationship between incentive fees and performance. In addition, studies such as Lim *et al*. (2016) considered the high importance of the indirect incentive on hedge funds' performance.

It is intuitively correct for an investor to expect that a higher performance fee means implicitly that the manager has high abilities (you get what you pay for). On the other hand she should know that in other cases these fees are excessive and do not justify managers' skills. Those skills are based on alpha, in other words the excess return due to managers' abilities (e.g. stock picking) and not on premia derived from hedge fund exposures (e.g. liquidity, credit risk). In addition to that, high performance fees do not guarantee future success (with respect to absolute returns). Last but not least, management and incentive fees are very often high thus eroding investors' capital and gains. Ultimately, the rule of 'you get what you pay for is' valid in the hedge fund industry and the extra costs deserve the extra returns (particularly regarding performance fees). Last but not least, investors who care about fund managers' incentives should pay attention not only to their direct incentives but also to their indirect incentives.

2.10.4 Other micro factors

Several other micro factors (such as lockup or notice redemption period and domicile) should be taken into account when someone try to attribute hedge funds returns. Table 10 shows the two studies that have researched this area.

Table 10. Performance and Other Micro Factors

This Table presents the main characteristics and results of the studies on performance and other micro factors.

Abbreviations: HFR: Hedge Fund Research, Lipper/TASS: Tremont Advisory Shareholders Services.

Study	**Sample**	**Methodology**	**Results**
Aragon, G. (2007)	TASS, 1994-2001	Probit regression, comparison of rankings	Lockup funds outperform no lockup funds
Joenvaara, J., Kosowski, R. and Tolonen, P. (2012)	BarclayHedge, EurekaHedge, HFR, Morningstar and TASS, 1994-2011	Cross-sectional regressions, comparison of rankings	Onshore funds outperform offshore funds and lockup funds do not significantly outperform no lockup funds

Lockup periods are important because they impose restrictions to investors. Long lockup periods means that fund managers are able to invest in more illiquid assets with a liquidity premium that results in higher returns. Aragon (2007) found that funds with lockup restrictions outperformed funds with non-lockups restrictions. However, Joenvaara *et al*. (2012) found that hedge funds imposing lockups did not produce significantly higher risk-adjusted returns compared to hedge funds with no lockup periods. Nevertheless, these two studies are close showing that there is a positive relationship between lockup periods. Ultimately, it is important for an investor should consider the balance of high lockup periods and liquidity premium that she may receive.

The domicile effect might indicate a relationship with fund performance. In their study Joenvaara *et al*. (2012) took into consideration the domicile aspect of hedge funds' performance. They found that on-shore hedge funds delivered higher performance than that of offshore-registered funds. However, investors invest in onshore or offshore hedge funds depending on their tax-exempt status. Certainly, from an economic perspective, no tax-exempt investor is willing to pay taxes through investing in an onshore hedge fund unless there is a very strong reason.

2.10.5 Returns and characteristics summary

Concluding, examining the micro-factors (specific to fund) it is considered that there is a negative correlation between size and hedge fund performance. However, an investor should not choose the appropriate hedge fund based only on the size factor. Regarding the age, it seems that younger hedge funds tend to outperform older hedge funds. Nevertheless, different market conditions should be also taken into consideration. Concerning performance fees there appears to be a positive relationship but again the investor should not rely only on that criterion. Long lockup period funds tend to outperform short lockups.

One important issue is that each fund should have an appropriate track record (at least two years) in order to have sufficient data to make calculations and judgments. Many private database vendors (such HFR) require at least two years of tracking records so as to include them in investable indices (HFRX). Furthermore, it is intuitively valuable to have at least two or three years of data in order to apply different econometrics and statistical models with reliable results.

2.11 Conclusion – Second part

This review has discussed two important topics that can help explain observed hedge fund returns: hedge fund performance persistence in the short and long term, and the factors idiosyncratic to individual hedge funds where a significant work has been done by many authors. It presented a synthesis of older literature to provide a historical perspective together with information from recent papers to illustrate advances in those topics. The findings both help hedge funds investors and make clear the opportunities for further research.

Contrary to earlier studies, a few later studies using advanced econometric methods showed that hedge funds do have long term performance persistence. However, further research is needed to confirm the results of these recent advanced studies. Furthermore, there is evidence that some non-directional strategies (e.g. Convertible Arbitrage or Merger Arbitrage strategies) demonstrate more persistence than aggressively directional strategies (e.g. Long Only strategy or Short Bias). However the difference in persistence is mainly related to the type of strategy each fund follows. Another important issue is that there is strong evidence that illiquidity and smoothing returns practices are widespread. This constitutes an essential element that a researcher that should take into consideration when examining short term persistence. Further research is needed to examine all these practices and use the appropriate quantitative models to identify and handle them. The question arises whether fund managers are able to handle hedge funds returns in a 'sophisticated way' to make their manipulation invisible to current models or techniques (e.g. autocorrelation identification).

As far the fundamental factors are concerned, they are able to explain a large part of hedge fund returns. There is also a relationship between certain hedge funds characteristics and performance. In particular, there is a negative correlation between size and hedge fund performance. Younger hedge funds tend to outperform older hedge funds. Concerning performance fees it appears to be a positive relationship. Long lockup period funds tend to outperform short lockups and domicile funds tend to outperform offshore.

In this survey, it is provided a framework to the investor to help her understand and evaluate funds with different characteristics. Ultimately, the investor should acknowledge all the above things together (e.g. performance persistence and micro-factors) and consider the factors that are important to her to get a deeper understanding of hedge fund performance attribution. She should get at least two years of track records so as to have sufficient basis for her calculations. She can use all the above factors as a guide in her investment decision process, knowing what to expect from hedge funds with certain micro-characteristics. For even better results, already having the broader picture, she should examine her underlying short–listed hedge funds with other complementary performance measures such as risk-adjusted returns and exposures. She should incorporate my findings in to her due diligence process so as to maximize her benefits. All the above results are useful to investors; however, a limitation of this survey is that there are differences in studies due to industry heterogeneity and authors using different hedge fund databases and time periods. This is a common issue for other authors as well, when they compare their results with earlier authors using different samples, methods and time periods. As is said in the fund management industry, "Past performance is no guide to future performance, but it's all we've got." Despite this limitation, there are some consistent trends and patterns that can reveal useful dimensions about hedge fund behaviour.

Identifying gaps for future research, there is not yet any unified model that is able to include all these factors and to quantify how they influence hedge fund performance and interact. This could include identifying the proportion of alpha for a given strategy that it is generated by each of these factors (e.g. including trading in illiquid securities, leverage and lockup periods). The performance persistence should be examined not considering one only dimension (such as only hedge fund strategy/style or only to specific attributes) but on a unified framework that utilizes all these dimensions together exploiting their interactions. Similarly, hedge fund performance (in terms of alphas and exposures) should be regarded not only on specific factors or hedging strategies/styles separately, but in an integrated framework.

Even though there are in the future more robust research results regarding performance persistence or the explanations of hedge funds returns based on fundamental factors, every investor should evaluate hedge fund performance on an individual basis. This is simply because what appears to be valid in the past does not guarantee a successful decision on an individual hedge fund basis. Beyond quantitative analysis there are many important qualitative criteria. For example, an investor should access other resources and, where possible, interview fund managers to verify the fund's risk management practices, investment policies, operational capabilities and management experience. Reviewing hedge funds' financial statements and business procedures and getting them certified by a reliable external firm, are pre-requisites for a successful investment decision.

2.12 Overall conclusion

In this chapter I have discussed two topics about hedge fund performance. The first part deals with how hedge funds returns can be explained using implicit or statistical factor models. The second part deals with hedge fund performance persistence in the short and long term, and the factors idiosyncratic to individual hedge funds. I presented a synthesis of older literature to provide a historical perspective together with information from recent papers to illustrate advances in those topics. The findings form each part (please see Conclusion sections) both help hedge funds investors and makes clear the opportunities for further research. Some of these opportunities are utilized in the next empirical chapters. More specific, there are specific research questions that emerge through my literature review.

The first is "*how and what is the impact of the (multiple) business cycles and different market conditions on hedge fund strategies in terms of performance?".*

The second is *"how and what is the impact of fundamental factors in hedge fund strategy performance within (multiple) business cycles and different market conditions?".*

The third is *"what is the impact of multiple business cycles and different market conditions on hedge fund performance persistence at strategy level and how investors can exploit this?"*.

The fourth is "*why there are such large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy?".*

All these issues are addressed in detail at the upcoming chapters.

3 Chapter: Performance at a strategy level

This chapter (paper) examines the first research question that deals with the impact of the (multiple) business cycles and different market conditions on hedge fund strategies in terms of performance (alpha and exposures). This is an empirical chapter and its structure has its own introduction, methodology, empirical analysis, and conclusion sections (a version of this paper is under review at Journal of Financial and Quantitative Analysis).

I investigate US hedge funds' performance across different economic and market conditions for 1990-2014. I use a piece-wise multi-factor parsimonious model with pre-defined and undefined structural breaks, based on a regime switching process conditional on different states of the market. During difficult market conditions the majority of hedge fund strategies do not provide significant alphas to investors. At such times hedge funds reduce both the number of their exposures to different asset classes and their portfolio allocations while some strategies even reverse their exposures. Directional strategies share more common exposures under all market conditions compared to non-directional strategies. Factors related to commodity asset classes are more common during these difficult conditions whereas factors related to equity asset classes are most common during good market conditions. Falling stock markets are harsher than recessions for hedge funds.

3.1 Introduction

The last financial crisis raised doubts about the hedge fund industry which has long been considered as being able to produce positive returns irrespective of the market conditions (Hentati-Kaffel and de Paretti, 2015). However this cannot be completely answered with strong comprehensive evidence as the existing knowledge cannot sufficiently explain hedge fund performance under different market conditions including any financial crisis. This paper investigates what the impact is of multiple business cycles and different market conditions on hedge fund strategies in a holistic approach, focusing on the North America region. I use the terms *multiple business cycles* and *market conditions* so as to examine hedge fund behavior in a more comprehensive way and not just isolating one or two economic periods or financial crisis events. There is a distinction between *business cycles* and different *market conditions* so as to shed light on the difference between them in hedge fund strategies, assisting investors in their decision process. By using the *piece-wise parsimonius* model, I focused on hedge funds that invest primarily in the North America region due to the use of three full U.S. business cycles. The North American hedge fund industry represents more than $1.9 trillion of assets under management corresponding to almost 72% of worldwide total (Preqin Global Hedge Fund Report, 2014).

This study's novelty lies in the use of multiple business cycles/market conditions in a holistic approach, in the exploitation of specific commodity factors including a factor related to the agriculture/food industry, in the use of a piece-wise parsimonious model which accurately captures changes in asset and portfolio allocations for each hedge fund strategy within a specific cycle/regime, and finally, the use of a systematic database merging and cleaning algorithm that can be used for a benchmark in future studies. The most important findings of this study are, first, that during stressful market conditions most hedge fund strategies do not provide significant alpha to investors (as during these times it is difficult to find opportinities) while fund managers are more concerned with minimizing their risk. At such times hedge fund strategies have fewer exposures in terms of different asset classes and portfolio allocations, and some strategies even reverse their exposures. During good times fund managers exploit the upward market movements by increasing their systematic risk but also deliver high alphas as well through availing themselves of opportunities. Second, as more directional strategies have by nature more systematic risk, they have more common exposures within different market conditions compared to less directional strategies. Third, during periods of market stress there is some switching of risk loadings from equity factors towards commodity related factors. Fourth, market volatility appears to affect hedge fund performance more than business cycle volatility.

Early studies (such as Sharpe, 1992) explained hedge funds in a linear framework. However there was soon a development toward non-linear models that explained the non-linear payoffs of hedge fund returns following the down-up approach. This approach begins with the underlying assets to find the sources of hedge fund returns and involves hedge fund replication portfolios by trading in the corresponding securities. These trading constructed factors are specified as asset-based style (ABS) factors (Fund and Hsieh, 2002a). I discern studies that explained hedge funds through option portfolios and trend followers (Fung and Hsieh 2001, 2002a, 2004) and option-based buy and hold strategies (Agarwal and Naik, 2000, 2004) or studies that showed that the so-called market neutral strategies are not so neutral for investors (Duarte, Longstaff, and Yu, 2007). Although important, these studies do not significantly help investors to choose and evaluate hedge funds for three reasons. First, these exposures are not static and change over time (as I show later). Second, the factors are not easy for investors to replicate (e.g. lookback straddles[12]). Third, some strategies (e.g. global macro or multi-strategy) are not well defined, and thus are difficult to replicate.

Another approach begins with identifying the sources of hedge fund returns and relates pre-specified risk factors for hedge fund performance attribution, and consists of two streams: the first uses additional refined factors that better explain hedge fund returns whereas the second stream, which can be regarded as an extension of the first, deals with methodological issues and funds' structural breaks. Although both streams use more advanced econometric techniques (e.g. regime-switching models) and confirmed previous studies that hedge funds have nonlinear returns and exposures, there remain significant gaps in many of the non-linear models mentioned above which I address in this paper. In particular, these non-linear models do not sufficiently describe the changing exposures across different business cycles and market conditions (many of them just use specific macro variables or isolate a specific crisis/event). Moreover a single model is not sufficient to describe all hedge fund strategies or conditions because it is over-simplistic. The single general commodity factor used to date is very broad, and (as it is showed later) hedge fund managers following many strategies switch from equities into commodities during hard times. Using a piece-wise parsimonius model with structural breaks, I show that hedge funds do not offer significant alpha during difficult times despite switching their holdings, as their primary concern is to minimize their risk exposures. The opposite holds for "good" times. Moreover, fund managers and investors have more to fear from falling markets than from economic recessions. These results, which are based on the longest period to date, will be valuable both to investors wanting to more accurately model hedge fund returns as economic conditions change, and to hedge fund principals who want to more accurately reward good investment performance.

In the first stream of the up-down approach, distinguished studies are from Bali, Brown and Caglayan (2011, 2014) and Avramov, Barras, and Kosowski (2013). Bali et al.

[12] A lookback straddle is a combination of a lookback call plus a lookback put. Both options are traded in Over-The-Counter markets. These respectively grant the holder the right but not the obligation to buy (sell) an asset at the lowest (highest) price identified during the lifetime of the option.

(2011) found that there is a positive correlation between hedge fund exposure to default risk premium and hedge fund returns, meaning that risk premia on risky assets are negatively correlated with present economic activity. Moreover, hedge funds with lower exposure to inflation derive higher returns in the future. Extending their previous work of 2011, Bali et al. (2014) found that macroeconomic risk factors such as default spread, term spread, short-term interest rates changes, aggregate dividend yield, equity market index, inflation rate, unemployment rate, and the growth rate of real gross domestic product per capital, are more powerful determinant on hedge fund returns compared to other common risk factors such as market, momentum, high minus low, especially for directional strategies. Similarly, Avramov et al. (2013), although focusing more on forecasting, showed that macro variables such as default spread, dividend yield, VIX index, and net flows in the hedge fund industry can assist in fund return predictability. Ibbotson, Chen, and Zhu (2011) examined hedge fund alphas, exposures and cost in a common framework. Their results showed that the average fund could add value both in bull and bear markets and their exposures were, in general, reduced during bear markets. Similarly Brown (2012) suggested a framework where hedge fund returns could be explained by their fees and systematic risk factors such as volatility, leverage, equity, credit, interest rates and commodities. He found that many hedge fund styles present significant exposures to traditional systematic risk factors such as equities, interest rates or credit. He observed (as I do) that exotic factors such as lookback straddles are not easy to replicate in practice or easily perceived by the average investor. Finally, Patton and Ramadorai (2013) discovered patterns where the exposure variation was higher early in the month and then got progressively lower until the reporting date.

Concerning the second stream of the up-down approach, which identifies structural breaks in hedge funds through the use of advance econometric methods (e.g. optimal change-point regression, regime-switching beta models, pooled benchmark models and the Bayesian approach) tremendous work has been done. An important study is that of Bollen and Whaley (2009). They showed that risk factors change over time and funds that switch their exposures over time outperform their peers. Their model examined just one change-point of hedge fund exposures, in a probabilistic manner. Another interesting study is from Billio, Getmansky and Pelizzon (2012), who found that hedge funds have non-linear exposures beyond the market factor, such as liquidity, volatility, credit, term spreads and commodities. Moreover, during the down regimes, market, credit spread and the spread between small and large cap stock returns are the most common hedge fund factors. Similarly, Jawadi and Khanniche (2012) showed that hedge fund returns are dynamic, realizing significant asymmetry and nonlinearity in accordance with different market conditions. At the same time, hedge fund exposures change over time depending on the strategy and the regime. Giannikis and Vrontos (2011), in accordance with the above studies, showed that different strategies present non-linear relationships to different risk factors. Meligkotsidou and Vrontos (2014) found that the market equity factor and the spread between small and large cap stock returns were the most significant factors. O'Doherty, Savin, and Tiwari (2015) confirmed that a selection of specific factors (e.g. equity, global and fixed income factors) is able to model hedge funds return with a lower error. Finally, Racicot and Theoret (2016) showed that macroeconomic uncertainty represented by the conditional variances of six macro and financial variables (growth on industrial production, interest rate, inflation, market return, growth of consumer credit, and the term spread) reduces hedge funds' market beta and increases the dispersion of hedge funds' returns and alphas.

Although there are studies that examine funds' variability over time, there is a need to examine hedge fund strategy behaviour in a more comprehensive way. More specifically, the direct impact of different business cycles and market conditions on hedge fund behaviour needs to be examined in a holistic approach. The current knowledge is fragmented (e.g. focusing on only one crisis or economic event). Also within current models there is no direct link between fund performance and market conditions, as some studies (e.g. Bollen and Whaley, 2009; Jawadi and Khanniche, 2012) focus on the internal change of funds' exposures, and the macro variables used by other authors (e.g. Avramov et al., 2013, Bali et al., 2014, and Racicot and Theoret, 2016) do not necessarily represent the different states of the economy. According to the National Bureau of Economic Research (NBER), a recession has as an *attribute* a significant decline in the economic activity lasting more than few months usually visible in the real GDP, industrial production, employment, real income, and wholesale-retail sales. Moreover, the single models used to describe all hedge fund strategies or conditions are over-simplistic and do not efficiently capture the exposures and excess returns delivered to investors.

This study uses multiple business cycles/regimes (not isolating one crisis/event) to examine the direct link between market conditions and hedge funds. The proposed modelling approach differs from the studies cited here, as it uses a parsimonious model that is flexible enough to accurately identify for each strategy changes in asset and portfolio allocations, within each of the underlying market conditions. In addition, it covers hedge funds that are directly affected by these cycles/conditions. This study closes an important gap and since there is a need to focus on one region as different regions of the world have different business cycles, I choose the most important economically: North America. This study covers three full U.S. business cycles, focusing in funds that invest primarily in the North America region. Because I examine hedge funds that focus the North American region the underlying changing economic conditions have a direct impact on these hedge funds. Hedge funds that invest only in the emerging markets do not have a direct exposure to these economic conditions.

Another important gap is the lack of an investigation of hedge fund behaviour within different business cycles and market conditions together (within a holistic approach) as these two different states do not necessarily coincide and they have different implications for hedge funds, causing confusion to investors. Thus, for the first time, there is a comparison of hedge funds' behavior under these two states that present different attributes (as shown later). Furthermore, instead of using one general commodity factor, I use specific ones (agriculture/food, energy, industrial and precious metals) for more accurate results. For the first time it is used a commodity factor related to the agricultural/food industry that caters specifically for hedge funds that invest in this "traditional" sector.

There are some important findings that contribute to the literature beyond those that agree with the authors discussed above, in terms of the dynamic nature of hedge funds (e.g. Bali, Brown and Caglayan, 2011, Jawadi, Khanniche, 2012 and Giannikis and Vrontos, 2011), common risk factors among strategies (e.g. Billio, Getmansky and Pelizzon, 2012) the changes in asset classes and portfolio allocations (e.g. Patton and Ramadorai, 2013) or high significance of specific factors (e.g. Meligkotsidou and Vrontos, 2014). First, during stressful market conditions the majority of hedge fund strategies do not provide significant alphas to investors and fund managers concern about minimizing their risk. Hedge fund strategies during these conditions have fewer exposures in terms of different asset classes and portfolio allocations (e.g. equity classes) and some strategies (e.g. Long Short and Market Neutral strategies) even reverse their exposures. Second, more directional strategies have, on average, more common exposures within different market conditions compared to less directional strategies that by nature have more systematic risk. Third, factors related to commodity asset classes (e.g. agriculture, energy, and industrial metals factors) are more common (in addition to the market factor) during these stressful conditions whereas factors related to equity asset classes (e.g. market, momentum, small minus big, high minus low factors) are most common during "good" market conditions. Fourth, down regimes are harsher than recessions for hedge funds (in terms of alpha and number of exposures). The findings are robust even when the pre 1994[13] period is excluded from the analysis.

The contribution of this study further lies in the fact that it provides the first examination of hedge funds within multiple U.S. business cycles and different (up/down) market conditions, using a holistic approach, to get a more comprehensive explanation of hedge fund performance. In addition, unlike previous studies, I do not use only one general commodity factor but many specific ones. This is important because commodities cannot be considered to behave in the same way in the market, as suggested by Bhardwaj and Dunsby (2014). In particular I use a commodity factor related to the agriculture/food industry. This study uses a custom-made multi-factor model that can accurately identify changes in asset and portfolio allocations for each strategy within different conditions, thus helping investors in their decision process as it enables them to know what to expect from different strategies, especially during multiple stressful financial conditions. Moreover, I perform a systematic database merging and cleaning approach that can be used as a benchmark for future studies since this is not a trivial process that can be followed easily. Finally, fund administrators can benefit by applying more flexible fee policies that more accurate reflect fund managers' performance under changing market conditions.

The remainder of the paper is organized as follows: the next section is the theoretical framework that provides the methodologies that used in the analysis. After that is the empirical analysis section presenting the data and discussing the results. The final section is the conclusion providing a summary of the discussion findings. Several appendices detail the data cleaning rules and give full model results, but due to space limitations these are available in the appendix.

[13] As I mention in more detail in section 3.2.2, I excluded pre-1994 data. The majority of studies use post-1994 data due to the limited data availability from most private hedge fund database vendors, as well as the survivorship bias they may contain for this early period.

3.2 *Methodology*

3.2.1 Theoretical framework

Linear factor models such as the CAPM model (Sharpe, 1964) and its extensions are represented by the APT model (Ross, 1976) are the foundation of most of the theoretical and empirical asset pricing literature. Within the linear multi factor model the rates of returns of funds are dependent via a linear relationship on several variables, that is, factors:

$$R_i = \alpha_i + \beta_{i,1}F_1 + \beta_{i,2}F_2 + \cdots + \beta_{i,k}F_k + \varepsilon_i \tag{1}$$

or equivalently:

$$R_i = \alpha_i + \sum_{j=1}^{k} \beta_{i,j}F_j + \varepsilon_i \tag{2}$$

Where R_i denotes the return on the *i*th fund (or strategy), K>0 is the number of factors, $F_1, \dots, F_K$ are the values of the factors, $\beta_{i,1}, \dots., \beta_{i,K}$ are the relevant sensitivities and ε_i is a zero mean random variable.

However, this theory constrains the factors to be linearly related to the fund (or security) returns. It cannot price funds where the payoffs are non-linearly related to risk factors, as in the case of hedge fund returns that characterized by the implementation of dynamic strategies. For this reason and in the spirit of other authors such as Fung and Hsieh (1997) and Agarwal and Naik (2004) I examine the hedge funds so as to capture dynamic strategies but in a different way. I propose a twin piece-wise parsimonious model[14] containing structural breaks so as to capture hedge funds' non-linearity. The

[14] In my analysis I move one step further towards other authors (mentioned in this section) by implementing the stepwise regression technique at a regime/cycle level (this represents the "agile" term) for more accurate results. The term"twin" refers to the fact that I examine different business cycles and different market conditions as they do not necessarily coincide. This custom model is not a typical non-linear model (e.g. non-linear in parameters). However the definition of a linear model is not an easy task because the term linear can be interpreted into different ways (e.g. in terms of parameters, independent variables, or structural changes).

first model contains pre-defined structural breaks that depend on the growth and recession periods of multiple business cycles[15]. The first twin-model takes the form of:

$$R_{iS} = \alpha_{iS} + \beta_{i,1}F_1(S) + \beta_{i,2}F_2(S) + \cdots + \beta_{i,k}F_k(S) + \varepsilon_i(S) \tag{3}$$

Where $S = \begin{cases} G \\ R \end{cases}$ is the state taking values of the vector G when we are in the growth period or values of the vector R when we are in recessions

(4)

Where vector $G = [G_1, G_2 \dots G_n]$ or $R = [R_1, R_2 \dots R_n]$ (5)

Hence, the first twin-model contains pre-defined structural breaks dependent on the state of the U.S. economy and is able to adjust itself taking into consideration only the variables (dependent and non-dependent) that belong to a particular stage of the economy. Employing a combination of statistical method and empirical judgement I use in this agile model the most appropriate factors for a given strategy under a specific state of the economy.

Within each state of the economy I apply a step-wise regression technique to limit the final list of factors for each strategy. This technique has been used by many authors such as Dor, Dynkin and Gould (2006) and Jawadi and Khanniche (2012). In this technique the variables are added or removed from the model depending on the significance of the F-value. 5% significance is used for both inclusion and exclusion. The single best variable is chosen initially. This initial variable is then paired with each of the other independent variables, one at a time; next, a second variable is chosen and so on, until no further variables are included or excluded from the estimation. Stepwise regression allows me to examine the importance of a large set of variables, even if there is a relatively small number of observations[16].

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[15] These business cycles are officially denoted by the National Bureau of Economic Research (NBER) and the Economic Cycle Research Institute (ECRI). The growth periods are: 01/1990-07/1990, 04/1991-03/2001, 12/2001-12/2007 and 07/2009-03/2014, and the recession periods are: 08/1990-03/1991, 04/2001-11/2001, and 01/2008-06/2009. We note that the prediction of business cycles or different market conditions is out of the scope of this paper.

[16] It is important to mention that the independent variables should be uncorrelated (as they have been already examined) otherwise the results would be spurious.

The second twin-model has structural breaks that are specified by a statistical stochastic process using a Markov regime-switching model (Hamilton, 1989, 1990). This is in the spirit of other authors such as Meligkotsidou and Vrontos (2014) and Billio, Getmansky and Pelizzon (2012) who measured the structural breaks of hedge fund returns and volatility. However, in the proposed model I measure the exposures of hedge funds returns taking into consideration the different states of the market index. I use the Wilshire 5000TRI including dividends, represented by two different states: up regime and down regime, covering a 24 year period[17].

Under the Markov switching model, systematic and un-systematic events may affect the output because of the presence of discontinuous shift in the average return and volatility. The change in regime should be regarded as a random and not as a predicable event. The model can be represented as:

$$R_t = \alpha + \beta(S_t)I_t + \omega u_t, \tag{6}$$

$$I_t = \mu(S_t) + \sigma(S_t)\varepsilon_t, \tag{7}$$

Where S_t is a Markov chain with n states and transition probability matrix P. Where u_t and ε_t are independent and both normally distributed with zero mean and unit variance.

Each states of the market index *I* has its own mean and volatility. Hedge fund returns are related to the states of the market index. They are defined by a parameter α plus a factor loading β, on the conditional mean of the factor. Also, hedge fund volatilities are related to the states of the market index *I*. They are defined by the factor loading β on the conditional volatility of the factor plus the volatility of the idiosyncratic risk factor ω. In both cases β could be different conditional on the state of the risk factor *I*.

For *n* = 2 (states are denoted as 0 or 1) the model is expressed as:

$$R_t = \begin{cases} \alpha + \beta_0 I_t + \omega u_t\,, & when\ S_t = 0 \\ \alpha + \beta_1 I_t + \omega u_t\,, & when\ S_t = 1 \end{cases} \tag{8}$$

Where the state variable S depends on time *t*, and β depends on the state variable as:

[17] The time period under examination is divided in to up regimes (01/1990-06/1990, 11/1990-10/2000, 10/2002-05/2008, 03/2009-03/2014) and down regimes (07/1990-10/1990, 11/2000-09/2002, 06/2008-02/2009).

$$\beta(S_t) = \begin{cases} \beta_0 , & when\ S_t = 0 \\ \beta_1 , & when\ S_t = 1 \end{cases} \tag{9}$$

The Markov chain S_t (the regime-switching process) is described by the following transition probability matrix P (for 2 states):

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \tag{10}$$

Where p_{ij} the transition probability from regime *i* to regime *j* with $p_{00} = 1 - p_{01}$ and $p_{11} = 1 - p_{10}$. Where p_{00} and p_{11} stand for the probability of being in regime zero, given that the system was in regime zero during the previous period, and the probability of being in regime one, given that the system was in regime one during the previous period, respectively.

In case where there are *m* states, the transition probabilities are best expressed in a matrix as:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{11}$$

Where $p_{i,j}$ is the probability of moving from regime *i* to regime *j*. Since, at any given time, the variable must be in one of the *m* states, it must be true that:

$$\sum_{j=1}^{m} P_{i,j} = 1\ \forall i \tag{12}$$

A vector of current state probabilities is then denoted as

$$\pi_t = [\pi_1\ \pi_2\ \ldots\ \pi_m] \tag{13}$$

Where π_t is the probability that the variable *y* is currently in state *i*. Given π_t and *P*, the probability that the variable y will be in a given regime next period can be forecast using:

$$\pi_{t+1} = \pi_t P \qquad (14)$$

Similar to the first twin-model, within each regime of the market index I apply a step-wise regression technique to limit the final list of factors for each strategy. Employing a combination of statistical method and empirical judgement I am able to use a parsimonious model using the most appropriate factors for a given strategy under a specific market regime. Unlike many authors, I did not rely on a single model just adding one or more factors on existing models. The reason is that I take a holistic approach selecting the most appropriate candidate factors for hedge funds, following other authors (e.g. Jawadi and Khanniche, 2012). Furthermore, many authors use a single model for all hedge fund strategies, mentioning nothing about the statistical properties of these factors (e.g. correlation between two or more factors). I take this issue into consideration. Due to the multifaceted nature of the hedge fund industry it is unwise to use exactly the same model when trying to explain hedge fund strategies. Different hedge fund strategies have different behavior and investment characteristics.

3.2.2 Data

I use three hedge fund databases (one with live/dead funds, one with live funds and one with dead funds) from two database vendors. These are EurekaHedge and BarclayHedge covering the period from January 1990 to March 2014[18]. To my knowledge, this is the longest period under examination in any hedge fund study. After the merging and cleaning process (such as removing records containing consecutive returns of zero, N/A and null) I select funds that invest primarily in the North America region. After the selection process, the total number of funds (live and dead) is 7,541. I remove outliers by implementing a “winsorizing” technique. The final dataset consists of 6,373 funds[19]. Details of all these procedures can be found in the appendices. Many authors do not give full details of their merging and database cleaning processes, but I believe that the used merging and elimination of duplicates algorithms can be regarded as benchmarks in the literature.

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[18] I include at least three business cycles so as to enable my analysis to be as comprehensive as possible. The majority of the databases for commercial use came into existence in the early/mid 1990 with a few exceptions such as EurekaHedge and BarclayHedge databases that came earlier. Moreover, my dataset contains pre 1994 dead funds hence I do not have this type of survivorship bias. However, in my robustness checks I have excluded the prior 1994 so as to verify my results.

[19] Similar to other authors (such as Ramadorai, 2012) I treat multiple share classes of funds as separate funds; this is to eliminate selection bias due to variations in liquidity restrictions, returns, and fee structures that describe different share classes of the same fund.

I adopt the strategies that fund managers reported in these databases[20]. I implement a mapping between database strategies that has been used by other authors (e.g. Joenvaara, Kosowski and Tolonen, 2012) using these two databases. Hence, I end up with eleven hedge fund strategies: Short Bias (SB), Long Only (LO), Sector (SE), Long Short (LS), Event Driven (ED), Multi Strategy (MS), Others (OT), Global Macro (GM), Relative Value (RV), Market Neutral (MN) and CTAs (CT)[21].

The fourteen candidate factors are selected according to specific criteria (availability, what other authors used based on their significance, the collinearity between them and correlation with strategies). They are related to different asset classes: equity factors, real estate factors, commodity factors, credit factors, currency factors and option factors. I take into consideration:

- Wilshire 5000 Total Return Monthly Index (MAI)
- MSCI World Excl. US U$ - Tot Return Index (GEMI)
- S&P GSCI Energy - Total Return Index (COEN)
- S&P GSCI Precious Metals - Total Return Index (COPM)
- S&P GSCI Industrial Metals - Total Return Index (COIM)
- S&P GSCI Agriculture Total Return Index (COAG)
- Differences in Promised Yields - Term Spread Premium (TERM) which is the spread between 10-year U.S. government bonds and 3-month U.S. treasury rate
- Differences in Promised Yields - Default Premium (DEF) which is the spread between Moody's corporate AAA and BAA bond yields
- DJ US Select Real Estate Sec - Tot Return Index (RLE)
- US Trade-Weighted Value of US Dollar Against Major Currencies (EXCH)
- CBOE SPX Volatility VIX (DVIX) - Price Index
- Small Minus Big (SMB)
- High Minus Low (HML)
- Momentum (MOM)

[20] Unfortunately, there is no universal classification scheme for hedge funds' strategies. Although fund managers may change their investment style over time, they are legally obliged to proceed according to the *offering memorandum* (used for private placements, contrary to the *prospectus* that is for publicly-traded issues) that describes the fund, its strategy, how it trades and operates, as well as the details of the organization.

[21] The *Others* strategy contains all hedge funds that do not belong to any of the other strategies mentioned in my paper. It does not include Emerging Markets hedge funds. I give more information about the *Others* strategy in section 3.3.4. *CTA* means Commodity Trading Advisors funds. This strategy makes extensive use of derivatives and commodity trading or uses systematic trading.

The first eleven factors are sourced from Datastream whereas the last three are derived from Fama and French's online data library (Ibottson Associates). I have not considered lookback straddles that according to the literature (e.g. Fung and Hsieh, 2001) are highly appropriate to the CT strategy. Unfortunately, there was no data available for the early examined period (early 1990s). However these are covered in the sub-section that details with the robustness tests.

Equity factors have been used widely in measuring the general market exposure of hedge funds. I use the most comprehensive index, the Wilshire 5000 index, as do Dor, Dynkin and Gould (2006) and Amenc, Goltz (2008). Fung and Hsieh (2004), Billio, Getmansky and Pelizzon (2009, 2012) and Patton and Ramadorai (2013) used the S&P 500, but that is mainly a large cap index. Commodity related factors have also been used by many authors such as Capocci and Hubner (2004), Agarwal and Nail (2000) to explain hedge funds' behaviour. Others such as Giannikis and Vrontos (2011) and Jawadi and Khanniche (2012) have also used commodity factors represented by the GSCI commodity index. In this study I do not use the composite GSCI total commodity index, or Gold-only indices as Billio, Getmansky and Pelizzon (2009, 2012) used. Instead, I use sub-indices related to energy, metals and agriculture for more precise results.

Credit factors have been also examined by many authors using the term and credit spread as proxies. For example Billio, Getmansky and Pelizzon (2009 and 2012) used the 10-year T-Bond rate minus 6-month LIBOR, and the difference between BAA and AAA indices provided by Moody's. Credit spread has also been examined by Ibbotson, Chen and Zhu (2011) using also the Moody's index. Giannikis and Vrontos (2011) used the Barclay high yield index as a credit spread factor. Bali, Brown and Caglayan (2011) also used these credit factors when analyzing hedge funds' risk exposures. Similar to Capocci (2009), I consider exchange rates by using the currency factor which is the Federal Reserve Bank Trade Weighted Dollar Index.

Following Billio, Getmansky and Pelizzon (2009 and 2012), I use as an option factor the VIX CBOE volatility index. This index is widely used as a measure of market risk. It represents market expectations of near term (30 days) volatility of the S&P 500 stock index. The VIX index is currently investable through various ETFs products.

It is known that fund managers reduce their leverage during crises, however in this dataset there is no sufficient information about it as there are funds that simply mention yes/no on the leverage field and there are many others that do not give this information. Moreover, there is no leverage information for different time periods so as to compare and analyse hedge fund responses under different conditions. In addition, there is no information about fund holdings to compute the net leverage, which is the difference between long and short exposure per share divided by the NAV (Net Asset Value), or the gross value of assets controlled (long plus shorts) and divide by the total capital (Gross Market Value/Capital). Prior work on hedge fund leverage (e.g. Duarte, Longstaff, and Yu, 2007) only estimates leverage, or relies on static leverage ratios or static yes/no leverage as reported in the databases (e.g. Agarwal and Naik, 2000). Nevertheless, not allowing for leverage can be regarded as one of the limitations of this paper.

3.3 Empirical analysis

In this section I set out some basic statistics on the data, give details of the regime switches I arrived at, then report the results from the one-factor and my multi-factor models.

3.3.1 Basic statistics

Following Bali, Brown and Caglayan (2011), I first present the results using the simple classification technique of dividing hedge fund strategies into directional, semi-directional and non-directional. I classified them according to their correlation with the market index Wilshire 5000TRI, including dividends. This index is more representative of the whole market than the S&P 500 since it captures almost all firms within the U.S. economy. Table 11 presents the correlation of each strategy and its corresponding classification. The most directional strategies are at the top of the table whereas the most non-directional strategies lie at bottom of the table. As expected, SB (Short Bias) has a large negative correlation with the market index of -0.924. The market neutral strategy MN has a very low correlation of 0.059. CT (CTAs) also has a very low correlation to market index of 0.048, which is not significantly different from zero.

Table 11. Simple Hedge Fund Classification and Market Correlation

This table presents for each strategy the correlation with the Wilshire 5000TRI including dividends over the entire period under examination (01/1990-03/2014). I rank conditionally on the correlation with the market index, from extreme directional strategies (Short Bias) to completely non-directional strategies (CTAs). Each strategy is a representative-average time series of all the relevant hedge funds. In results not tabulated, all correlations are significantly different from zero at the 0.01% level except for CTAs, with a t-statistic of 0.739 and a p-value of 0.46.

Directional Strategies	Code	Coefficient	Std. Error
Short Bias	SB	-0.924	0.042
Long Only	LO	0.707	0.023
Sector	SE	0.637	0.026
Long Short	LS	0.550	0.019
Semi-Directional Strategies			
Event Driven	ED	0.338	0.019
Multi Strategy	MS	0.271	0.021
Others	OT	0.232	0.018
Global Macro	GM	0.223	0.026
Non-Directional Strategies			
Relative Value	RV	0.211	0.015
Market Neutral	MN	0.059	0.013
CTAs	CT	0.048	0.048

Table 12 provides basic statistics on the raw returns of the eleven hedge fund strategies. Each strategy is a representative-average time series of their relevant (equally weighted) hedge funds. There are some strategies (e.g. Sector, Long Short, Others, CTA) that provide high monthly mean returns (more than 1.1%) and are more aggressive than non-directional strategies (e.g. Event Driven, Market Neutral). On the other hand some strategies (e.g. Short Bias) provide low monthly mean returns (0.1%). On average, directional strategies have more volatile returns than all the non-directional strategies except the CTA strategy. Full statistical information (with raw and excess returns) along with histograms is presented in the appendices.

Table 12. Raw Returns by Strategy

This table provides the basic statistics of monthly raw returns for each hedge fund strategy.

Strategy	Mean	Standard Deviation	Strategy	Mean	Standard Deviation
Short Bias	0.050%	5.197	Others	1.349%	1.091
Long Only	0.999%	3.437	Global Macro	0.934%	2.017
Sector	1.151%	3.259	Relative Value	0.821%	1.238
Long Short	1.125%	2.663	Market Neutral	0.525%	0.874
Event Driven	0.937%	1.839	CTA	1.184%	3.415
Multi Strategy	1.062%	1.713			

It is important to comment on the assumptions needed for the parametric techiques used (t-values, etc.). As presented in the appendix, hedge fund data are typically not normally distributed (but stationary as there is no trend in their mean and volatility); this is an issue that is shared by many other authors as well. However the large number of observations does not affect the significance of the tests and the use of the winsorizing technique for the extreme outliers mitigates this issue. Serial correlation (also see the appendix) is another common problem when dealing with time-series data, hence, with hedge funds too (this is shared by many other authors too). The estimation regression coefficients (see section 3.3.3 and 3.3.4) are still unbiased and consistent but may be inneficient. This means that the standard errors of the estimate of the regression parameters can be underestimated. Taking that into consideration I have used the HAC/Newey-West estimator for verification purposes (see appendix).

3.3.2 Regime switching model

From January 1990 to March 2014 there are three official business cycles. Hence the period under examination is divided into growth periods (01/1990-07/1990, 04/1991-03/2001, 12/2001-12/2007 and 07/2009-03/2014) and to recession periods (08/1990-03/1991, 04/2001-11/2001, and 01/2008-06/2009). I implement the Markov Switching process in order to identify the regimes (up and down) based on the mean and volatility of the Wilshire 5000TRI. I select two regimes so as to compare the two different stages with business cycles.

Table 13 shows the results of the Markov Switching process. Both up and down regime coefficients are highly significant. The second panel shows the probabilities of the transitions between the regimes. For example, if, at time t, we are in regime one (down) then the probability of staying in the same regime at time t+1, is 38.02%, whereas the probability of moving to regime two (up) is 61.98%. The third panel shows that up regime periods lasted on average almost 12 times as long as down regimes during this generally benign period for the U.S. economy. An up regime could be expected to last 18 months whereas a down regime lasted on average only two months.

Table 13. Different Market Conditions

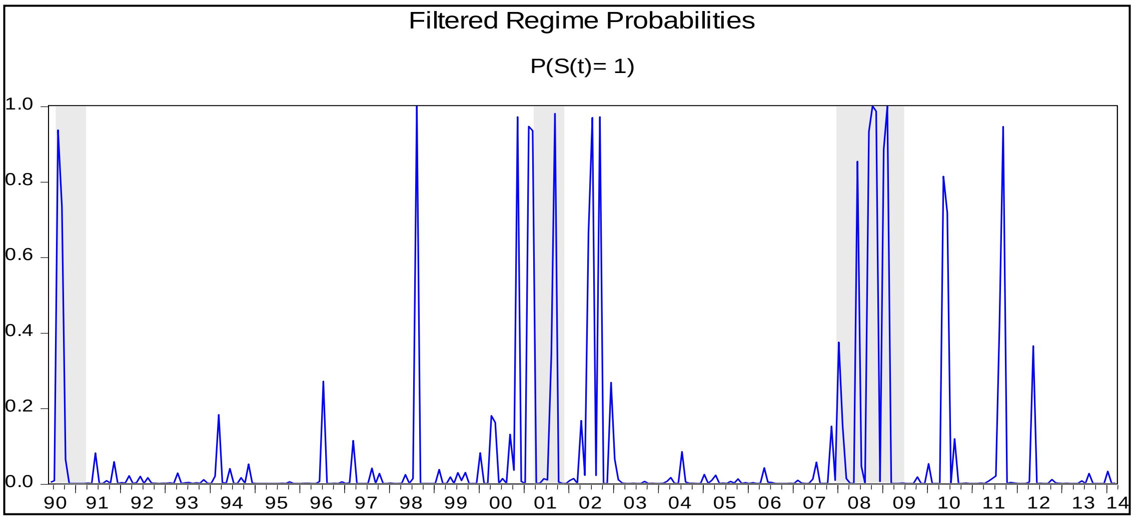
This table shows the two regimes calculated for the market index (Wilshire 5000TRI including dividends) using the Markov Switching model.

Panel A: Regime coefficients		
	Coefficient	Std. Error
Down regime	-8.6530	1.2982
Up regime	1.5804	0.2166
Panel B: Transition probabilities		
	Down	Up
Down regime	0.3802	0.6198
Up regime	0.0532	0.9468
Panel C: Regime duration		
Constant expected durations:	Down	Up
	1.6135	18.7934

Figure 1 presents the business cycles and the down regime probabilities. With only two regimes, P(up) = 1 – P(down). The down regime is not simply the result of splitting of the data sample into periods of positive or negative returns, but captures periods when the market volatility was high and there were substantial return downturns, not necessarily just a single shock[22]. In all these different regimes there might be positive or negative returns. The period is divided into four up regimes (01/1990-06/1990, 11/1990-10/2000, 10/2002-05/2008 and 03/2009-03/2014) and three down regimes (07/1990-10/1990, 11/2000-09/2002 and 06/2008-02/2009). Down regime periods cover higher oil prices in summer 1990 due to the Persian Gulf crisis, the Japanese down market in March 2001, 9/11 and the financial crisis 2008-2009. There are other negative shocks outside my identified down regimes, however the Wilshire 5000TRI was not then characterized by high volatility and substantial return downturns.

[22] The combination of substantial return downturns and market volatility can be regarded as a down regime's *attribute*.

Figure 6. Recessions and Down Regimes



Probabilities for the down regime: This figure demonstrates the probabilities of being in the down regime. The vertical axis shows the probabilities between 0 and 1 and the horizontal axis is the time period under examination. The shadow areas represent the business cycle recession periods.

3.3.3 One –Factor model

I first examine hedge fund strategies' alphas[23] and exposures using the basic market model within multiple business cycles and different market conditions. The market index MAI is the Wilshire 5000 TRI, including dividends. This is to be able to compare the market model to the used multi-factor model and judge its robustness, which is implemented in the next section.

Table 14 shows the results of the market model when applied in the growth periods. Contrary to the recession periods, the majority of the hedge fund strategies deliver strongly significant alpha to investors. All hedge fund strategies except the CTA have strongly significant exposures to the MAI factor. As expected, the directional strategies have, on average, higher exposures compared to the non-directional strategies. On average, all hedge fund strategies have higher exposures than in the recession period, meaning that fund managers adjust their portfolios to benefit from the upward market movement. Regarding the recession period, the majority of the hedge fund strategies do not deliver significant alpha to investors. The majority of the hedge fund strategies have significant exposures to the MAI (market index) factor.

[23] The alpha is the intercept of the equation. Also called Jensen's alpha (1968), it is usually interpreted as a measure of out-or under- performance relative to the market proxy used. In the subsequent tables of this study, alpha denoted as the (mean) excess return per month in percentage terms.

All strategies deliver strongly significant alpha to investors during the up regime. Almost all strategies have strongly significant exposures to the MAI, as with the growth period. During the down regime the majority of hedge fund strategies do not deliver significant alpha to investors, which is similar to the recession period. Overall, hedge fund managers adjust their market exposures lower during the down regime to get lower risk or minimize their losses.

Table 14. Market Model Results

This table shows the results of the market model for the growth (G), recession (R), up (U) and down (D) regimes. The market index (MAI) used is the Wilshire 5000 TRI including dividends (excess risk free returns). The risk free return is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates). Hedge funds returns are raw returns minus the risk free return. * denotes significance at $P < 0.05$ and ** denotes significance at $P < 0.01$. In this and subsequent tables, the left hand columns contain more directional strategies (Short Bias is extremely directional) and as I move to the right I deal with non-directional strategies (CTA strategy is extremely non-directional). For space reasons, I do not present standard errors and t-statistics.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Markets	Relative Value	Market Neutral	CTAs
C(G) (excess return)	0.5149**	0.4306**	0.5097**	0.4498**	0.5851**	0.7119**	0.7261**	0.4747**	0.5086**	0.2534**	0.9233**
C(R) (excess return)	-0.6242	-0.1918	0.5461	0.3387	-0.0111	0.4118	0.6500**	0.6509*	0.3688	-0.0383	0.7073
C(U) (excess return)	0.5399**	0.3789**	0.5303**	0.3969**	0.5447**	0.6914**	0.7235**	0.4267**	0.5149**	0.2083**	0.8187**
C(D) (excess return)	0.2721	0.1401	0.2851	0.2719	0.1011	0.5698	0.7894**	0.7417**	0.3621	0.0703	0.7828
MAI(G)	-0.9785**	0.6554**	0.6188**	0.5362**	0.2831**	0.2173**	0.1893**	0.2522**	0.1426**	0.0605**	0.0167
MAI (R)	-0.9769**	0.7614**	0.5782**	0.4869**	0.3555**	0.2599**	0.1902**	0.0278	0.2839**	-0.0359	-0.1189
MAI (U)	-1.0364**	0.6740**	0.6148**	0.5546**	0.3010**	0.2232**	0.1842**	0.2403**	0.1584**	0.0601**	0.0394
MAI (D)	-0.8386**	0.7077**	0.5685**	0.4448**	0.2879**	0.2411**	0.2094**	0.1009*	0.2246**	-0.0273	-0.1497*
Adj. R-squared(G)	0.6333	0.7406	0.6403	0.7233	0.5171	0.3105	0.3506	0.2349	0.3486	0.0843	0.0004
Adj. R-squared (R)	0.7901	0.8171	0.7454	0.8075	0.5596	0.4376	0.5271	0.0110	0.5459	0.0186	0.0487
Adj. R-squared (U)	0.6284	0.7323	0.6111	0.7161	0.5017	0.2879	0.3185	0.1890	0.3634	0.0693	0.0018
Adj. R-squared (D)	0.7628	0.7362	0.7173	0.7707	0.4232	0.4011	0.5178	0.1433	0.3481	0.0032	0.0827
F-statistic(G)	443.0553	731.9991	456.7479	670.1322	275.1056	116.2779	139.231	79.6289	137.989	24.5709	0.0908
F-statistic (R)	125.215	148.4602	97.5917	139.4363	42.9395	26.6813	37.7866	0.3554	40.6694	1.6259	2.6893
F-statistic (U)	430.4875	695.8302	400.083	641.5502	256.7249	103.7361	119.7107	60.2157	145.9832	19.9029	0.458
F-statistic (D)	113.5508	98.6913	89.8181	118.6361	26.6769	24.4423	38.5827	6.8546	19.6888	1.1127	4.157
Prob (F-stat)(G)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7634
Prob (F-stat) (R)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5553	0.0000	0.2115	0.1108
Prob (F-stat) (U)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4992
Prob (F-stat) (D)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0131	0.0001	0.2989	0.0493

The single factor (market) model, while simple, demonstrates that hedge funds present different behaviour in terms of the alphas and exposure to the market factor. As expected, directional strategies are more sensitive to business cycles and market conditions. Nevertheless, these strategies are able to deliver, on average, higher excess returns to investors. It is important to mention that the market model is over-simplistic in this context and cannot capture a large part of hedge fund strategies' behavior. Other well-known models (e.g. Fama and French model or Carhart model) might be more efficient than the single factor model, using my framework. However, hedge funds are complex vehicles and need more advanced techniques with more factors representing a wider range of different asset classes within multiple business cycles/regimes.

3.3.4 Multi-Factor model

This sub-section presents the results for the multi-factor twin-model. First, I discuss some key findings concerning the general behaviour of hedge funds during each of the underlying periods under examination. I then describe hedge fund behaviour for each strategy (briefly since there 11 of them), followed by a detailed exposure analysis at the strategy group level.

3.3.4.1 Growth periods

Table 15 presents the findings for growth periods. All hedge fund strategies deliver strongly significant alpha to investors and increase their exposures so as to benefit from the overall market movement. Thus, in terms of exposures the most common factor across all strategies is the MAI factor, as expected. The second most common factor is the MOM factor and the third is the SMB factor. The MOM factor is the essential factor when the market is in a growth state as fund managers keep up their investments' momentum. The SMB factor is also an important element as when there is market growth, small companies tend to outperform large companies, being more sensitive to market conditions. The DEF factor is negative for five strategies as the uncertainty and therefore the spread between promised yields are lower during growth periods. Hence, strategies that have strongly negative DEF deliver high alpha to investors. In total there are fifty exposures to the various asset classes. Overall, within the growth period, hedge fund managers trying to benefit from the upward market movement and have relatively high asset class and portfolio exposures for higher hedge fund returns. Fund managers pay more attention to returns than the systematic risk derived from investing in equity asset classes.

Table 15. Multi-Factor Model During Growth Periods

This table shows the results in terms of alphas and exposures of my multi-factor model for growth periods. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global	Relative Value	Market Neutral	CTAs
C (excess return)	0.5741**	0.2903**	1.5764**	1.4655**	0.4965**	1.4297**	1.4816**	0.3725**	0.2545**	0.5242**	0.8174**
	(3.3184)	(3.4816)	(3.8089)	(5.4502)	(8.5422)	(4.5960)	(6.1593)	(3.2733)	(3.1474)	(2.9978)	(3.7917)
Market Index-MAI	-0.8544**	0.6725**	0.5930**	0.5279**	0.3045**	0.2198**	0.1552**	0.3057**	0.14826**	0.0684**	
	(-13.3174)	(31.7104)	(22.6857)	(29.9863)	(20.4472)	(10.7826)	(6.5516)	(8.3602)	(12.5996)	(6.2038)	
Momentum-MOM	-0.1836**	0.0417*	0.1020**	0.0899**		0.0429*	0.0397**			0.0760**	0.1153*
	(-4.5980)	(2.1941)	(4.1671)	(5.6980)		(2.3595)	(2.8038)			(7.3612)	(2.2867)
Small minus Big-SMB	-0.2556**	0.2502**	0.1562**	0.2006**	0.1638**	0.0910**			0.0703**		
	(-4.9304)	(9.7241)	(4.9638)	(9.1875)	(9.0695)	(3.6407)			(4.8214)		
Global Market Index (excl.	-0.1941**						0.0725**				
	(-3.3394)						(3.5418)				
Comm. Industry Metals-COIM	0.1126**										
	(3.3252)										
High minus Low-HML		0.2077**		0.0666**	0.1774**	0.0580*			0.0676**		
		(7.2650)		(2.8075)	(8.8007)	(2.1147)			(4.2406)		
Comm. Energy-COEN		0.0226*	0.0436**	0.0316**							
		(2.2440)	(3.3348)	(3.7329)							
Comm. Precious Metals-COPM			0.0735**	0.0319*		0.0427*		0.0888**			
			(3.2081)	(2.1592)		(2.5119)		(3.7381)			
Default Spread-DEF			-1.3262**	-0.9403**		-0.8946**	-0.8748**			-0.3826*	
			(-2.9148)	(-30885)		(-2.6214)	(-3.3064)			(-1.9932)	
Term Spread-TERM				-0.1649**					0.1235**		
				(-2.9027)					(3.3405)		
Real Estate Index-RLE							-0.0371*				
							(-2.3581)				
Change in VIX-DVIX								0.0214**			
								(2.6184)			
Exchange Rate-EXCH											-0.4015**
											(-2.9292)
Adj. R-squared:	0.6971	0.8250	0.7201	0.8253	0.6699	0.3757	0.4287	0.2873	0.4507	0.2576	0.0417
F-statistic:	118.8076	242.3137	110.7509	152.1313	174.1677	26.6785	39.4161	35.3934	53.5171	30.6072	6.575
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016

3.3.4.2 Recession periods

Table 16 shows that the majority of hedge fund strategies do not deliver significant alpha during recessions as fund managers are trying to minimize their exposures. All hedge fund strategies have less exposure compared to the growth period. Moreover there are differences in exposures in terms of asset allocation and portfolio allocation. It is clear that hedge fund managers adjust their portfolios by minimizing their exposures during recessions in terms of asset and portfolio allocations. Again, MAI is the most common factor across all hedge fund strategies. However, the average exposure is 0.147 compared to 0.214 to the growth period. Furthermore, only seven strategies have exposure to MAI compared to twelve within the growth period. The second and third more common exposures are COAG (agriculture total return index) and COEN (energy total return index) respectively. This is interpreted as fund managers moving towards more counter-cyclical industries using agricultural/food or energy commodities. Indeed, agricultural/food commodities are obvious essentials for people. Food consumption cannot easily be disturbed by “bad” economic conditions, thus its demand can be considered as inelastic. Energy can be also regarded as an essential service or good, with an inelastic demand. In general, cycles in economic activity are not the main drivers of the evolution of commodity prices (Cashin, McDermott, Scott, 2002). Thus, fund managers have an incentive to increase their exposures to these factors during bad economic times. Overall, there are 28 exposures to assets classes compared to 50 during growth periods.

Table 16. Multi-Factor Model During Recessions

This table shows the results in terms of alphas and exposures of my multi-factor model during recession periods. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
C (excess returns)	-0.4633	-0.4417	0.5627*	0.3497	0.0696	0.3990	2.0808**	-1.1783	0.3688	0.1356	0.8365
	(-0.9518)	(-1.2102)	(2.0864)	(1.4670)	(0.2082)	(1.3481)	(3.6397)	(-1.5418)	(1.2350)	(0.7977)	(2.0359)
Market Index-MAI	-1.0123**	0.6094**	0.5409**	0.4663**	0.2892**				0.2839**		-0.1474*
	(-13.8966)	(9.4005)	(12.4293)	(12.1225)	(5.2282)				(6.3773)		(-2.3962)
Comm. Energy-COEN	0.1302**						0.0246*	0.0735**			0.1045**
	(3.9577)						(2.1341)	(4.3722)			(3.7649)
Small minus Big-SMB		0.4291**					0.1491**				
		(3.5949)					(2.9841)				
Comm. Agriculture-COAG		0.1118*	0.1445**	0.0781*				0.1399**		0.0600*	
		(2.2248)	(3.8158)	(2.3317)				(4.1236)		(2.6532)	
High minus Low-HML			-0.3843**	-0.2013**							
			(-5.0381)	(-2.9864)							
Comm. Industry Metals-					0.1158*	0.1096**		-0.0858*			
					(2.7056)	(3.1212)		(-2.6899)			
Change in VIX-DVIX						-0.0613**					
						(-5.0613)					
Global Market Index (exc.							0.1349**				
							(6.7292)				
Term Spread-TERM							-0.6613*	0.9206*			
							(-2.6003)	(2.6859)			
Momentum-MOM										0.0559**	
										(2.8421)	
Adj. R-squared:	0.8561	0.8727	0.8830	0.8608	0.6323	0.5677	0.7258	0.5326	0.5459	0.2324	0.3261
F-statistic:	99.1289	76.4402	84.0448	69.0318	29.3702	22.6712	22.8366	10.4024	40.6694	5.9962	8.9853
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0063	0.0008

3.3.4.3 Up regime

Table 17 shows the performance behaviour of hedge fund strategies when the Wilshire 5000 is rising. Almost all strategies deliver strongly significant alphas to investors. Similar to the growth period, almost all hedge fund strategies are trying to increase their exposures so as to gain higher returns. Similar also to the growth period, fund managers take advantage of the upward market movement and invest in more risky assets such as small cap equities in order to have higher returns. They pay more attention to returns than to systematic risk during these conditions. On average, less directional strategies deliver lower alpha to investors as they benefit less from the upward market movement. However, they have fewer exposures compared to the other strategies, as by nature these are less risky strategies. In total, there are fifty one asset class exposures across all strategies. As for growth periods, the most common exposures across all strategies are MAI followed by MOM then SMB.

Table 17. Multi-Factor Model During a Rising Market

This table shows the results in terms of alphas and exposures of my multi-factor model for the up regime. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
C (excess returns)	0.4899**	0.2880**	0.4838**	0.6267**	0.4967**	0.6387**	1.2702**	0.2970*	-0.2192	0.1528**	0.8312
	(2.6382)	(3.3733)	(4.4458)	(4.6581)	(7.9609)	(7.5211)	(6.7701)	(2.4371)	(-1.3816)	(3.0690)	(3.851
Market Index-MAI	-0.9337**	0.6690**	0.5878**	0.5737**	0.2523**	0.2256**	0.1482**	0.2846**	0.1505**	0.0751**	
	(-13.7157)	(30.2888)	(20.9548)	(23.0726)	(10.9270)	(10.3531)	(5.9860)	(7.3072)	(12.0191)	(5.9065)	
Small minus Big-SMB	-0.2704**	0.2581**	0.1428**	0.1990**	0.1639**	0.0949**			0.0696**		
	(-4.8304)	(9.4069)	(4.3638)	(8.2788)	(8.3147)	(3.4741)			(4.3992)		
Momentum-MOM	-0.1431**	0.0517**	0.1048**	0.0923**		0.0565**		0.0503*	0.0237*	0.0751**	
	(-3.6275)	(2.8137)	(4.5153)	(5.8522)		(3.1235)		(2.0351)	(2.1054)	(7.2279)	
Comm. Industry Metals-COIM	0.1067**										
	(3.1326)										
Global Market Index (exc. U.S.)-	-0.1477*				0.0561**		0.0806**				
	(-2.5269)				(2.8826)		(4.0705)				
High minus Low-HML		0.2348**		0.0856**	0.1838**	0.0853**			0.0760**	0.0347*	
		(7.3084)		(3.0792)	(7.9487)	(2.6828)			(4.2019)	(2.0222)	
Comm. Energy-COEN		0.0338**	0.0468**	0.0420**	0.0187*			0.0341*			
		(3.3503)	(3.5352)	(4.8566)	(2.5082)			(2.3862)			
Comm. Precious Metals-COPM			0.0757**			0.0434*		0.0931**			0.1373
			(3.3752)			(2.5700)		(3.8755)			(2.988
Term Spread-TERM				-0.1829**					0.1114**		
				(-3.0336)					(2.7577)		
Change in VIX-DVIX				0.0111*				0.0176*			
				(2.1083)				(2.0842)			
Default Spread-DEF							-0.5920**		0.5683**		
							(-2.9541)		(3.4555)		
Real Estate Index-RLE							-0.0318*				
							(-2.1332)				
Adj. R-squared:	0.6787	0.8182	0.6942	0.8082	0.6633	0.3499	0.3829	0.2761	0.4795	0.2260	0.0302
F-statistic:	108.3144	229.6584	116.2964	153.948	101.056	28.3362	40.3992	20.3706	40.0062	25.7152	8.9304
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0031

3.3.4.4 Down regime

Table 18 presents the findings for when the Wilshire 5000 is falling. Similar to the recession period, most hedge fund strategies do not produce significant alpha for investors as fund managers are more concerned about risk. Similarly to business cycles, during the down regimes there are fewer exposures compared to the up regimes. On average there are 29 asset class exposures across all hedge fund strategies compared to 51 for the up regime. This is because fund managers during difficult market conditions, are trying to minimize their exposures and consequently their losses. The most common exposure across all hedge fund strategies is MAI. This is consistent with all the other regimes and business cycle conditions. There is almost the same number of exposures across all strategies for both stressful market conditions (28 exposures for the recession periods and 29 exposures for the down regimes). However, in the down regimes there is a lower average number of factors within groups compared to the recession periods (see Table 16). This means that during down regimes, fund managers are trying even harder to minimize their exposures than they do during recessions. Last but not least, similar to recessions, during bad market conditions fund managers have an incentive to invest in counter-cyclical industries and more specifically in agriculture/food and energy commodities. This is interpreted as commodities constitute essential goods or services for people and economy, and the driving forces have more to do with global demand and supply shocks or supply risks (Gleich, Achzet, Mayer and Rathgeber, 2013).

Table 18. Multi-Factor Model During a Falling Market

This table shows the exposures of my multi-factor model for when the Wilshire 5000 is falling. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
C (excess returns)	0.3522	-0.3603	0.4854	-0.0660	0.1776	0.5781*	0.7432**	0.8767**	0.0502	0.1579	0.8324
	(0.7968)	(-0.8730)	(1.4854)	(-0.2702)	(0.5356)	(2.3134)	(3.6741)	(4.3127)	(0.1900)	(1.3120)	(1.7790)
Market Index-MAI	-0.8491**	0.5509**	0.5016**	0.3117**	0.2028**		0.1858**	0.0810*			-0.1562*
	(-13.0650)	(8.1254)	(9.8764)	(6.1120)	(3.7053)		(6.0885)	(2.7081)			(-2.2707)
Comm. Energy-COEN	0.1091**							0.0401**			0.0676*
	(4.1149)							(3.2188)			(2.4078)
Small minus Big-SMB		0.4113**		0.1976**					0.1987**		
		(4.2053)		(3.4591)					(2.9516)		
Comm. Agriculture-COAG		0.1131*	0.1224**							0.0445*	
		(2.0826)	(2.7412)							(2.5907)	
High minus Low-HML			-0.2175**					-0.1650**		-0.0702**	
			(-3.8436)					(-4.5526)		(-2.8440)	
Change in VIX-DVIX				-0.0253*		-0.0313**			-0.0314**		
				(-2.1933)		(-2.7992)			(-2.9077)		
Comm. Industry Metals-COIM					0.1547**	0.1175**			0.1236**		
					(3.4023)	(3.2737)			(3.4409)		
Global Market Index (excl. U.S.)-GEMI						0.0919*					
						(2.1294)					
Exchange Rate-EXCH							-0.2678**				
							(-3.3022)				
Momentum-MOM										0.0780**	
										(4.7392)	
Adj. R-squared:	0.8385	0.8281	0.8218	0.8429	0.5600	0.6302	0.6266	0.4938	0.5639	0.4396	0.1962
F-statistic:	91.8462	57.2018	54.7957	63.6048	23.275	20.8836	30.3635	12.3816	16.0859	10.1524	5.2707
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0103

3.3.4.5 Analysis by strategy

This sub-section presents an overview and a brief analysis of the most important findings for each of the 11 hedge fund strategies. See Table 19.

The Short Bias strategy does not deliver significant alpha during "bad" market conditions. It was expected that this strategy would perform well when the market goes down. However, this strategy was very successful in the early 1990s with high returns[24]. This strategy delivers high returns from specific unexpected negative events and not necessary only during stressful market conditions. During the growth and up regimes this strategy provides frequent small losses accompanied with less frequent large gains that provide significant alpha to investors. There are many negative exposures compared to all the other strategies, as expected. The Long Only strategy does not deliver significant alpha during stressful conditions and behaves similarly to other "conventional" investments. It is not surprising that it has one of the highest correlations with the market index across all hedge fund strategies and one of the lowest alphas. The Sector strategy delivers significant alpha during "good" times and recessions. It seems that at such times hedge fund managers are able to identify the most profitable companies/sectors, or at least those that are less affected by recession. An interesting point (explained later in the sub-section on opposite/reverse exposures) is the negative exposures for DEF and HML. The Long Short strategy also has negative exposures to DEF and HML. This strategy has on average higher alphas and fewer exposures compared to the Long Only strategy when investing in the same asset classes, because it utilizes short-selling tools. Nevertheless, this strategy is unable to provide significant alpha to investors during recession periods and down regimes.

The Event Driven strategy, similar to most hedge fund strategies, does not provide significant alphas to investors during recessions and down regimes. By nature, it has relatively few exposures. The Multi Strategy, due to the fact that is a mixture of other strategies, is able to provide significant alpha to investors even in down regimes, whereas during growth periods it delivers one of the highest alphas across all hedge fund strategies. It also has negative exposure to the DEF factor during growth periods, as other strategies have (e.g. Sector and Long Short). Similarly, the Others strategy has

[24] I went through the Short Bias time series and found that during the early 1990s, the returns were much higher compared to other time periods. During the first nine months of 1990 the average monthly raw return was 5.94% (only May's return was negative). Practitioners made high returns from specific events such as the Russian default in 1998, the technology bubble crash in 2000, the Lehman Brothers bankruptcy in 2008 and the Eurozone debt crisis in 2010.

negative exposure to the DEF factor during “good” times (see opposite/reverse exposures section). This strategy has a GEMI exposure, meaning that a part of its portfolio is invested in global markets for higher returns. The Others strategy contains all hedge funds that do not belong to any of the other ten strategies (not including Emerging Market hedge funds). Thus, funds with strategies reported as “PIPES”, “No Category”, “Close-End funds” or “Other” belong here[25]. Beyond different styles/tools (e.g. PIPES, Close-End), the Others strategy may use allocations (such as start-up companies financed by venture capital) that are not used anywhere else. Hence, this strategy has styles/tools (PIPES, Close-Ended strategies) or allocations (start-ups) that allow them to invest in promising shares or utilizing illiquidity premia. The Global Macro strategy delivers higher alpha in down compared to up regimes. This may have to do with the fact that Global Macro strategies are able to invest in other regions beyond the North America region. Hence, when there are stressful market conditions they are able to switch to other regions for a relatively short period of time as their main focus is on North America.

The Relative Value along with the Market Neutral strategy is trying to exploit market pricing anomalies between similar assets and to minimize the risk exposure for investors, thus having very few exposures compared to other strategies. The Relative Value strategy delivers significant low alpha during growth periods as not being able to exploit upward market movement during “good” times. Similarly, the Market Neutral strategy has few exposures compared to other strategies having one of the lowest alphas during “good” times. Contrary to other strategies, it has a positive MOM exposure during down regimes (moreover it is unable to deliver significant alpha). It is not also a trivial task to keep a market neutral portfolio balanced for all market conditions. The CTA strategy has an extensive use the trend-trading and derivatives thus it has one of the fewest exposures across all hedge fund strategies. Their exposures are related to lookback straddles. During recessions and down regimes CTA does not deliver significant alpha to investors.

[25] PIPES (Private Investment in Public Equity) funds purchase of stock in a company at a discount to the current market value of share for the purpose of raising capital. With PIPES there are fewer regulatory issues with the SEC, it is less time consuming, and there is no need for an expensive IPO roadshow. Thus, it is more efficient for small to medium sized businesses. The allocation of shares is directly to private investors and not through a public offering on a stock exchange.

Table 19. Exposures per Strategy

This table is a summary of Tables 15, 16, 17, and 18. It shows the exposures of my multi-factor model for all hedge fund strategies across all market conditions. The up-left side contains more directional strategies whereas the down-right side contains more non-directional strategies. The exposures (in each strategy and according to each market condition) are presented according to their importance (the intensity in absolute terms) from left (more intense) to the right (less intense). In order to facilitate the reader I mention again the acronyms of the factors: COAG: Commodity Agriculture/Food, COEN: Commodity Energy, COIM: Commodity Industrial Metals, COPM: Commodity Precious Metals, DEF: Default Spread, TERM: Term Spread, DVIX: Change in VIX, EXCH: Exchange Rate, HML: High minus Low, GEMI: Global Market Index excluding U.S. MAI: Market Index, MOM: Momentum, RLE: Real Estate Index, SMB: Small minus Big.

1. Short Bias	Significant alpha	Significant Exposures	2. Long Only	Significant alpha	Significant Exposures	3. Sector	Significant alpha	Significant Exposures
Growth	0.574	-MAI, -SMB, -GEMI, -MOM, -COIM	Growth	0.290	MAI, SMB, HML, MOM, COEN	Growth	1.576	-DEF, MAI, SMB, MOM, COPM,
Recession	-	-MAI, COEN	Recession	-	MAI, SMB, COAG	Recession	0.563	MAI, -HML, COAG
Up	0.490	-MAI, -SMB, -GEMI, -MOM, COIM	Up	0.288	MAI, SMB, HML, MOM, COEN	Up	0.484	MAI, SMB, MOM, COPM, COEN
Down	-	-MAI, COEN	Down	-	MAI, SMB, COAG	Down	-	MAI, -HML, COAG
4. Long Short	**Significant alpha**	**Significant Exposures**	**5. Event Driven**	**Significant alpha**	**Significant Exposures**	**6. Multi-Strategy**	**Significant alpha**	**Significant Exposures**
Growth	1.466	-DEF, MAI, SMB, -TERM, MOM, HML,	Growth	0.497	MAI, HML, SMB	Growth	1.430	-DEF, MAI, SMB, HML, MOM,
Recession	-	MAI, - HML, GOAG	Recession	-	MAI, COIM	Recession	-	MAI, COIM, -DVIX
Up	0.627	MAI, SMB, -TERM, MOM, HML, HML,	Up	0.497	MAI, HML, SMB, COEN	Up	0.639	MAI, SMB, HML, MOM, COPM
Down	-	MAI, SMB, -DVIX	Down	-	MAI, COIM	Down	0.578	COIM, GEMI, -DVIX

Table 19. Exposures per Strategy (continued)

7. Others	Significant alpha	Significant Exposures	8. Global Macro	Significant alpha	Significant Exposures	9. Relative Value	Significant alpha	Significant Exposures
Growth	1.482	-DEF, MAI, GEMI, MOM, -RLE	Growth	0.373	MAI, COPM, DVIX	Growth	0.255	MAI, TERM, SMB, HML
Recession	2.081	-TERM, SMB, GEMI, COEN	Recession	-	TERM, COAG, -COIM, COEN	Recession	-	MAI
Up	1.270	-DEF, MAI, GEMI, -RLE	Up	0.297	MAI, COPM, MOM, DVIX, COEN	Up	-	DEF, MAI, TERM, HML, SMB, MOM
Down	0.743	-EXCH, MAI	Down	0.877	-HML, MAI, COEN	Down	-	SMB, COIM, DVIX

10. Market Neutral	Significant alpha	Significant Exposures	11. CTA	Significant alpha	Significant Exposures
Growth	0.524	-DEF, MOM, MAI	Growth	0.817	-EXCH, MOM
Recession	-	GOAG, MOM	Recession	-	-MAI, COEN
Up	0.153	MAI, MOM, HML	Up	0.831	COPM
Down	-	MOM, -HML, COAG	Down	-	-MAI, COEN

The next subsections present an MAI exposure analysis, alpha analysis, and exposure analysis, followed by a discussion.

3.3.4.6 MAI exposure analysis

Table 20 presents the MAI exposure changes for all hedge fund strategies comparing growth to recession periods and up regimes to down regimes. Almost all hedge fund strategies have low or negative exposures stressful market conditions as fund managers try to minimize their risk. This suggests that fund managers are able to hedge market exposures at such times. Comparing growth to recession periods, most hedge fund strategies decrease their exposures to MAI during recessions. The Short Bias strategy in the growth period already has negative exposure, however during recession periods its exposure becomes more negative so as to benefit from expected downward market movement. Relative value has one of the lower exposures during the growth period but it is almost double that during recession periods. This is unusual; however, this strategy during the recession period has the lowest exposure to the MAI factor across all hedge fund strategies. Furthermore, during the growth period this strategy has three more factor exposures (SMB, HML and TERM) and these may interact positively overall (e.g. this portfolio with these asset class exposures is better in terms of risk incurred and alpha produced to the investor).

Regarding the up-down regimes all the strategies decrease their exposures to the market factor during falling markets. The largest decrease is by the Global Macro strategy, equal to 72%, whereas the smallest decrease is by the SB strategy at 9%. This is because during stressful market conditions, Global Macro strategies are able to switch to other regions (relying on the top-down approach) for a relatively short period of time as their main focus is in North America. Hence they can demonstrate a high decrease in their MAI exposure. On the contrary, the Short Bias strategy already has a negative correlation with MAI, thus there is no need for a large change in their position. Moreover, during down regimes the SB strategy has only two exposures, compared to the five within the up regimes as it tries to reduce its exposures (to protect themselves from "bad" conditions).

Table 20. Exposures to the Market

This table shows the exposures to the MAI market index for all hedge fund strategies during growth and recession periods as well as the up and down regimes. Since the growth periods and up regimes times are the longest I use them as the base to measure the percentage change of the exposure.

MAI	Growth	Recession	% Difference (Base = Growth)	Up	Down	% Difference (Base = Up)
Short Bias	-0.854	-1.012	18%	-0.934	-0.849	-9%
Long Only	0.672	0.609	-9%	0.669	0.551	-18%
Sector	0.593	0.541	-9%	0.588	0.502	-15%
Long Short	0.528	0.466	-12%	0.574	0.312	-46%
Event Driven	0.304	0.289	-5%	0.252	0.203	-20%
Multi-Strategy	0.219	-	-	0.226	-	-
Others	0.155	-	-	0.148	0.186	-
Global Macro	0.306	-	-	0.285	0.081	-72%
Relative Value	0.148	0.284	91%	0.151	-	-
Market Neutral	0.068	-	-	0.075	-	-
CTAs	-	-0.147	-	-	-0.156	-

3.3.4.7 Alpha analysis

Before I move to the common factor analysis, there is a brief discussion of the alphas for all strategies. Within business cycles all strategies except CTA provide average alpha for growth periods of 0.847 while for the up regime this is 0.558. This is because during growth periods some strategies (e.g. Sector, Others) provide extra alpha compared to the up regime. For recession periods the average alpha is 1.322 compared to 0.733 for the down regime; the difference has to do with the excess high alpha produced by some strategies (e.g. the ‘Others’ strategy) during recession periods. CTA during growth and up periods provides 0.817 and 0.831 respectively. During recessions and down regimes CTAs’ alphas are not significant, meaning that this strategy performs well only in good times (one of the highest alphas across all strategies). Overall, concerning bad economic or market conditions, down regimes seem to be harsher for hedge fund strategies in terms of excess returns. Fund managers are more concerned with minimizing their risk in down regimes than in recessions, even at the cost of lower returns.

3.3.4.8 Common factors excluding MAI

Table 21 presents the important factors (excluding MAI) across all strategies. During growth periods fund managers invest more in equity factors such as MOM, SMB and HML. Hence, momentum sub-strategies, investing in small firms compared to large or investing in value versus growth stocks are efficient in delivering high excess returns to investors. During recession periods, the three most important factors are COAG, COEN, and COIM. Fund managers change their asset allocations and are trying to invest in commodity factors (food/agriculture, energy, and industrial metals) that relate to more defensive or counter-cyclical industries. This is in agreement with Cashin, McDermott, Scott (2002) who found that economic cycles are not the fundamental drivers of the evolution of commodity prices and Gleich, Achzet, Mayer, and Rathgeber (2013) who found that commodity prices depend on other fundamental factors such as economic scarcity and supply risk. However, the Others strategy is able to deliver significant excess returns to investors as it has significant exposures to the GEMI factor meaning that is investing in global markets. The same is true for the Sector strategy that invests in certain (counter-cyclical) industries, providing significant alpha.

During the up regime, similar to growth periods, the most common exposures are to MOM, SMB and HML. Fund managers invest in equity factors and implement momentum sub-strategies investing more heavily in smaller firms and value stocks. Like the growth periods, directional and semi-directional strategies mainly have these exposures. During down regimes, fund managers invest primarily in equity and commodity factors. Although SMB is still a main exposure for hedge fund strategies, nevertheless this exposure is lower compared to the up regime. Similarly to the recession period, in the down regime fund managers take exposures to the factors COAG and COIM, as they are related to more defensive counter-cyclical industries. This aligns with the results of the studies of Cashin, McDermott and Scott (2002) and Gleich, Achzet, Mayer and Rathgeber (2013) mentioned above.

Table 21. Most Common Factors Excluding MAI

This table shows the most frequent exposures for all strategies across business cycles and during different market conditions. The *X* symbol represents the existence of a statistically significant exposure. During down regimes there are more common exposures (e.g. COAG), however I present the three most intense.

Growth Period	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTA
MOM	X	X	X	X		X	X			X	X
SMB	X	X	X	X	X	X			X		
HML		X		X	X	X			X		
Recession Period											
COAG		X	X	X				X		X	
COEN	X						X	X			X
COIM	X						X	X			
Up Regime											
MOM	X	X	X	X		X		X	X	X	
SMB	X	X	X	X	X	X			X		
HML		X		X	X	X			X	X	
Down Regime											
SMB		X		X					X		
COIM					X	X			X		
COEN	X							X			X

Table 22 examines the portfolio allocation exposures (in terms of intensity) of the asset classes for all hedge fund strategies. According to the analysis the most common asset classes across all hedge fund strategies within business cycles/different regimes are: first, the Equity class (MAI, SMB, MOM, HML and GEMI), then the commodity class (COIM, COAG, COEN and COPM), then Credit (DEF and TERM) and finally the Option (DVIX) class. On average, during recession and down regimes hedge fund managers lower their exposures to the equity class factors by 17% and 22% respectively. It is the opposite for commodities: during recession and down regimes, on average, hedge fund managers increase their exposures to the commodity asset classes by 50% and 57% respectively. Concerning the credit factors (which are less common than the two previous classes), during recessions hedge fund managers change their average exposures and go from negative to positive (please see the sub-section on opposite/reverse exposures). The opposite is true for the option class factor: here, during stressful market conditions, hedge fund managers on average change their exposures from positive to negative to protect themselves against risk.

Table 22. Portfolio Allocations

This table shows the average allocations to the most common asset classes for all hedge fund strategies within business cycles and different market conditions.

Asset Class	Growth	Recession	% Difference (Base = Growth)	Up regime	Down regime	% Difference (Base = Up)
Equity	0.112	0.093	-17%	0.109	0.085	-22%
Commodity	0.056	0.084	50.%	0.063	0.099	57%
Credit	-0.637	0.130	120%	-0.024	-	
Option	0.021	-0.061	-390%	0.014	-0.029	-307%

3.3.4.9 Opposite/Reverse exposures

So far we have seen that hedge fund strategies, conditional on market conditions, reduce both the number of their exposures to different asset classes and their portfolio allocations. However, I have found that there are some exposures for a few hedge fund strategies that are systematically negative (positive) during stressful market conditions and positive (negative) during good times. For example, during growth and recession periods fund managers (e.g. Sector, Long Short, Others) take positions with negative exposures toward DEF (default premium) and HML (High minus Low), respectively. In this study, I computed that the DEF spread is lower during growth periods (average equal to 0.88) than during recessions (average equal to 1.60) due to market uncertainty. Hence, fund managers during growth periods take negative exposure against DEF for higher returns. The HML spread is higher during growth periods (average equal to 0.51) compared to recessions (average equal to -0.39), as value stocks are in better (worse) position than growth stocks during growth periods (recessions). Thus, fund managers during recessions take negative exposures against HML (e.g. buying fewer asset-rich stocks). Overall, there is evidence that fund managers take negative positions to some factors conditional on changing market conditions.

There are also fund managers who reverse their exposure from negative to positive and vice versa in the same asset class, depending on market conditions. For example, Long Short and Market Neutral strategies have positive HML exposure during “good” times and negative HML exposure during “bad” times. By doing this they provide high excess returns when there is upward market movement and protect themselves from risk during "bad" times. Ultimately, fund managers, beyond taking negative positions in some asset classes as mentioned in the precious paragraph, move further by taking negative or positive positions on the same asset class conditional on changing market conditions.

3.3.4.10 Exposure by group

I now examine the most common exposures for the three groups of strategies: directional, semi-directional and non-directional[26]. For directional the most common exposures (excluding MAI) during "good" times are SMB and MOM as fund managers exploit the momentum and the size effect. During stressful market conditions fund managers are trying to minimize their risk. Hence, for recession periods the exposures are COAG and then HML (with negative exposures) while for the down regime these are SMB and COAG. Semi-directional strategies have less common exposures between them as they have less systematic risk than directional strategies. The most important for growth periods (in terms of intensity) are DEF (negative exposures) and SMB. For recession periods the most common are COIM and TERM. For the up regime they are the HML and SMB (in terms of intensity) whereas for the down regime it is the COIM factor. Regarding the non-directional strategies these by nature have very low systematic risk and are less sensitive to business cycles and market conditions. For growth periods the most common is the MOM factor whereas for the up regime there is an additional factor, the HML. For recession periods and down regimes, except for the MAI, there is no common factor as each strategy may exploit different factors.

Table 23 shows that directional strategies have less dispersed (more common) factors concerning their asset class exposures within different business cycles and market conditions (on average, 2.2 asset class exposures per group). Next are the semi-directional strategies (on average 1.8 asset class exposures per group) and then the non-directional strategies (1.3), i.e. the last group has the least common exposures within its hedge fund strategies. This dispersion increases gradually when moving from directional to non-directional strategies.

[26] Recall that I consider directional strategies to be Short Bias, Long Only, Sector and Long Short, semi-directional strategies to be Event Driven, Multi Strategy, Others and Global Macro and non-directional strategies to be Relative Value, Market Neutral and CTAs. There is a grading from extreme directional strategies such as Short Bias to extreme non-directional strategies such as CTAs.

Table 23. Exposures per Group (excluding MAI)

This table shows the number of exposures and the most common factor within different business cycles and market conditions across three groups: directional, semi-directional and non-directional strategies (depending on their correlation with the MAI market index).

	Growth	Recession	Up	Down
Panel A	Directional Strategies			
Average number of factors within group	2.4	2.2	2.2	1.8
Total number of factors	10	5	10	6
Most common factors	SMB, MOM	COAG, HML	SMB, MOM	SMB,GOAG
Panel B	Semi Directional Strategies			
Average number of factors within group	1.9	1.5	1.9	1.4
Total number of factors	8	8	10	7
Most common factors	DEF, SMB	COIM, TERM	HML, SMB	COIM
Panel C	Non-Directional Strategies			
Average number of factors within group	1.3	1.3	1.4	1
Total number of factors	7	4	7	8
Most common factors	MOM	-	MOM, HML	-

Table 24 examines the portfolio allocation exposures (the intensity) for each group[27]. In general, all strategies change their exposures during stressful market conditions. Concerning the equity factors in growth/recession periods the change is driven mostly by the directional strategies. For the up/down regimes it is driven mostly by semi/non directional strategies. Regarding the commodity factors in growth/recession regimes, the change is driven mainly from directional strategies whereas for up/down regimes the change is driven mainly by directional and non-directional strategies.

[27] I remind the reader that there is a gradual market classification, hence it is difficult to impose strict limits on each group.

Table 24. Portfolio Allocation

This table shows the average changes of the most common asset classes for each group of strategies within business cycles and different market conditions. Non-directional strategies do not have any significant commodity asset classes during growth periods.

Asset Class	Growth	Recession	% Difference (Base = Growth)	Up regime	Down regime	% Difference (Base = Up)
Directional strategies						
Equity	0.095	0.064	-33%	0.100	0.129	29%
Commodity	0.053	0.116	119%	0.061	0.115	89%
Semi-directional strategies						
Equity	0.148	0.191	29%	0.140	0.079	-44%
Commodity	0.066	0.063	-5%	0.047	0.104	121%
Non-directional strategies						
Equity	0.091	0.064	-30%	0.072	0.013	-82%
Commodity	-	0.082	-	0.137	0.079	-42%

3.3.4.11 Discussion

The results confirm the initial assumption that hedge funds have exposures to different factors and are time-varying, conditional on different cycles and regimes. Moreover, the results do not confirm the assumption that hedge funds are superior investment vehicles, i.e. they do not deliver excess returns to investors in all business cycles and market conditions. In general, the findings agree with other authors (e.g. Bali, Brown and Caglayan, 2011, Jawadi and Khanniche, 2012 and Giannikis and Vrontos, 2011) that hedge fund strategies are dynamic in terms of exposures and returns. More specifically, the model used agrees with the literature that returns and factor exposures change over time, as there are major switches of hedge fund returns (as modelled by Jawadi, Khannich, 2012) occurring in stressful market conditions. In addition, there is partial agreement with Bollen and Whaley (2009) since I found that only one of their two samples, containing spikes of exposures' switching to appear during stressful market conditions. However, it is important to mention that they focus (contrary to this study) on the internal change of funds' exposures examining funds during the period 1994 to 2005, allowing for a single shift in the parameters (asset weightings) of the funds. I have shown that different strategies (especially between directional and non-directional) have different exposures. In addition, there are some common risk factors such as the market, credit, the term spread and commodities that are shared between many hedge fund strategies (as mentioned by Billio, Getmansky and Pelizzon, 2012) and there are some other factors such as default spread and VIX that are economically important (Avramov et.al. 2013). The findings agree with Meligkotsidou and Vrontos (2014) that the market index and the spread of small cap minus large cap were the most significant factors in hedge fund returns. Furthermore, there are changes in portfolio allocations that are more intense than changes in exposures to asset classes, as Patton and Ramadorai (2013) found. There is partial agreement with Ibbotson, Chen and Zhu (2011) as only a few strategies add significant value to investors during bear market conditions because fund managers are concerned about risk. Nonetheless, they examined alpha and exposures only during the 2008 financial crisis. There is also agreement with Brown (2012) that traditional systematic factors such as equities or credit impose significant exposures on hedge funds although the author took into consideration performance before fees. Last but not least, as Agarwal and Naik (2004) found, there are many hedge fund strategies exhibiting significant exposures to Fama and French's (1993) three-factor model and Carhart's (1997) momentum factor.

3.3.4.12 Robustness

The proposed piece-wise parsimonious multifactor model is a flexible twin model; the first component contains pre-specified structural breaks used (multiple business cycles) incorporating the stepwise regression technique and the second component is without pre-specified breaks (but using a regime switching statistical process that specifies them also) incorporating the stepwise regression technique. The model used sufficiently captures hedge fund behaviour and it is robust. This is because the statistical significance of the factor loadings on the Wilshire 5000TRI, conditional on the different regimes, is almost the same as that obtained in the simple market model with only the Wilshire 5000 TRI risk factor. This indicates that the analysis performed above is robust to the inclusion of other factors that may affect hedge index returns. Moreover, the average adjusted R^2 for all strategies (excluding CTA) within all periods/regimes is 0.61 for the proposed multi-factor model. The average highest is 0.84 for the Long Only strategy and the lowest is 0.29 for the Market Neutral strategy; it is 0.15 for CTA. This is compared to 0.48 for the simple market model.

I tested the proposed model by using Carhart's (1997) four-factor model and all the regressors in the model had the same sign and most were statistically significant. This process took place for all periods/regimes under consideration. Moreover, the proposed model adjusted R^2 was higher than Carhart's model which was 0.53. An essential robustness test is that I performed the analysis again by excluding the first 48 months

(1/1990-12/1993) and implementing the proposed model again. Within all cycles/regimes, all the regressors had the same sign and mostly statistically significant, making my findings more robust. Another robustness test I implemented was to model only the first 48 months (1/1990-12/1993). The results were qualitatively similar. I confirmed that during "good" times hedge fund strategies invest mainly in equity asset classes (MAI, MOM, SMB, and HML). An additional robustness check was to examine the model for the post-1994 period (1/1994-3/2014) using lookback straddles on bonds, currencies, commodities, short term interest rates and stock indices. As well as the lookback straddles, I found that COAG, COEN, and COIM were significant for this hedge fund strategy. I also proceed to another statistical test of my model for all hedge fund strategies using the HAC/Newey-West estimator for any unknown residual autocorrelation and heteroskedasticity and the results are still valid[28].

3.4 Conclusion

In this study I have modelled 11 different hedge fund strategies using predefined structural breaks, based on multiple business cycles during 1990-2014 (the longest period in any hedge fund paper to date), using a comprehensive merged database. Beyond this, I used a Markov Switching model to identify in the proposed model the structural breaks conditional on the different states of the market index incorporating the stepwise regression technique so that the proposed model adjusts to different economic and market conditions, providing more accurate and useful results.

There are some important conclusions that contribute significantly to the hedge fund literature, beyond those that agreed with the extant literature discussed above. First, stressful market conditions have a negative impact on hedge fund performance in terms of alphas as the majority of hedge fund strategies do not provide significant excess return to investors; at such times it is difficult to find opportunities. In addition, fund managers are concerned more about risk so as to protect themselves from losing money. Hedge fund strategies have much less exposure during stressful market conditions in terms of different assets classes and portfolio allocations (e.g. equity classes) as fund managers are concerned more about risks even at the cost of low returns. There are

[28] The results concerning (1) Carhart's model, (2) those concerning the pre-1994 period that was omitted, (3) those that include the first four years e.g. 1/1990-12/1993 (I implemented my model for "good" only times as in recessions and down regimes there were only 8 and 4 monthly observations, respectively), and (4) those of the CTA strategy concerning the post-1994 period, e.g. 1/1994-3/2014, using lookback straddles (Fung and Hsieh, 2001), and (5) the HAC/Newey-West estimator test in the robustness part of section 3.3 are in the appendix.

some strategies such as Long Short that even reverse their exposures to some factors, to protect themselves from risk. However, there are some strategies such as Market Neutral that are little affected by these conditions in terms of exposures, although it is not a trivial process to keep a market neutral portfolio balanced for all market conditions. Second, directional strategies have, on average, more common exposures between themselves, within all business cycles / different market conditions, compared to less directional strategies as by nature they have more systematic risk than non-directional strategies. Third, factors related to commodities such as COAG, COEN and COIM are the most common exposures during stressful market conditions (in addition to the MAI factor) as they are regarded counter-cyclical industries or essential goods/services. On the contrary, some factors such as MAI, MOM, SMB and HML are the most common factors for the "good" time periods because fund managers benefit from the upward market movement, paying attention more to high returns compared to the systematic risk. Fourth, market volatility appears to affect hedge fund performance (in terms of alpha and exposures) more than business cycles volatility as down regimes are difficult to predict or to instantly realize once they happen.

The results are important because they enable us to better understand hedge funds' behaviour and I reveal aspects that have not been examined before. Although hedge funds are complex investment vehicles and difficult to model, there are nevertheless some consistent patterns in their behavior at a strategy level. These patterns are related to fund managers' responses in terms of the excess returns delivered to investors and their exposures to factors within multiple business cycles and different market conditions. The long period of the used database (to my knowledge, the longest of any extant paper) enables us to examine hedge fund behavior in more a comprehensive way, not isolating a relatively short period of time containing just one financial crisis. In the proposed model, instead of using one general commodity factor I used specific ones for more precise results including for the first time (to my knowledge) the commodity factor COAG (agricultural/food industry). This is one of the prime exposure factors during recession and down regimes for many strategies.

Investors can benefit from the findings as, at strategy level, they are able to know what to expect from different strategies taking into consideration stressful market conditions, having a clear distinction between business cycles and bull/bear market conditions. This is crucial as these two different states do not necessarily coincide and they have different implications for hedge funds. The results should help investors and fund of fund managers in their strategic asset allocation process (e.g. selecting specific strategies during “bad” times that do not suffer a lot) although investors should predict by themselves with high accuracy these market conditions. Another use of the findings could be by fund administrators to use more flexible performance fee policies that can capture in a better way hedge fund managers’ performance (e.g. higher watermarks during “good” times). Last but not least, financial governance authorities could benefit by better understanding hedge funds’ risks and returns, in case there is a need for closer monitoring or a more restrictive legal framework in the future.

I have focused on hedge funds that invest primarily in the North America region due to the use of U.S. business cycles. Whether similar results hold for the European and Asia-Pacific regions would be a valuable out of sample test, but the definition of business cycles in these regions may be problematic. A further limitation is that I do not use in the main analysis lookback straddles that are appropriate for CTAs, due to data unavailability in the early 1990s. There is a need to examine hedge fund behaviour investing in other regions (e.g. Emerging Market strategies) within my approach. Last but not least, due to data unavailability (e.g. time-series of long and short position holdings or leverage ratios) the leverage is not considered that can play a role in hedge fund performance.

4 Chapter: Performance at fundamental and mixed level

This Chapter (paper) examines the second research question that deals with what the impact is of fundamental factors on hedge fund strategy performance within (multiple) business cycles and different market conditions. Similar to the previous chapter, this is an empirical study therefore its structure has its own introduction, methodology, empirical analysis, and conclusion sections (a version of this paper is to be submitted to a journal).

I explain hedge fund performance as a part of a holistic approach taking into consideration fund specific characteristics, fund strategies, and both business cycles and different market conditions using a long U.S. dataset from 1990 to 2014. Using the proposed piece-wise parsimonous model I have found, first, that irrespective of the underlying fundamental factors, hedge funds on average deliver significant excess returns to investors only during "good" times. During "bad" times they try to minimize their systematic risk. Secondly, during "good" times, small funds, young funds and funds with redemption restrictions deliver higher alpha with respect to their peers; however, during "bad" times small funds suffer more than large funds, young funds continue to outperform old ones, and funds that do not impose restrictions (and survive) outperform funds with lockups. Third, at the mixed level there are strategies with specific characteristics that deliver significant negative alpha to investors, conditional on stressful market conditions.

4.1 Introduction

In the hedge fund literature there are many studies that investigate the relationship between fund returns and fund specific characteristics such as size, age, lockup, and fees (e.g. Harri and Brorsen, 2004; Frumkin and Vandegrift, 2009; Bae and Yi, 2012). There have been also studies that investigate the relationship between fund returns and specific strategies or investment styles (e.g. Bollen and Whaley, 2009; O'Doherty, Savin, and Tiwari, 2015; Racicot and Theoret, 2016). Despite the fact that these studies use different databases and time periods, they can provide a useful guide to investors. Although these studies are important, until now there has been no investigation under a holistic approach of the relationship between funds' performance and fund strategies and characteristics, within both different business cycles and market conditions. Given the complexity of hedge funds, knowing all the above interactions within a holistic approach is a major issue for investors to deal with. Consequently, this study which uses an accurate parsimonious model discussed later, closes an important gap and helps investors in their asset and portfolio allocation process. In this study I use both multiple business cycles and market conditions as these two do not coincide necessarily. I have classified and ranked four different states of economic activity beginning from the most desirable state to the least desirable state. I focus on North American due to the use of three full U.S. business cycles and the importance of this market, counting for $1.9 trillion of assets under management corresponding to almost 72% of the worldwide total of hedge funds (Preqin Global Hedge Fund Report, 2014).

The novelty of this study lies to the use of a holistic approach examining the relationship between fund performance, fund strategies and fund characteristics exploiting both multiple business cycles and different market conditions (there is a clear distinction between them), and using the longest dataset ever used in a study. The proposed econometric model is flexible enough to capture hedge fund behaviour within these regimes/periods helping investors in their asset and portfolio allocations. The results are robust and the most important findings are, first, that hedge funds, on average, deliver significant alpha to investors only during "good" times irrespective of their characteristics whereas during "bad" times they try to minimize their systematic risk. Secondly, during "good" times small, young and funds with redemption restrictions outperform their peers; nevertheless, during "bad" times small funds suffer more than large funds, young funds continue to outperform old ones, and funds that impose restrictions (and survive) outperform funds with lockups. Third, strategies with specific characteristics can even deliver significant negative alpha, conditional on stressful market conditions.

Several papers (e.g. Schneeweis, Kazemi, and Martin, 2002; Hedges, 2003; Harri and Brorsen, 2004; Ammann and Moerth, 2005; Meredith, 2007; Joenavaara, Kosowski, and Tolonen, 2012) showed that there is a negative relationship between fund performance and size. Agarwal, Daniel, and Naik (2004) found that there is a negative correlation and diseconomies of scale. Commercial studies (e.g. Pertrac Corp, 2012) also showed that there is a negative relationship between size and performance. However, there are some others studies (e.g. Gregoriou and Rouah, 2002) that found no evidence of a relationship, whereas yet other papers (e.g. Amenc and Martellini, 2003; Koh, Koh, and Teo, 2003) found a positive relationship and economies of scale. Getmansky (2004) found that there is a positive and concave correlation and suggested that there is an optimal asset size. Although there are contradictory results due to different time periods, databases and methodologies, most studies conclude that there is a negative relationship between hedge fund size and performance. The age factor usually has to do with when the fund was launched, or the date the hedge fund entered vendor database(s). There are many studies (e.g. Howell, 2001; Amenc and Maertellini, 2003; Meredith, 2007; Frumkin and Vandegrift, 2009) that found young funds outperform old funds and commercial studies (e.g. Pertrac Corp, 2012) have also confirmed this. An exception is from Schneeweis, Kazemi and Martin (2002) who found strong evidence that there is a negative relationship between age and performance. However, Schneeweis et.al. (2002), contrary to other studies, took into consideration funds with the same starting month.

As for the management fee, many studies (e.g. Ackerman, McEnally, and Ravenscraft, 1999; Amemc and Martellini, 2003; Bae and Yi, 2012; Joenvaara, Kosowski, and Tolonen, 2012) have found that there is a positive relationship between performance fees and hedge funds' performance. An exception is Schneeweis et al. (2002) and Koh et al. (2003) who found no significant relationship although the latter considered Asian hedge funds. This is intuitive for an investor to expect that higher performance fee corresponds to managers with higher skills (you get what you pay for). Regarding other fundamental factors, studies (such as Aragon, 2007; Joenvaara et al., 2012) showed that funds that impose lockup periods outperform funds that do not impose redemption restrictions as they are able to exploit liquidity premia for higher returns. Later studies (e.g. Hong, 2014) showed that although funds may have lower returns after decreasing share restrictions, nevertheless, investors reward fund managers by increasing flows. There are also many studies focusing on hedge fund strategies showing that funds' exposures change over time and different strategies demonstrate different exposures in a non-linear framework (e.g. Bollen and Whaley, 2009; Billio, Getmansky and Pelizzon, 2012; Melighotsidou and Vrontos, 2014; O'Doherty, Savin, and Tiwari, 2015).

All the above studies present different perspectives of hedge fund performance and almost all agree that there is an association between specific fund characteristics (fundamental factors) and fund performance, and that funds' exposures change over time. These studies are important for understanding hedge fund behaviour; nevertheless, investors are still confused by hedge fund complexity as these associations are investigated on fundamental-only or strategy-only levels, without also examining their conditional changes over time. There is no holistic approach between performance, and the three elements of fundamental factors, strategies and market conditions. This study closes an important gap, as this is the first investigation of hedge funds in a comprehensive, holistic approach that examines the relationship of performance with the previous three elements. I examine funds' performance at the fundamental (fund characteristics) and mixed level (strategy and fund characteristics, together). As these relations are dynamic, I use multiple business cycles and different market conditions (thus not isolating one only recession or financial event) making a clear distinction between them as they do not coincide necessarily, having a different impact on funds' performance. In addition, I rank favorable economic states from the most desirable state to the least desirable within the above approach (see section 4.3.2.6). Beyond that I examine hedge funds that invest primarily in one only region, which is the North American[29] for more robust and concrete results, within the flexible adjusted model, I am the first to use specific commodity factors (e.g. agriculture/food, energy, industrial and precious metals) instead of one only general factor that is over simplistic.

There are some important findings that contribute to the academic literature beyond those that agree with the literature, in terms of the negative relation between size and performance (Agarwal, Daniel, and Naik, 2004; Ammann, and Moerth, 2005; Meredith, 2007; Joenvaara, Kosowski, and Tolonen, 2012), the negative relation between age and performance (Amenc and Martelini, 2003; Meredith, 2007; Frumkin, and Vandegrif, 2009; Pertrac Corporation, 2012), and funds that impose redemption restrictions outperforming those that do not (Aragon, 2007; Joenvaara, Kosowski, and Tolonen, 2012), as well as the changing exposures over time of funds in a non-linear framework (Bollen and Whaley, 2009; Billio, Getmansky and Pelizzon, 2012; Melighotsidou and Vrontos, 2014; O'Doherty, Savin, and Tiwari, 2015): First, irrespective of the underlying fundamental factors, all funds, on average, during "good" times deliver excess returns to investors, contrary to "bad" times where there are no significant excess returns. In terms of the market exposures, irrespective of the fundamental factors, during stressful conditions funds, on average, decrease their market exposures. Secondly, at the fundamental level, during "good" times, small funds, young funds, and funds with redemption restrictions deliver higher alpha with respect to their peers. For

[29] As I have mentioned North America is the most economically important region and I cover three full U.S. business cycles. I examine what the direct impact is of the underlying economic conditions on hedge funds' performance. Funds that invest in equity emerging markets or fixed income emerging markets that do not have direct exposure to the North America region should be treated separately in another paper.

"bad" times, small funds seem to suffer more than large, young funds continue to outperform old funds, and funds that do not impose restrictions (and survive) outperform funds with lockups. It seems that fund managers feeling the pressure of not having the "safety" of redemption restrictions are more innovative and do better than their peers. Third, at the mixed level, there are strategies with specific characteristics, conditional on stressful market conditions that deliver significant negative alpha to investors. The findings are robust even after having excluding the pre 1994 period from my analysis to the robustness checks (many papers exclude pre-1994 data because the majority of the databases for commercial use came into existence from the early/mid 1990s with a few exceptions such as the Eurekahedge and Barclayhedge databases that include also pre 1994 dead funds) or using the pre-1994 only time period.

This study contributes to the hedge fund literature being the first to examine fund performance in a holistic approach of funds' fundamental characteristics, funds' strategies, and both multiple business cycles and different market conditions. I have revealed useful findings on hedge fund behaviour, helping investors in their investment decision processes as they now know how these different aspects are related and what to expect from hedge funds. I used multiple business cycles and market conditions (not isolating only one recession or financial stressful event) and I make a clear distinction between them as they have different implications for hedge funds. An extension of this is the analysis of ranking favorable economic states from the most desirable state to the least desirable. By using a systematic database merging and cleaning process, the proposed piece-wise parsimonious econometric model with pre-defined and undefined structural breaks is flexible enough to capture changes in asset and portfolio allocations of hedge funds over time. Lastly, I use several specific commodity factors (e.g. agriculture/food, energy, industrial and precious metals) for more accuracy as different commodities do not behave in the same way in the market, as suggested by Bhardwaj and Dunsby (2014).

The remainder of the paper is organized as follows: section 4.2 is the methodology detailing the theoretical framework and the data I use in the analysis. Section 4.3 is the empirical analysis with key statistics, the regime switching model, and fund performance at fundamental and mixed level with some robustness tests. Section 4.4 is the conclusion providing a summary of the findings and some opportunities for further research.

4.2 Methodology

This section presents the theoretical framework along with the data.

4.2.1 Theoretical framework

I use the custom proposed model with pre-defined and non-defines structural breaks. The pre-defined structural breaks depend on the growth and recession periods of multiple business cycles. For the non-defined structural breaks there is a use of a statistical stochastic process using the Markov regime-switching model (Hamilton, 1989, 1990). This agile model is flexible enough to capture changes in asset and portfolio allocations due to the use of the stepwise regression technique in each regime/period. For more details about the above please see Chapter Three – methodology section. This approach takes place at the fundamental and the mixed level.

In order to examine hedge funds at fundamental level I form portfolios (groups) for all hedge funds according to size, age, and lockup redemption restriction. Furthermore, in order to examine hedge funds at mixed level I form sub-portfolios (sub-groups) for each of the 11 hedge fund strategies (see next section).

4.2.2 Data

I use the same databases as I used in the Chapter Three covering the period from January 1990 to March 2014 and the same factors form the Datastream and Fama and French's online data library (Ibottson Associates). For more information about the data, the database merging and cleaning processes, the hedge fund strategies, and the factors please the empirical paper one – data section. However, in this empirical chapter I use an extra dataset that deals with hedge fund fundamental factors (hedge fund specific characteristics).

As fundamental factors I use three hedge fund characteristics: the size, the age and the lock-up period. The objective is to examine the differences between small versus large funds, young versus old funds, and lockup-yes versus lockup-no funds regarding their performance (alpha and exposures) within multiple business cycles and different market conditions. I implemented an analysis concerning all hedge fund strategies excluding CTAs, which I examine separately in my empirical section. Beginning from the size fundamental factor, I calculated the median asset under management (AUM) of all hedge funds to be $34.4 million. For each individual hedge fund I computed the average AUM since its inception. This is because the AUM are not steady and usually grow over time. Thus I formed two portfolios of funds, those that were below $34.4m classifying them as small and those above $34.4m classifying them as large. Concerning the age fundamental factor, I computed the median age in months since the inception of each fund to be 62 months. Hence, I formed two portfolios of funds, those with age less than 62 months classifying them as young and those that were more than 62 months classifying them as old funds. Regarding the lockup fundamental factor I formed two portfolios with lockup-yes restrictions and lockup-no restrictions[30].

I formed sub-portfolios for each of the eleven strategies. Hence I formed six portfolios for each of the 11 strategies (in total 66 portfolios): the size portfolios (small and large funds based on their median), the age portfolios (young and old funds based on their median age since the inception period), and lockup portfolios (lockup-yes and lockup-no)[31]. Table 25 provides the overall portfolio analysis structure.

[30] This dual categorization has been used by other authors as well. I found that about half of the funds do not have an explicit lockup period. There are other implicit restrictions such as the redemption frequency or the redemption notice period that can be considered as "soft" restrictions, however too many records were missing to enable further analysis. I considered young/old and large/small categorization similar to other authors mentioned in the introduction section. The industry has grown over time however this does not mean that small funds will be in the early years only, as the number of hedge funds has been increased significantly over the past years.

[31] Those funds that had missing information such as missing size (794) or lockup information (672) were excluded from the sample.

Table 25. Portfolio Analysis Structure

This table presents the overall structure of the portfolio analysis. At the fundamental level analysis, I formed six portfolios whereas at the mixed level analysis I formed 66 portfolios. (All data containing fundamental factor information were mapped to each appropriate fund return and AUM time series data).

All Hedge Funds (at fundamental level)		Hedge Funds (at mixed level)		
Portfolio 1	Size Small Funds (SS)	Strategy 1		
Portfolio 2	Size Large Funds (SL)		Portfolio 1	Size Small Funds (SS)
Portfolio 3	Age Young Funds (AY)		Portfolio 2	Size Large Funds (SL)
Portfolio 4	Age Old Funds (AO)		Portfolio 3	Age Young Funds (AY)
Portfolio 5	Lockup-Yes Funds (LY)		Portfolio 4	Age Old Funds (AO)
Portfolio 6	Lockup-No Funds (LN)		Portfolio 5	Lockup-Yes Funds (LY)
			Portfolio 6	Lockup-No Funds (LN)
		…………...		
			…………….	………………………..
		Strategy 11		
			Portfolio 1	Size Small Funds (SS)
			Portfolio 2	Size Large Funds (SL)
			Portfolio 3	Age Young Funds (AY)
			Portfolio 4	Age Old Funds (AO)
			Portfolio 5	Lockup-Yes Funds (LY)
			Portfolio 6	Lockup-No Funds (LN)

4.3 Empirical analysis

This section presents the basic statistics at strategy and fundamental level and market classification into broader categories of the hedge fund strategies (from directional to non-directional), and giving details of the regime switches that arrived at. Finally it reports the results from multi-factor models at fundamental and mixed levels.

4.3.1 Basic statistics

The basic statistics of the raw returns for each of the 11 hedge fund strategies are presented in the Chapter Three's data section. The reader is reminded that, on average, directional strategies have more volatile returns than non-directional strategies.

Table 26 presents some statistics for all hedge funds based on the fundamental factors. Each fundamental group is a representative-average time series of their relevant (equally weighted) hedge funds. In absolute returns large funds, old funds, and funds with lockups outperform their peers.

Table 26. Raw Returns by Main Portfolios

This table provides the basic statistics of monthly raw returns for each of the 6 portfolios.

Fundamental Group	Mean	Standard Deviation
Size Small	0.92%	2.069
Size Large	1.02%	2.022
Lockup-Yes	1.07%	2.269
Lockup-No	0.91%	1.884
Age Young	0.77%	2.336
Age Old	0.99%	2.040

I classified the strategies into directional, semi-directional, and non-directional strategies according to their correlation with the market index Wilshire 5000TRI, including dividends. The reader can see the correlation of each strategy and its corresponding classification in the Chapter Three’s empirical analysis section.

I implement the analysis taking into consideration different business cycles and market conditions. I remind the reader that within the January 1990 to March 2014 period there are three official business cycles. Hence the period under examination is divided into growth periods (01/1990-07/1990, 04/1991-03/2001, 12/2001-12/2007 and 07/2009-03/2014) and to recession periods (08/1990-03/1991, 04/2001-11/2001, and 01/2008-06/2009). Regarding the different market conditions, the Markov Switching process determines (up and down regimes) based on the mean and volatility of the Wilshire 5000TRI. In order to compare the two different stages with business cycles I selected two regimes. Hence the period under examination is divided into up regimes 01/1990-06/1990, 11/1990-10/2000, 10/2002-05/2008 and 03/2009-03/2014) and to down regimes (07/1990-10/1990, 11/2000-09/2002 and 06/2008-02/2009). It is mentioned that the average monthly MAI (excess risk free) return for down regimes is -3.69% whereas for recessions it is -1.03%. Hence, in the twin model, the classification of the market conditions (from favourable to less favourable overlapping states) is: Up regimes, Growth periods, Recession periods, Down regimes (Best, Good, Bad, Worst) (see section 4.3.2.6 for more details).

The assumptions needed for the parameter techniques used are discussed in chapter 3, section 3.2.2.

4.3.2 Fundamental level

This section takes into consideration all hedge funds and measures hedge fund behaviour based on their characteristics[32].

4.3.2.1 Growth periods

Table 27 shows the results for the growth period under examination. When grouped according to each of the nine fundamental factors all hedge funds deliver strongly significant alphas[33]. The highest is 1.322 and the lowest is 0.823, delivered from funds that impose redemption restrictions and funds that do not impose restrictions accordingly. Regarding the exposures, as expected, there is no wide distribution of different exposures as I take into consideration all strategies. In other words, there is no large difference in terms of exposures of different asset allocations compared to my analysis at strategy level in the empirical chapter one. The most common exposure is MAI, SMB and then MOM and DEF in terms of intensity (portfolio allocations). In total there are 37 exposures to the various asset classes. Overall, within the growth period, hedge funds have relatively high asset allocation exposures for higher returns, irrespective of their fundamental characteristics.

[32] I have also examined hedge funds including the CTA strategy. The results are similar except that, on average, large funds appear to outperform small funds.

[33] Concerning the alphas and exposures, the significant term means significantly different from zero. Alpha is the monthly excess return delivered to investors, expressed as a percentage.

Table 27. Multi-Factor Model During Growth Periods

This table shows the results in terms of alphas and exposures of my multi-factor model for growth periods, at fundamental level. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses. (In this and the subsequent tables empty cells mean that there is no significant exposure to these factors).

Dep. Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (excess return)	1.2188**	0.9055**	1.7091**	1.0016**	1.3220**	0.8228**
	(4.8329)	(4.3329)	(3.7400)	(5.0070)	(5.1951)	(4.4444)
Market Index - MAI	0.3756**	0.3828**	0.3930**	0.3937**	0.4297**	0.3554**
	(23.5797)	(27.6861)	(14.9596)	(29.8729)	(25.6305)	(29.0154)
Small minus Big - SMB	0.1266**	0.1536**		0.1523**	0.1727**	0.1284**
	(6.6024)	(9.0928)		(9.4607)	(8.4346)	(8.5813)
Momentum - MOM	0.0625**	0.0480**	0.1029**	0.0504**	0.0466**	0.0603**
	(4.1856)	(3.8675)	(4.6570)	(4.2688)	(3.0987)	(5.4834)
Commodity Energy - COEN	0.0262**	0.0206**	0.0288*	0.0217**	0.0224**	0.0213**
	(3.2979)	(3.1339)	(2.2989)	(3.4244)	(2.7754)	(3.6623)
Default Spread - DEF	-0.9408**	-0.4914*	-1.4060**	-0.6521**	-0.9207**	-0.5153*
	(-3.3934)	(-2.1456)	(-3.0333)	(-2.9709)	(-3.2969)	(-2.5397)
Commodity Previous Metals - COPM	0.0460**			0.0323**	0.0348*	
	(3.2904)			(2.9166)	(2.4692)	
High minus Low - HML		0.0941**	-0.0812*	0.0841**	0.0815**	0.0642**
		(5.0484)	(-2.4780)	(4.7450)	(3.6155)	(3.8860)
Adj. R-squared:	0.7423	0.7902	0.6388	0.8207	0.7734	0.8069
F-statistic:	123.9101	161.7340	60.4222	168.3790	125.8359	179.2989
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.3.2.2 Recession periods

Table 28 shows the results during recession periods. On average, hedge funds do not provide significant alphas to investors, irrespective of their characteristics. Concerning the exposures there are fewer compared to the growth period in terms of asset allocation and portfolio allocation. The most common exposures are MAI and COAG. The highest exposure is, on average, in large funds and the lowest, on average, in funds that impose redemption restrictions on investors. In total, there are 20 exposures to asset classes compared to 37 during growth periods. Overall fund managers during recessions try to minimize their exposures even at the cost of lower alpha.

Table 28. Multi-Factor Model During Recessions

This table shows the results in terms of alphas and exposures of my multi-factor model during recession periods, at fundamental level. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dep. Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (excess return)	0.2516	0.4043	0.3066	0.3417	0.2463	0.3849
	(1.2998)	(1.5336)	(1.9611)	(1.4835)	(0.9528)	(1.9492)
Market Index - MAI	0.2277**	0.3802**	0.2944**	0.3684**	0.2774**	0.3469**
	(5.4665)	(8.9358)	(11.2112)	(9.9131)	(4.9877)	(10.8859)
Commodity Energy - COEN	0.0483**		0.0435*			
	(3.5140)		(2.7571)			
Change in VIX - DVIX	-0.0269*				-0.0344*	
	(-2.4561)				(-2.3586)	
Commodity Agriculture - COAG	0.0598*	0.0855*	0.0526*	0.0913**	0.0841*	0.0811**
	(2.0598)	(2.3088)	(2.5001)	(2.8207)	(2.2968)	(2.9255)
High minus Low - HML		-0.1897*	-0.2533**	-0.1420*		-0.1312*
		(-2.5438)	(-6.3516)	(-2.1803)		(-2.3484)
Adj. R-squared:	0.8365	0.7811	0.9161	0.8182	0.7892	0.8426
F-statistic:	43.2033	40.2533	69.2761	50.5051	42.1903	59.9072
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.3.2.3 Up regimes

Table 29 presents results showing that during up regimes all hedge funds deliver strongly significant alphas or excess returns to investors. The highest alpha is 0.507, delivered from funds that impose redemption restrictions and the lowest is 0.301, delivered from young funds. The most important exposures are MAI and MOM. The highest exposure is 0.422 and the lowest 0.367 delivered from lockup-yes and lockup-no, respectively. Similarly to the growth period there is, as expected, no wide distribution of exposures in hedge funds in terms of asset allocations. In total, there are 32 asset class exposures across all strategies. In general fund managers during “good” times try to exploit the upward market movement increasing their exposures.

Table 29. Multi-Factor Model During a Rising Market

This table shows the results in terms of alphas and exposures of my multi-factor model for the up regime, at fundamental level. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dep. Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (excess return)	0.3133**	0.4757**	0.3010**	0.4283**	0.5073**	0.3719**
	(4.2796)	(8.2110)	(2.6501)	(7.8143)	(7.3898)	(7.2230)
Market Index - MAI	0.4101**	0.3898**	0.4032**	0.3992**	0.4222**	0.3669**
	(17.3091)	(26.0117)	(14.5904)	(28.1500)	(23.7737)	(27.5416)
Commodity Energy - COEN	0.0325**	0.0269**	0.0340**	0.0277**	0.0304**	0.0260**
	(3.8644)	(3.9292)	(2.6814)	(4.1946)	(3.6815)	(4.2849)
Small minus Big - SMB	0.1329**	0.1507**		0.1487**	0.1645**	0.1271**
	(5.9324)	(8.0935)		(8.4239)	(7.4432)	(7.6842)
Momentum - MOM	0.0696**	0.0515**	0.1116**	0.0521**	0.0664**	0.0528**
	(4.6395)	(4.1310)	(5.3557)	(4.4165)	(4.4994)	(4.7672)
Commodity Precious Metals - COPM	0.0435**			0.0320**	0.0351*	
	(3.0807)			(2.8800)	(2.5196)	
High minus Low - HML	0.0692**	0.1001**		0.0950**	0.0952**	0.0798**
	(2.6241)	(4.5908)		(4.6056)	(3.6841)	(4.1187)
Change in VIX - DVIX	0.0102*					
	(2.0334)					
Adj. R-squared:	0.7050	0.7737	0.6060	0.8041	0.7486	0.7911
F-statistic:	87.7017	174.7268	84.0608	174.7865	127.0627	193.3936
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.3.2.4 Down regimes

Table 30 presents the results during down regimes. Hedge funds, irrespective of their fundamental characteristics, do not provide significant alphas to investors. Most hedge fund strategies do not provide significant alphas to investors. Any significant alphas delivered from particular strategies are shadowed by the other strategies, as in the current sample they are taken into consideration all eleven hedge fund strategies. Regarding the exposures, there are fewer compared to the growth period in terms of asset allocation and portfolio allocation. MAI, SMB and then COIM are the most common exposures. Small funds and no lockup funds deliver market exposures equal to 0.237 and 0.165, which are the lowest and highest, respectively. The total number of exposures during the down regimes is 26 across all hedge fund strategies. Similar to recessions, fund managers try to minimize their exposures.

Table 30. Multi-Factor Model During a Falling Market

This table shows the exposures of my multi-factor model for when the Wilshire 5000 is falling, at fundamental level. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

Dep. Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (excess return)	0.2105	0.0729	0.3592	0.0821	0.0367	0.0971
	(1.1433)	(0.2761)	(1.9243)	(0.3613)	(0.1417)	(0.4995)
Market Index - MAI	0.2366**	0.1487*	0.2227**	0.1747**	0.1961**	0.1649**
	(6.0250)	(2.4669)	(7.1105)	(3.3687)	(3.3132)	(3.7177)
Exchange Rate - EXCH	-0.1927*					
	(-2.5528)					
High minus Low - HML	-0.0699*		-0.1760**			
	(-2.2676)		(-6.1706)			
Commodity Energy - COEN	0.0434**					
	(3.7543)					
Change in VIX - DVIX	-0.0211*	-0.0315*		-0.0278*	-0.0344**	-0.0229*
	(-2.4214)	(-2.5173)		(-2.5791)	(-2.8010)	(-2.4832)
Small minus Big - SMB	0.1027*	0.1926**	0.1424**	0.1591**	0.2055**	0.1404**
	(2.3779)	(3.0794)	(3.2257)	(2.9560)	(3.3468)	(3.0524)
Commodity Industrial Metals - COIM		0.0974**	0.1132**	0.1003**	0.0858*	0.0874**
		(2.8113)	(4.4656)	(3.3623)	(2.5214)	(3.4277)
Adj. R-squared:	0.8729	0.7594	0.8981	0.8112	0.8082	0.8239
F-statistic:	41.0543	28.6188	69.3116	38.6023	37.8663	41.9512
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.3.2.5 Analysis by funds characteristics

In this sub-section I present an overview and a brief analysis of the most important findings for each of the six fundamental groups based on Tables 27-30. Then I proceed to detailed market exposure and alpha analysis.

Concerning the size (small versus large funds), during "good" market conditions the most important exposures are the market, small minus big and momentum. Both groups try to exploit the upward market movement providing significant alpha to investors. They have also a negative DEF exposure as the DEF premium is negative during "good" times. On average, small funds appear to have larger exposures to these factors, and deliver higher alpha than large funds. During stressful market conditions, both groups decrease their exposures and they do not deliver significant alpha to investors. The market exposure is still the most important for both groups although there are other important exposures such as the energy and agriculture commodities that fund managers switch to during stressful times. Large funds seem to be more successful than small funds in minimizing their risk as they have a small number of exposures. Overall small funds are more successful that large funds and we explain this as the most talented fund managers building experience in large funds, who then self-select to start their own firms. Small funds have better niche opportunities than large funds and as fund managers have a limited set of "good" ideas. When the fund increases in size they have to incorporate other less profitable ideas. Moreover in small funds there is higher pressure due to lower assets under management (thus management fees). In addition we conjecture that the bigger the fund, the further away the fund managers are from security-level analysis.

Regarding the age (young versus old funds), during "good" times both groups exploit upward market movement by increasing their exposures. Young funds appear to be more successful in this. The most important exposures are the market, momentum, and the small minus big factor. During "bad" times, neither group provides significant alpha to investors; instead fund managers try to minimize their risk. The most important exposures are the market, and the energy and agriculture commodities. In addition both groups have negative high minus low exposure during "bad" times, however young funds appear to have more exposure to this factor. It seems that young funds are more successful in this. We would like to mention that young funds by definition have a timing advantage over old funds. This is because young funds tend to be formed at times that are advantageous for specific strategies. An example could be funds that specialize in securitized credit strategy after a recession in response to opportunities in this area. In addition, young funds appear to be more returns driven because they have not created their fortune yet.

Concerning lockups (yes versus no-redemption restrictions funds), both groups during “good” times deliver significant alpha to investors although funds that impose lockup restrictions are more successful because they can exploit liquidity premia. The most important factors for both groups are the market, small minus big, momentum, and the default spread (negative). Overall, funds that impose redemption restrictions are riskier, having more exposures in terms of asset allocations than funds that do not impose restrictions. During “bad” times both groups reduce their exposures, although funds with no lockups appear to have slightly fewer exposures. Overall it seems that funds that impose lockup restrictions are more successful as they can have more exposures than their peers (because of their protection) and exploit more liquidity premia. However during stressful conditions funds with no restrictions (that survive) are more successful than funds with restrictions. See section “alpha analysis” for more details.

4.3.2.6 MAI analysis

Overall, there are no large differences in exposures between funds that belong to different groups, according to the underlying fundamental factors. This has to do with the fact that differences in strategies and styles matter more in explaining hedge fund behaviour. In general, all funds during stressful market conditions try to minimize their exposures in terms of asset and portfolio allocations. Moreover, they do not provide significant alphas to investors (even for funds with lockup periods that in theory can exploit the liquidity premia) meaning that, in terms of alphas and exposures, fundamental characteristics are less important in the strategic asset allocation process than strategies or different styles of hedge funds. Table 31 provides the different MAI exposures for all hedge funds taking into consideration only the fundamental factors. As expected, on average, all groups decrease their exposures during stressful market conditions. There is a large decrease in exposures across all groups during the down regimes, however, during the recessions large, old and lockup-no funds do not change their exposures a lot meaning that recessions are less fierce than down regimes for hedge funds.

I move one step further toward the market state analysis where I examine the MAI behaviour of the underlying groups within different states. I classified and ranked four different states of the economic activity beginning from the most desirable state to the least desirable state. Based on the Markov Switching Model the worst or most severe state is the down regime, because it captures market downturns accompanied with great volatility. The next (less severe) state is the recession period, as it contains mostly negative market returns due to general low economic activity. The next (better) state is the growth period which contains mostly positive market returns. Finally, best state is the up regime which contains very high market returns. Regarding the up regime, it contains the whole time period under investigation minus the down (very severe) regimes. Similarly, the growth period contains the whole time period under investigation minus the recession (severe) periods.

Table 31 shows that, in general, groups have the highest market exposures during the *best* state and in almost all cases these exposures gradually diminish when approaching the *worse* state. At a group level, small funds have higher exposures into the extreme good and bad financial conditions compared to large funds. Young funds have higher exposures in the extremely good and bad conditions compared to the old funds. Regarding the lockup groups, funds with lockup periods provide higher exposures during “good” times whereas in the bad and worst states this group provides higher and lower exposures, respectively, compared to the lockup-no funds. However, the differences in exposures in each pair group are not significant different from zero when we consider all states together - four observations (states) per each group.

Table 31. MAI Analysis per Fundamental Group

This table shows market exposures of my multi-factor model for all the groups (portfolios). ** denotes significance at P < 0.01.

Market Index -MAI	Growth (Good State)	Recession (Bad State)	Difference (Base Growth)	Up (Best state)	Down (Worst State)	Difference (Base Up)
Size Small	0.376**	0.228**	-39.40%	0.410**	0.237**	-42.31%
Size Large	0.383**	0.380**	-0.68%	0.390**	0.149**	-61.85%
Age Young	0.393**	0.294**	-25.09%	0.403**	0.223**	-44.77%
Age Old	0.394**	0.368**	-6.43%	0.399**	0.175**	-56.24%
Lockup-Yes	0.430**	0.277**	-35.44%	0.422**	0.196**	-53.35%
Lockup-No	0.355**	0.347**	-2.39%	0.367**	0.165**	-55.06%

4.3.2.7 Alpha analysis

I have mentioned that hedge funds, on average, do not provide significant alpha to investors during stressful market conditions as fund managers are more concerned about risks in the cost of alpha. However, hedge funds provide strongly significant alpha to investors during the growth and up regimes, and increase their market exposure so as to benefit from the upward market movement. Table 32 reports the average performances of the different groups within "good" and "bad" times. Small funds outperform large funds during "good" times; however, during "bad" times small funds seem to be more vulnerable. Young funds outperform old funds during all conditions, especially during "good" times. As expected, lockup-yes outperforms lockup-no hedge funds during the "good" times. Nevertheless, during "bad" times lockup-no slightly outperforms lockup-yes. It seems that lockup-yes funds cannot successfully exploit the liquidity premia (e.g. by investing in real estate) during "bad" times, contrary to the lockup-no funds that try to do something more efficient (e.g. investing in counter-cyclical industries).

In the "states" alpha analysis I present the non-linearity in groups' performances. In Table 32, in general, contrary to market exposures, that there is non-linearity across all different states regarding the excess returns in each of the different groups. Especially in the *best* state hedge funds, irrespective of the groups that they belong to, do not provide the highest excess returns to investors, meaning that hedge funds are rather exploiting the upward market conditions just by increasing their exposures to the market factor. Large funds compared to small funds perform very well during the extremely good conditions such as the up regimes (0.476) but suffer a lot during the extremely bad conditions such as the *worst* state (0.073) perhaps due to sensitivity to cash redemptions. The opposite happens with small funds with 0.313 and 0.211 in the extremely good and extremely bad states, accordingly. It appears that in the extremely negative conditions large funds do not have the flexibility to adapt and in consequences these have a worse impact on their performance. In extremely good conditions, large funds just enjoy the benefits of economies of scale. Concerning the age factor, old funds perform better than young funds in extremely good market conditions (0.428) but they suffer more during extreme negative market conditions (0.082). It appears that extremely negative market conditions have more negative impact on old funds, especially for those funds that have a proven good track record and remain in the market for a relatively long time period. Lockup-yes funds outperform lockup-no funds during the "good" time (0.507 and 1.322 for the *best* and *good* states) as these funds are exploiting liquidity premia. However, during the “bad” time, even though lockup-yes funds do not suffer from money redemptions, they underperform compared to the lockup-no funds, even though the differences are not large. It seems that fund managers try to find new investment opportunities (e.g. better resource sector allocation) or hedge their portfolios in a better way toward market risk. Nevertheless, the differences in alphas in each pair group are not significantly different from zero when all states are considered together - four observations (states) for each group.

One last comment concerning the relationship of small versus large and young versus old that is different for growths and up regimes: in the extremely good conditions (up regimes) large funds and old funds just enjoy the benefits of the economies of scale and their long establishment (reputation) within the existing opportunities, respectively. However, this does not work in just good conditions (growth) where there might be some fluctuations in market returns and investing opportunities are somewhat scarcer. The opposite happens to the extremely negative conditions (down regimes) where large funds and old funds suffer a lot because of the reduced flexibility and their negative impact on the proven track record of their existence in the market. However, during “bad” times (recessions) large and old funds seem not to suffer as much as in the exremely “bad” times, as the issues of flexibility and the negative impact on the previous track record are not so intense.

Table 32. Alpha Analysis by Fundamental Group and “State”

This table shows excess returns for all groups between different “states” and the average excess returns for groups between “good” and “bad” market conditions (“Good ” market conditions is the average between up regimes and growth periods whereas “Bad” market conditions is the average between down regimes and recessions). ** denotes significance at P < 0.01.

Fundamental Group	Up regimes (Best state)	Growth periods (Good state)	“Good” market conditions	Recessions (Bad state)	Down regimes (Worst state)	“Bad” market conditions
Size Small	0.313**	1.219**	0.766	0.252	0.211	0.232
Size Large	0.476**	0.906**	0.691	0.404	0.073	0.239
Age Young	0.301**	1.709**	1.005	0.307	0.359	0.333
Age Old	0.428**	1.002**	0.715	0.342	0.082	0.212
Lockup-Yes	0.507**	1.322**	0.915	0.246	0.037	0.142
Lockup-No	0.372**	0.823**	0.598	0.385	0.097	0.241

4.3.3 Mixed level

In this section I proceed to the mixed level analysis i.e. taking into consideration hedge fund strategies and fundamental factors together within different business cycles and market conditions. Since strategies are more important in explaining hedge fund returns than fundamental factors my analysis is based on the 66 portfolios mentioned before (six groups times 11 strategies – see data section). I begin with the more directional strategies and then I move gradually to the non-directional strategies.

Table 33 presents the results at a mixed level for all strategies focusing on the excess returns delivered to investors. The findings are mostly strategy dependent as each strategy is unique having different relationship with fund characteristics and specific performance behaviour under different market conditions.

4.3.3.1 Analysis by strategy

The Short Bias strategy does not provide significant alpha during stressful market conditions. During "good" times, large funds outperform small funds, whereas old funds outperform young ones. Surprisingly, lockup-no funds outperform the lockup-yes funds meaning that fund managers do not rely on liquidity premia for high performance. The Long Only strategy, in general, does not provide excess returns during stressful market conditions. During "good" times, large funds outperform small funds as they are able to exploit economies of scale concerning the transaction/investing process (e.g. lower trade spreads). Young funds appear to outperform old funds whereas lockup-yes funds outperform lockup-no funds as they do not suffer from redemptions or liquidations and they are able to exploit the liquidity premia for high returns. An interesting point is that lockup-no funds provide strongly significant negative alpha during recessions. This means that lockup-no funds are struggling during recessions because of redemptions by investors forcing losses to be crystallized. For the Sector strategy, during "bad times", only old and large funds provide significant alpha as they can benefit from their experience and their exploitation of the counter-cyclical sectors. During "good" times large and young funds outperform their peers as it seems that they can benefit from upward market movement. Lockup-yes funds outperform lockup-no funds as they are able to exploit the liquidity risk and do not suffer from investor redemptions. For the Long Short strategy, during "bad" times, only young funds provide significant alpha because of the timing advantage (see section 4.3.2.5). During "good" times, young funds appear to outperform old funds (although mainly for growth periods). The same is with small funds in relation to large funds being able to exploit the upward market movement efficiently. As expected, lockup-yes funds outperform lockup-no funds as they exploit liquidity premia for higher returns.

The Event Driven strategy does not deliver significant alpha during stressful market conditions, except for funds imposing lockup restrictions. During “good” times large and old funds outperform their peers. It seems that large funds are more efficient in terms of the economies of scales and old funds are in a better position to use their experience. As expected, lockup-yes funds outperform lockup-no funds due to the exploitation of the liquidity premia and protection. For the Multi Strategy, during “bad” times, small fund outperform large funds due to their higher flexibility in their mixture use of other strategies. An interesting point is that young funds suffer more than old funds and during down regimes they provide even significant negative alpha to investors. This suggests a lack of the necessary experience of implementing this type of “mixture” strategy. Funds with lockup restrictions outperform funds without lockups because they do not rely on the liquidity premia as fund managers are more innovative from their peers having more alternatives (e.g. invest in different markets). During “good” times large and lockup-yes funds outperform their peers due to the economies of scale and the exploitation of the liquidity premia, accordingly. In general, old funds outperform young funds due to their experience and establishment in the market. The Others strategy delivers significant alpha in almost all cases. This is because it uses different styles/tools (e.g. private investment in public equity, close-ended) or even allocations (e.g. start-ups) not widely used by other fund strategies. During “bad” times there are cases such as small, old and funds without redemption restrictions that provide high returns to investors. Similar applies during “good” times as these kind of funds have the flexibility and innovation to benefit more from the upward market movement.

For the Global Macro strategy, during “bad” times, funds with lockups and old funds outperform their peers as fund managers do not rely on lockup protections having experience, accordingly. Regarding the age the mixed results do not give a clear picture. During “good” times lockups-no and old funds outperform their peers. Regarding the size factor the results are mixed and this suggests that the investor cannot rely on the size of her investment decision. The Relative Value strategy, during “bad” times, does not provide significant alpha except for the young funds having the timing advantage. During “good” times small, young and funds with redemption restrictions outperform their peers. This is because small funds have the “right” capacity (as arbitrage opportunities are in a shortfall), young funds have the time advantage, and lockup restrictions provide a protection against redemptions or opportunities for liquidity premia exploitation. The Market Neutral strategy, during “bad” times, does not provide significant alpha exempt for the small and old funds due to the “right” capacity and the experience within the old funds. During “good” times large and old funds are able to exploit better the upward market movement than their peers. Funds with redemption restrictions outperform their peers due to the protection against investors and due to the liquidity premia. For the CTA strategy, during “bad” times, large, young and funds with lockups outperform their peers because of the economies of scale, the timing advantage and the protection-liquidity premia, accordingly. The same applies for the lockup-yes funds during “good” times. However, small and old funds outperform their peers due to their flexibility-“right” capacity and experience, respectively.

Table 33. Mixed Level Analysis

This table shows the exposures of my multi-factor model for all conditions of the Wilshire 5000, at a mixed level. Panel A shows Short Bias and Long Only, Panel B shows Sector and Long Short, Panel C shows Event Driven and Multi Strategy, Panel D shows Others and Macro, Panel E shows Relative Value and Market Neutral, and Panel F shows the CTA. Hedge funds returns are raw returns minus the risk free return. SS: Size Small, SL: Size Large, AY: Age Young, AO: Age Old, LY: Lockup Yes, LN: Lockup No. The Risk free return (RF) is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I do not present the t-statistics.

Panel A

1a. Short Bias – Growth

Dep. Var:	SB_SS	SB_SL	SB_AY	SB_AO	SB_LY	SB_LN
C	0.545**	1.659**	0.243	0.569**	0.043	0.661**
MAI	-0.874**	-0.764**	-0.672**	-0.874**	-0.916**	-0.870**
SMB	-0.276**			-0.264**	-0.189**	-0.270**
MOM	-0.163**	-0.275**		-0.200**		-0.197**
COIM	0.119**		-0.156*	0.127**	0.166**	0.093**
GEMI	-0.178**	-0.199*		-0.194**		-0.226**
TERM		-0.585**				

1b. Short Bias - Recessions

Dep. Var:	SB_SS	SB_SL	SB_AY	SB_AO	SB_LY	SB_LN
C	-0.624	0.445	0.389	-0.570	-0.116	-0.726
MAI	-0.984**	-0.881**	-0.820**	-1.010**	-0.867**	-1.069**
COEN	0.140**			0.131**	0.150**	0.114**

1c. Short Bias – Up Regimes

Dep. Var:	SB_SS	SB_SL	SB_AY	SB_AO	SB_LY	SB_LN
C	0.476*	1.788**	0.311	0.479**	0.152	0.547**
MAI	-0.955**	-0.754**	-0.615**	-0.957**	-0.989**	-0.955**
SMB	-0.290**			-0.275**	-0.209**	-0.281**
MOM	-0.127**	-0.253**		-0.150**		-0.137**
COIM	0.114**		-0.153**	0.120**	0.170**	0.086*
GEMI	-0.134*	-0.211*		-0.150*		-0.178**
TERM		-0.692**				

1d. Short Bias – Down Regimes

Dep. Var:	SB_SS	SB_SL	SB_AY	SB_AO	SB_LY	SB_LN
C	0.2836	0.333	-0.739	0.392	0.627	0.317
MAI	-0.818**	-0.758**	-0.964**	-0.826**	-0.451**	-0.892**
COEN	0.122**			0.114**	0.124**	0.101**
RLE		-0.109*			-0.170*	

2a. Long Only - Growth

Dep. Var:	LO_SS	LO_SL	LO_AY	LO_AO	LO_LY	LO_LN
C	0.073	0.451**	1.408*	0.293**	0.555**	0.167
MAI	0.826**	0.592**	0.576**	0.680**	0.440**	0.783**
SMB	0.123**	0.290**	0.174*	0.257**	0.253**	0.250**
MOM	0.074**		-0.129**	0.044*		0.073**
HML		0.270**	-0.151*	0.215**	0.219**	0.187**
COEN		0.032**		0.025*		0.029*
DEF			-1.361*			
GEMI					0.099**	

2b. Long Only - Recessions

Dep. Var:	LO_SS	LO_SL	LO_AY	LO_AO	LO_LY	LO_LN
C	0.286	-0.517	-0.060	-0.426	1.734	-3.524**
MAI	0.785**	0.541**	0.663**	0.601**		0.723**
HML	-0.248**					
SMB	0.271**	0.414**	0.691**	0.413**	0.296*	0.432**
COIM	0.092*		0.127*			
COAG		0.127*		0.112*		0.173**
DVIX					-0.079**	
COEN					0.155**	
MOM					-0.147**	
DEF					-1.109*	
TERM						1.467**

2c. Long Only – Up Regimes

Dep. Var:	LO_SS	LO_SL	LO_AY	LO_AO	LO_LY	LO_LN
C	0.110	0.413**	0.224	0.285**	0.533**	0.166
MAI	0.842**	0.586**	0.343**	0.677**	0.405**	0.800**
SMB	0.103**	0.304**	0.279**	0.263**	0.259**	0.262**
HML		0.295**		0.240**	0.255**	0.215**
COEN		0.044**		0.037**		0.037**
MOM		0.055**	-0.078**	0.055**	0.057*	0.053*
GEMI			0.132*		0.106**	

2d. Long Only – Down Regimes

Dep. Var:	LO_SS	LO_SL	LO_AY	LO_AO	LO_LY	LO_LN
C	0.054	-0.331	-1.121	-0.379	0.362	-0.515
MAI	0.663**	0.529**	1.508**	0.535**	0.341**	0.607**
SMB	0.320**	0.387**	0.553**	0.409**	0.390**	0.396**
COIM	0.139**				0.237**	
HML			-0.279*			
GEMI			-0.793**			
COAG			0.171*	0.114*		0.144*
COPM			0.164*			

Panel B

1a. Sector - Growth

Dep. Var:	SE_SS	SE_SL	SE_AY	SE_AO	SE_LY	SE_LN
C	1.440**	1.595**	4.175**	1.484**	1.775**	1.149*
MAI	0.611**	0.618**	0.803**	0.577**	0.591**	0.604**
COPM	0.149**			0.079**		0.074**
MOM	0.113**	0.101**	0.326**	0.083**	0.072*	0.131**
SMB	0.112**	0.174**		0.153**	0.154**	0.161**
DEF	-1.296*	-1.264**	-3.915**	-1.160**	-1.389*	-0.985*
COEN	0.039*	0.052**		0.043**	0.054**	0.041**
COIM	-0.061*					
HML			-0.356**			

1b. Sector - Recessions

Dep. Var:	SE_SS	SE_SL	SE_AY	SE_AO	SE_LY	SE_LN
C	0.516	0.596	0.005	0.665*	0.461	0.421
MAI	0.703**	0.532**	0.410**	0.519**	0.673**	0.442**
HML	-0.499**	-0.353**	-0.559**	-0.334**	-0.428**	-0.361**
COPM	0.182*					
COAG		0.140**	0.114**	0.130**		0.086*
COEN			0.131**			0.047**
MOM			-0.116**			

1c. Sector - Up Regimes

Dep. Var:	SE_SS	SE_SL	SE_AY	SE_AO	SE_LY	SE_LN
C	0.425**	0.543**	0.371	0.509**	0.628**	0.323**
MAI	0.651**	0.600**	0.850**	0.578**	0.585**	0.593**
COPM	0.174**			0.080**		0.087**
MOM	0.100**	0.108**	0.318**	0.083**	0.083**	0.136**
COIM	-0.070*					
SMB	0.103*	0.158**		0.142**	0.143**	0.140**
COEN		0.061**		0.045**	0.058**	0.045**

1d. Sector -Down Regimes

Dep. Var:	SE_SS	SE_SL	SE_AY	SE_AO	SE_LY	SE_LN
C	0.063	1.980**	0.197	0.349	0.147	0.409
MAI	0.241*	0.604**	0.446**	0.408**	0.436**	0.438**
HML	-0.372**	-0.347**	-0.555**			-0.327**
COIM	0.162**		0.227**			0.100**
RLE	0.129*					
MOM		0.188**				0.102**
SMB		0.231**				0.143*
TERM		-0.677*				
COAG		0.095*				
DVIX				-0.0446*	-0.057*	
EXCH						-0.201*

Table 33. Mixed Level Analysis (continued)

2a. Long Short - Growth

Dep. Var:	LS_SS	LS_SL	LS_AY	LS_AO	LS_LY	LS_LN
C	1.629**	1.422**	2.586**	1.426**	1.610**	1.360**
MAI	0.540**	0.506**	0.405**	0.537**	0.560**	0.493**
SMB	0.196**	0.206**	0.090*	0.206**	0.231**	0.165**
MOM	0.099**	0.078*	0.105**	0.087**	0.080**	0.099**
COEN	0.038**	0.029**	0.055**	0.032**	0.033**	0.034**
DEF	-1.211**	-0.760**	-2.385**	-0.880**	-1.014**	-0.887**
COPM	0.042*	0.030*		0.035*	0.042*	
TERM	-0.147*	-0.190**		-0.165**	-0.187**	-0.136*
HML		0.094**		0.075**	0.096**	

2b. Long Short - Recessions

Dep. Var:	LS_SS	LS_SL	LS_AY	LS_AO	LS_LY	LS_LN
C	0.110	0.397	2.280*	0.251	0.100	0.388
MAI	0.429**	0.496**		0.430**	0.476**	0.480**
COAG	0.083*			0.087*	0.092*	
HML	-0.144*	-0.218*	-0.245**	-0.163*	-0.211**	-0.187*
GEMI			0.342**			
TERM			-0.899*			
SMB				0.158*		

2c. Long Short – Up Regimes

Dep. Var:	LS_SS	LS_SL	LS_AY	LS_AO	LS_LY	LS_LN
C	0.554**	0.779**	0.573*	0.647**	0.670**	0.650**
MAI	0.576**	0.520**	0.506**	0.593**	0.599**	0.516**
SMB	0.175**	0.202**		0.209**	0.218**	0.178**
MOM	0.096**	0.080**	0.115**	0.085**	0.093**	0.090**
COEN	0.048**	0.037**	0.077**	0.042**	0.045**	0.035**
TERM	-0.172*	-0.203**	-0.273*	-0.187**	-0.205**	-0.179**
DVIX	0.014*		0.031*	0.011*	0.012*	
COPM	0.038*			0.040**	0.041*	
HML		0.095**		0.098**	0.116**	0.054*
COIM				-0.027*		

2d. Long Short – Down Regimes

Dep. Var:	LS_SS	LS_SL	LS_AY	LS_AO	LS_LY	LS_LN
C	0.033	0.045	0.354	-0.070	-0.092	-0.080
MAI	0.451**	0.275**	0.191**	0.322**	0.320**	0.297**
SMB	0.210**	0.208**	0.146*	0.197**	0.240**	0.174**
COAG	0.072*					
RLE	-0.056*					
DVIX		-0.030*	-0.031*	-0.023*	-0.034*	-0.021*
HML			-0.121**			
COIM			0.109**			

Panel C

1a. Event Driven - Growth

Dep. Var:	ED_SS	ED_SL	ED_AY	ED_AO	ED_LY	ED_LN
C	0.472**	0.514**	0.272*	0.493**	0.616**	0.433**
MAI	0.195**	0.315**	0.209**	0.307**	0.235**	0.300**
SMB	0.185**	0.160**	0.112**	0.165**	0.185**	0.148**
HML	0.181**	0.176**	0.108**	0.183**	0.163**	0.170**
GEMI	0.074*		0.111*		0.073**	
COPM				0.027*		

1b. Event Driven - Recessions

Dep. Var:	ED_SS	ED_SL	ED_AY	ED_AO	ED_LY	ED_LN
C	-0.001	0.090	-0.099	0.100	0.184	0.044
GEMI	0.162**					
COEN	0.088**		0.099**		0.084**	
MAI		0.323**		0.301**		0.411**
COIM		0.117*		0.125**	0.122*	
DVIX			-0.040**		-0.051**	

1c. Event Driven – Up Regime

Dep. Var:	ED_SS	ED_SL	ED_AY	ED_AO	ED_LY	ED_LN
C	0.426**	0.529**	0.156	0.507**	0.611**	0.427**
MAI	0.173**	0.270**	0.172**	0.254**	0.189**	0.277**
HML	0.203**	0.182**	0.133**	0.191**	0.182**	0.185**
SMB	0.174**	0.163**	0.118**	0.171**	0.184**	0.154**
GEMI	0.085**	0.047*	0.171**	0.059**	0.096**	0.048*
COEN		0.019*		0.019*	0.028**	
MOM			0.069**			

1d. Event Driven – Down Regime

Dep. Var:	ED_SS	ED_SL	ED_AY	ED_AO	ED_LY	ED_LN
C	0.303	0.109	0.185	0.184	1.950**	0.158
COIM	0.188**	0.149**	0.108*	0.163**	0.136*	0.127*
DVIX	-0.032*				-0.046**	
MAI		0.228**	0.123*	0.211**		0.234**
DEF					-1.371**	

2a. Multi Strategy - Growth

Dep. Var:	MS_SS	MS_SL	MS_AY	MS_AO	MS_LY	MS_LN
C	0.498**	0.665**	0.200**	1.394**	2.173**	0.601**
MAI	0.228**	0.201**	0.133**	0.223**		0.179**
MOM	0.108**			0.042*		
GEMI	0.110**				0.238**	
DVIX	0.018*					
SMB		0.135**		0.092**		0.076**
HML		0.151**		0.060*		0.086**
COIM		0.039*				0.027*
RLE			0.041*			
COEN			0.026**			
COPM			0.030*	0.043*		
DEF				-0.832*	-2.085*	
TERM					0.322*	

2b. Multi Strategy - Recessions

Dep. Var:	MS_SS	MS_SL	MS_AY	MS_AO	MS_LY	MS_LN
C	0.610*	0.509	-0.4297	0.449	0.459	0.689*
GEMI	0.119**					0.142**
COEN	0.079**				0.153**	
HML	-0.294**	-0.233*				
RLE	0.061*					
MAI		0.266**				
COAG		0.121*				0.101*
DVIX			-0.030*	-0.066**	-0.064**	-0.034*
COIM			0.083*	0.119**		
EXCH					0.434*	

2c. Multi Strategy – Up Regime

Dep. Var:	MS_SS	MS_SL	MS_AY	MS_AO	MS_LY	MS_LN
C	0.618**	0.661**	0.926**	0.662**	0.785**	0.601**
MAI	0.170**	0.226**		0.231**	0.252**	0.187**
MOM	0.113**			0.051**	0.102*	
GEMI	0.088*		0.120**			
COPM	0.057*		0.029*	0.046**	0.081*	
HML		0.181**		0.087**		0.113**
SMB		0.156**		0.095**		0.088**
DEF			-0.618**			
DVIX			-0.013*			
COEN						0.024**
COAG						0.027*

2d. Multi Strategy – Down Regime

Dep. Var:	MS_SS	MS_SL	MS_AY	MS_AO	MS_LY	MS_LN
C	0.674**	0.536	-1.316*	0.602*	0.402	0.710*
GEMI	0.210**			0.093*		0.159**
HML	-0.188**					-0.117*
COEN	0.061**					
DVIX		-0.049**		-0.035**	-0.046**	
COIM		0.160**	0.232**	0.122**	0.135**	0.128**
DEF			0.919*			

Table 33. Mixed Level Analysis (continued)

Panel D

1a. Others - Growth

Dep. Var:	OT_SS	OT_SL	OT_AY	OT_AO	OT_LY	OT_LN
C	1.524**	1.456**	2.017**	1.441**	0.863**	1.569**
MAI	0.214**	0.199**	0.326**	0.147**		0.162**
GEMI	0.095**			0.067**	0.079**	0.068**
MOM	0.054**	0.036*		0.057**		0.040*
DEF	-0.979**	-0.825**	-1.390*	-0.897**		-1.034**
COPM	0.052**					
RLE	-0.050*	-0.042*		-0.032*	0.037*	-0.046*
COIM		-0.030*				
EXCH			-0.255**			
DVIX			0.025*			

1b. Others - Recessions

Dep. Var:	OT_SS	OT_SL	OT_AY	OT_AO	OT_LY	OT_LN
C	4.142**	1.265**	0.807**	2.462**	0.521**	2.794**
GEMI	0.181**			0.142**	0.106**	0.159**
TERM	-1.627**			-0.851*		-1.007**
DVIX	-0.032*					
MAI		0.070**	0.274**			
HML		-0.143**	-0.155**			
MOM		-0.056**				
DEF		-0.550**				
SMB						0.149*

1c. Others – Up Regimes

Dep. Var:	OT_SS	OT_SL	OT_AY	OT_AO	OT_LY	OT_LN
C	0.673**	1.288**	0.649**	1.101**	0.853**	1.189**
MAI	0.177**	0.188**	0.388**	0.123**		0.156**
GEMI	0.104**			0.075**	0.103**	0.075**
MOM	0.049**			0.034*	0.034*	
COPM	0.040*					
DEF		-0.663**		-0.469*		-0.557*
SMB		-0.063**			0.079**	
RLE		-0.036*	-0.068*			-0.040*
DVIX			0.028*			
EXCH			-0.200*			

1d. Others – Down Regimes

Dep. Var:	OT_SS	OT_SL	OT_AY	OT_AO	OT_LY	OT_LN
C	0.655	0.585**	1.965**	0.429	0.447**	0.789**
MAI	0.262**	0.117**	0.169**	0.137**		0.216**
EXCH	-0.558**			-0.308**		-0.311**
HML		-0.069**	-0.229**			
SMB		0.107**				
COEN			0.042*			
RLE			0.063*		0.051**	
TERM			-0.317*			
COAG					0.044*	

2a. Global Macro - Growth

Dep. Var:	GM_SS	GM_SL	GM_AY	GM_AO	GM_LY	GM_LN
C	0.770*	0.421**	-0.016	0.299*	-0.128	0.355**
MAI	0.566**	0.191**		0.290**	0.657**	0.234**
DVIX	0.070**			0.024**	0.053**	0.019*
COPM	0.144**	0.062**	0.101**	0.090**	0.174**	0.058*
HML	-0.183**					
COEN	0.066**					
TERM	-0.363*					
MOM		0.052*		0.052*		0.087**
GEMI			0.284**			

2b. Global Macro - Recessions

Dep. Var:	GM_SS	GM_SL	GM_AY	GM_AO	GM_LY	GM_LN
C	1.204*	0.559*	0.168	-1.139	0.859	0.752**
COAG	0.206**			0.151**	0.156*	
COEN		0.073**	0.092*	0.072**		0.053**
DVIX		-0.024*	-0.070**			
EXCH		0.255*	0.821**			
COIM				-0.090*		
TERM				0.937*		
COPM						0.102**

2c. Global Macro - Up Regimes

Dep. Var:	GM_SS	GM_SL	GM_AY	GM_AO	GM_LY	GM_LN
C	0.124	0.342**	-0.009	0.288*	-0.032	0.304*
MAI	0.525**	0.204**		0.319**	0.559**	0.246**
COPM	0.181**	0.068**	0.080*	0.113**	0.228**	0.069**
HML	-0.185*					
DVIX	0.070**			0.018*	0.046**	0.018*
COEN	0.075**			0.043**		0.034*
MOM		0.049*	0.098**			0.053*
GEMI			0.294**	-0.083*		
EXCH						0.142*

2d. Global Macro – Down Regimes

Dep. Var:	GM_SS	GM_SL	GM_AY	GM_AO	GM_LY	GM_LN
C	-0.854	0.595**	0.653	0.624**	0.547	0.652**
MOM	-0.105*				-0.162*	
HML	-0.160*			-0.151**		
MAI	0.168**		0.454**		0.514**	
DEF	1.035*					
EXCH		-0.313**		-0.259**		
RLE			-0.173**		-0.257**	
COEN					-0.082*	0.033*
COPM						0.103**

Panel E

1a. Relative Value – Growth

Dep. Var:	RV_SS	RV_SL	RV_AY	RV_AO	RV_LY	RV_LN
C	0.289**	-0.138	0.617**	0.239**	0.333**	-0.1262
MAI	0.173**	0.134**		0.152**	0.173**	0.137**
SMB	0.064**	0.064**	0.034*	0.073**	0.081**	0.070**
TERM	0.091*	0.120**		0.131**	0.153**	
HML		0.083**		0.070**	0.069**	0.067**
DEF		0.462*				0.609**
GEMI			0.081**			

1b. Relative Value - Recessions

Dep. Var:	RV_SS	RV_SL	RV_AY	RV_AO	RV_LY	RV_LN
C	0.462	0.224	0.620**	0.342	0.483	0.305
MAI	0.308**		0.174**	0.302**	0.316**	0.271**
RLE		0.141**				
COIM		0.116**				
HML		-0.362**	-0.116**			
COEN			0.042**			

1c. Relative Value – Up Regimes

Dep. Var:	RV_SS	RV_SL	RV_AY	RV_AO	RV_LY	RV_LN
C	-0.165	-0.114	0.139	-0.134	0.370**	-0.225
MAI	0.193**	0.135**		0.153**	0.173**	0.113**
SMB	0.096**	0.055**		0.067**	0.085**	
DEF	0.685**	0.429*	0.424**	0.467**		0.517**
MOM	0.034*					
HML	0.058**	0.083**		0.074**	0.064*	
COIM	-0.021*					
TERM		0.128**		0.122**	0.168**	0.098*
GEMI			0.098**			
RLE						0.035**
COEN						0.012*

1d. Relative Value – Down Regimes

Dep. Var:	RV_SS	RV_SL	RV_AY	RV_AO	RV_LY	RV_LN
C	0.098	0.1650	1.417**	0.064	-0.132	0.154
MAI	0.134*					
SMB	0.200*	0.180*		0.195*	0.235**	0.178**
COIM	0.107*	0.123**	0.107**	0.143**	0.137**	0.116**
DVIX		-0.034**	-0.020**	-0.035**	-0.030*	-0.033**
TERM			-0.303*			

Table 33. Mixed Level Analysis (continued)

2a. Market Neutral - Growth

Dep. Var:	MN_SS	MN_SL	MN_AY	MN_AO	MN_LY	MN_LN
C	0.151*	0.191**	-0.036	0.368**	1.397**	0.155**
MOM	0.109**	0.055**	0.082**	0.078**		0.085**
MAI	0.089**	0.057**	0.139**	0.054**	0.057**	0.067**
HML		0.039*				
RLE			-0.044*	0.024*		
TERM				-0.084*		
DEF					-1.117**	

2b. Market Neutral - Recessions

Dep. Var:	MN_SS	MN_SL	MN_AY	MN_AO	MN_LY	MN_LN
C	0.074	0.161	0.027	-0.454	0.177	0.098
COAG	0.093*			0.066**	0.105**	0.051*
MOM	0.065*	0.035*		0.082**	0.80**	
HML			-0.168*		-0.196**	
GEMI			0.081*			
DEF				0.409*		
COPM					-0.086*	

2c. Market Neutral – Up Regimes

Dep. Var:	MN_SS	MN_SL	MN_AY	MN_AO	MN_LY	MN_LN
C	0.152*	0.174**	0.005	0.335**	0.610**	0.132**
MOM	0.110**	0.053**	0.058**	0.077**	0.068**	0.070**
RLE	0.062**			0.026*		0.026*
COEN	0.025**			0.013*		0.013*
MAI		0.067**	0.095**	0.049**	0.056*	0.050**
HML		0.043*				
TERM				-0.082*	-0.150*	

2d. Market Neutral – Down Regimes

Dep. Var:	MN_SS	MN_SL	MN_AY	MN_AO	MN_LY	MN_LN
C	1.022**	0.1010	-0.190	0.688**	-0.117	0.142
GEMI	0.106**					
MOM	0.139**	0.059**		0.092**		0.080**
HML	-0.157**		-0.167**	-0.077**		-0.056*
TERM	-0.321*			-0.219*		
COAG				0.052**	0.082*	0.035*
RLE					-0.078**	
EXCH						-0.128*

Panel F

1a. CTA - Growths

Dep. Var:	CT_SS	CT_SL	CT_AY	CT_AO	CT_LY	CT_LN
C	0.895**	0.739**	0.284	0.820**	0.984**	0.788**
EXCH	-0.383*	-0.293*	-0.501**	-0.409**		-0.425**
COPM	0.124*					
MOM		0.144**	0.202**	0.116*		0.128*
COIM		0.092*				

1b. CTA - Recessions

Dep. Var:	CT_SS	CT_SL	CT_AY	CT_AO	CT_LY	CT_LN
C	0.848	0.915	1.371**	0.840*	0.852	0.816
COEN	0.130**	0.091*		0.106**		0.105**
MAI	-0.183**			-0.149*		-0.151*
COAG			0.243**		0.176**	
COIM			-0.121*			
COPM			-0.123*			

1c. CTA – Up Regimes

Dep. Var:	CT_SS	CT_SL	CT_AY	CT_AO	CT_LY	CT_LN
C	0.821**	0.720**	0.215	0.836**	0.962**	0.809**
COPM	0.176**		0.087*	0.140**		0.141**
COIM		0.120**				
MOM		0.138**	0.095*			
COEN			0.084**			
HML			0.252*			

1d. CTA – Down Regimes

Dep. Var:	CT_SS	CT_SL	CT_AY	CT_AO	CT_LY	CT_LN
C	0.964	2.682**	1.481	0.821	1.438**	0.656
COEN	0.104**			0.068*		
MAI	-0.186*			-0.157*		-0.208**
MOM		0.134**				
TERM		-0.820*				
COIM					0.197**	
EXCH						-0.504*

4.3.3.2 Analysis by strategy group

4.3.3.2.1 MAI analysis

In this section I provide an alpha analysis taking into consideration the strategy groups and the fundamental factors so as the reader to get a broader perspective. As I have already mentioned, there are three broad groups of strategies: Directional, semi directional and non-directional. Table 34 Panel A presents the results for all the groups that are directional strategies. Regarding the growth-recession periods, all groups lower their exposures during recession periods. This means that all funds regardless of their characteristics try to protect against negative market movements. Regarding the up/down regimes, most groups decrease their exposures during down regimes. However, young funds and lockup-yes funds are not successful in this. Young funds have the timing advantage (hence there is no need to adjust considerably their portfolio) and lockup-yes are protected from the restrictions (thus there is also no need to adjust considerably their portfolio). Panel B shows the results for all the groups that are semi-directional strategies. Regarding the growth-recession periods the majority of groups do not lower their exposures during the recession period. This means that funds regardless of their characteristics do not rely on changing their exposures toward the market factor. However, when combining up/down regimes, all the groups change their exposures against the market factor as the down regimes are fiercer than recessions. One exception is the lockup-yes funds that do not suffer from redemptions. This seems to work for this group as its excess returns are one of the highest among the groups. Panel C present the results for all the groups that are non-directional strategies. Regarding the growth-recession periods there is no great change in exposures among groups. This is probably because non-directional strategies, in general, are not correlated with market movements. Concerning the up/down regimes, some groups decrease their exposures substantially. It appears that during down regimes (low market returns with high volatility) hedge funds are trying not only to minimize their exposures but even to have negative exposures in order to protect themselves from the risk.

Table 34. MAI Analysis by Strategy Group

This table shows the average exposures to the MAI market index for all groups that are directional, semi-directional and non-directional strategies during growth and recession periods as well as the up and down regimes. Since the growth periods and up regimes are the longest I use them as the base to measure the percentage change of the exposure (MAI exposure for each mixed case is statistically significant from zero).

MAI Expos	Growth	Recession	Difference	% Difference (Base Growth)	Up	Down	Difference	% Difference (Base Up)
				Panel A. Directional Strategies				
Size Small	0.276	0.234	0.042	-15.28%	0.279	0.134	0.145	-51.88%
Size Large	0.238	0.172	0.066	-27.69%	0.238	0.162	0.076	-31.84%
Age Young	0.278	0.084	0.194	-69.73%	0.271	0.295	-0.024	8.87%
Age Old	0.230	0.135	0.095	-41.27%	0.223	0.110	0.113	-50.74%
Lockup-Yes	0.169	0.094	0.075	-44.58%	0.150	0.162	-0.012	7.83%
Lockup-No	0.252	0.144	0.108	-42.90%	0.239	0.112	0.126	-52.87%
				Panel B. Semi-Directional Strategies				
Size Small	0.301	-	-	-	0.261	0.215	0.046	-17.72%
Size Large	0.226	0.220	0.007	-2.94%	0.222	0.173	0.049	-22.14%
Age Young	0.223	0.274	-0.052	23.15%	0.280	0.248	0.031	-11.18%
Age Old	0.241	0.301	-0.059	24.75%	0.232	0.174	0.058	-24.81%
Lockup-Yes	0.446	-	-	-	0.333	0.514	-0.181	54.29%
Lockup-No	0.219	0.411	-0.192	88.04%	0.216	0.225	-0.009	3.97%
				Panel C. Non-Directional Strategies				
Size Small	0.131	0.063	0.068	-52.06%	0.193	-0.026	0.219	-113.42%
Size Large	0.096	-	-	-	0.101	-	-	-
Age Young	0.139	0.174	-0.035	24.91%	0.095	-	-	-
Age Old	0.103	0.077	0.026	-25.69%	0.101	-0.157	0.258	-255.06%s
Lockup-Yes	0.115	0.316	-0.202	175.52%	0.114	-	-	-
Lockup-No	0.102	0.060	0.042	-41.50%	0.082	-0.208	0.290	-354.12%

4.3.3.2.2 Alpha analysis by strategy group

In this section I provide an alpha analysis taking into consideration the strategy groups and the fundamental factors. As I have already mentioned before there are three broad groups of strategies: Directional, semi directional, and non-directional[34]. Table 35 shows the results. Large directional funds outperform small directional funds in both "good" and "bad" conditions as they are able to benefit from the upward market movement and avoid the downward market movement, accordingly. The same applies to young directional funds versus old directional funds due to the timing advantage. Lockup-yes directional strategies outperform lockup-no directional strategies in all market conditions due to the liquidity premia exploitation and the redemption protection. The semi-directional large funds outperform small funds during "good" market conditions (due to better exploitation of the upward market movement) whereas during "bad" market conditions small semi-directional strategies outperform large funds due to their flexibility. Old semi-directional strategies outperform young directional funds in all market conditions due to their experience and market establishment. Moreover, lockup-yes semi-directional strategies outperform lockup-no in good market conditions (due to the liquidity premia) whereas the opposite is true during "bad" market conditions. It seems that funds with no redemption restrictions (that survive) during "bad" times are more innovative and efficient than their peers as fund managers feel high pressure. Small non-directional funds outperform large funds during "good" times as small funds use some market exposure to benefit from the upward market movement and this explain also that during "bad" times small fund underperform compared to large funds. Old non-directional funds outperform young funds because of their experience and the market establishment, whereas young funds outperform during "bad" times due to the timing advantage (they enter the market when it is for their benefit). Lockup-yes non-directional funds outperform lockup-no funds in all market conditions as fund managers have the "protection" of the redemption restrictions.

[34] There is a gradual classification from extreme directional strategies (e.g. Short Bias strategy) to the extreme non-directional strategies (e.g. CTAs).

Table 35. Alpha Analysis for Group Strategies

This table shows the alphas for all groups belonging to the directional, semi-directional and non-directional strategies during growth and recession periods as well as the up and down regimes (during "good times" alphas for most mixed cases are statistically significant from zero).

	Directional		Semi-Directional		Non-Directional	
	Up/Growth	Recession/ Down	Up/Growth	Recession/ Down	Up/Growth	Recession/ Down
Size Small	0.656	0.090	0.638	0.842	0.357	0.578
Size Large	1.081	0.368	0.735	0.531	0.262	0.708
Age Young	1.236	0.163	0.524	0.242	0.204	0.788
Age Old	0.711	0.027	0.773	0.464	0.411	0.383
Lockup-Yes	0.746	0.403	0.718	0.671	0.776	0.450
Lockup-No	0.628	-0.414	0.685	0.823	0.255	0.362

4.3.3.2.3 Mixed level rankings: Top two and last two performers

It is expected that top (bottom) performers are related with how well (or not) the strategy can benefit from the upward market movement during "good" times and how well it can deal with the "bad" conditions. For example for top performers we expect that some directional strategies may have an asset and portfolio allocation that maximize the returns during upward market movement even with high exposures. During "bad" times top performers should be less directional strategies that are not affected to a large extent by these "bad" times. In addition to this it is expect that characteristics such as flexibility (e.g. small size funds or funds with short selling), experience (e.g. old funds), and deep knowledge/innovation (e.g. specializing in specific industries or exploiting allocations that are not widely used by other strategies) are essential for "good" fund performance.

The above assumptions (forecasts) are confirmed by Table 36 which presents the results of the best two and worst two strategy funds with specific fundamental characteristics during "good" and "bad" times. During "good" conditions, Sector young funds and Long Short young funds are the top in terms of excess return delivered to investors with 4.175% and 2.856%, respectively on monthly basis. This is explained in a way that both strategies are directional strategies and young that in general provide superior returns than old funds. Sector funds specialize in specific sectors having a deeper knowledge of specific cyclical industries/sectors (increasing also their systematic risk). Long short strategy is conceptually easy to understand but difficult to implement strategy hence fund managers with superior stock picking capabilities can benefit from this. Moreover as Long Short strategy is superior to the Long Only as it utilizes the short selling. On the other hand, during "good" times, the bottom performers are the Market Neutral young, and the Relative Value no-lockup funds (although the last two results are not significantly different from zero). This can be explained as these are non-directional strategies that cannot benefit from the upward market movement. For the "bad" conditions the Others strategy and especially small funds deliver high excess returns to investors as this strategy is investing mainly in start-ups with "good" promised yields. On the other hand Long Only funds without redemption restrictions and Multi Strategy young funds deliver significant negative alphas to investors. It seems that the last two funds perform very poorly, with investors losing money. We can explain this poor performance as Long Only funds with no restrictions having no alternative but to stay long while they are not protected from redemptions. Multi strategy young funds may lack the necessary experience of implementing this type of complex strategy which it is a combination of other strategies.

Table 36. Bottom/Top Performers

This table shows the returns of the top two and bottom two performers during "good" and "bad" conditions. * denotes significance at $P < 0.05$ and ** denotes significance at $P < 0.01$.

"Good Conditions"		"Bad" Conditions	
Sector – Young Funds	4.175**	Others - Small Funds	4.142**
Long Short -Young Funds	2.586**	Others - Old Funds	2.462**
Market Neutral – Young Funds	-0.036	Long Only – Lockup-No Funds	-3.524**
Relative Value – Lockup-No Funds	-0.225	Multi-Strategy – Young Funds	-1.316*

4.3.3.3 Discussion

Concerning the relationship between size and performance, the results agree with other authors (such as Agarwal, Daniel, and Naik, 2004; Ammann, and Moerth, 2005; Meredith, 2007; Joenvaara, Kosowski, and Tolonen, 2012) that there is a negative correlation, on average. These results are in alignment with commercial studies (e.g. Pertrac Corporation, 2012). Getmansky (2004) found that there is a positive and concave correlation and suggested that there is an optimal size of AUM. A few studies are exceptions that found no relationship, such as Gregoriou and Rouah (2002) or a negative relationship such as Koh, Koh, and Teo (2003)[35] but the differences are mainly due to the use of different samples and methods. In this study I show that this relationship is not static, in other words it changes according to different market conditions. Although this negative relationship holds for "good" times, during "bad" times it is questionable. Small funds seem to suffer more than large as they are not able to absorb the turbulence during "bad" times. These findings allow investors to be more knowledgeable than before about this relationship.

Concerning the relationship between age and performance, there is again agreement with the literature (such as Amenc and Martelini, 2003; Meredith, 2007; Frumkin, and Vandegrif, 2009; Pertrac Corporation, 2012) that there is a negative relationship, on average. One exception is the study from Schneeweis, Kazemi and Martin (2002)[36] that showed a positive relationship. This study proceeds further and examines this relationship for "good" and "bad" market conditions. I found that this holds for "good" and "bad" times. This finding allow investors to be more confident than before when considering this relationship in their investment decision process.

Regarding the relationship of the lockup restrictions to performance there is an agreement with other authors (such as Aragon, 2007; Joenvaara, Kosowski, and Tolonen, 2012) that there is positive relationship. However in this study I show that this relationship is not static as this negative relationship holds only during "good" times. During "bad" times, no lockups funds (that survive) outperform funds with lockups. I rationalize this as fund managers becoming more innovative with respect to their peers, under the pressure of not having the "safety" of redemption restrictions. These findings facilitate investors in their decision process, as having redemption restrictions does not necessarily mean high expected returns, particularly during stressful market conditions.

Beyond the above there was an investigation into hedge funds at the mixed level (strategies and fund specific characteristics concurrently). Directional strategies with specific characteristics (such as young and small funds) can provide high returns to investors. On the contrary, non directional strategies especially those with no redemption restrictions and young suffer during "good" times. I also found that

[35] Greogoriou and Rouah used the AUM at the inception date of each fund and not the average that is most commonly used by the other authors. Koh, Koh, and Teo in their study considered Asian hedge funds.

[36] Schneeweis, et al. (2003), contrary to the other studies, took into consideration funds with the same starting point (same inception date).

directional strategies (e.g. strategies similar to traditional investments taking long only positions) with no redemption restrictions present negative alpha to investors whereas some less directional strategies (perhaps due to lack of experience) e.g. young funds also present negative alpha. My findings are important because investors know what to expect from hedge funds at the mixed level and sometimes it is possible to pay high fees for negative alpha during stressful market conditions.

4.3.3.4 Robustness

This piece-wise parsimonious model is sufficient and robust because the statistical significance of the factor loadings on the Wilshire 5000TRI, conditional on the different regimes, is almost the same as that derived in the simple market model with only the Wilshire 5000 TRI risk factor and adds significant explanatory power. This suggests that the analysis performed above is robust to the inclusion of other factors (see section 4.3.2) that may affect hedge index returns. Irrespective of fund fundamental factors, during stressful market conditions there is no significant alpha to hedge funds, on average. This is in alignment with the analysis at the mixed level during "good" times, where almost all funds deliver significant excess returns to investors and during "bad" times where the majority of funds do not deliver significant excess returns. In addition to the above tests, I repeated another robustness check by excluding the first 48 months (1/1990-12/1993) and implemented my model again at the fundamental level. All the regressors had the same sign and were mostly statistically significant making my findings more robust. Moreover, I confirmed the relative performance between funds with different characteristics, and irrespective of the fundamental factors I confirmed that hedge funds deliver significant alpha only during "good" times, contrary to "bad" times where fund managers are concerned with minimizing their risks. Another robustness check was when I implemented the model for the first 48 months (1/1990-12/1993) where there are comparable qualitative results. A final robustness check was by using the HAC/Newey-West estimator for any unknown residual autocorrelation and heteroscedasticity where the results remain valid[37].

4.4 Conclusion

In this paper I have modelled hedge funds taking into consideration the fundamental factors that can affect hedge funds' performance during different market and financial

[37] The robustness tests of the proposed model are not presented here for space reasons but are in the appendix.

conditions. I pursue the analysis further at the mixed level. In order to do that I used an extra dataset with fund characteristics that was associated with the underlying hedge funds. Thus, I extended my basic model that exploits predefined structural breaks, based on multiple business cycles during 1990-2014, using a comprehensive merged database and a Markov Switching model to identify in the proposed model the structural breaks conditional on the different states of the market index. I used the stepwise regression technique, thus allowing the model to adjust to these different conditions, providing more accurate and useful results. In order to study the impact of the fundamental factors on hedge fund performance I formed portfolios based on fund characteristics: the age, size, and whether lockup period exist. Then I moved further by examining the impact of these fundamental factors at strategy level, so as to facilitate investors in their investing decision process with more accurate and detailed results.

This study has some important findings that contribute significantly to the literature, beyond those that agreed with the extant literature discussed above. First, on average, hedge funds during "good" times deliver significant excess returns to investors, irrespective of the underlying fundamental factors. On average none of these factors was able to significantly assist in delivering excess returns to investors. Secondly, at the fundamental level, during "good" times, small funds, young funds, and funds with redemption restrictions deliver higher alpha with respect to their peers. For "bad" times, small funds seem to suffer more than large, young funds continue to outperform old funds, and funds that do not impose restrictions (and survive) outperform funds with lockups. We can explain this as fund managers feeling the pressure of not having the "safety" of redemption restrictions, thus being more innovative and doing better than their peers. Third, at the mixed level, there are strategies with specific characteristics, conditional on stressful market conditions that deliver significant negative alpha to investors. Two examples are the Long Only funds with no redemption restrictions, and the Multi Strategy young funds. On the contrary, there are some strategies with specific characteristics that provide extraordinary excess returns to investors during stressful market conditions: Two examples are Others strategy small and old funds. Accordingly there are specific strategies that perform extremely well or badly in "good" or ""bad" conditions and investors should be conscious of this. Even after I exclude the pre 1994 period from the analysis or using pre-1994 only data the findings are robust.

The results are important as they extend previous knowledge about the relations between fund performance and fund specific characteristics, by examining it in a holistic approach between different business cycles and financial conditions. Thus, I provide a deeper understanding of hedge funds' behaviour and I reveal dimensions that have not been examined previously. Beyond this extension, I proceed further by examining fund behaviour at a mixed level, meaning I investigate fund performance taking into consideration different strategies and different fundamental factors together. Despite the fact that hedge funds are complex investment vehicles and difficult to model, there are some consistent patterns which are related to managers' behaviour in terms of the excess returns and their exposures to factors within both multiple business cycles and different market conditions. The longest covered period (compared to any extant paper) of this dataset enables me to investigate hedge fund behaviour in a more comprehensive way (not choosing a short period of time with just one financial crisis or event). Moreover, instead of using one general commodity factor I used specific ones for more precise results as commodities do not behave in the same way in the market.

The findings can benefit investors enabling them to have a better sense of what to expect from funds with different characteristics, taking into consideration business cycles and different market conditions. The results should help investors and fund of fund managers in their strategic asset allocation process. However, in this study it is assumed that investors are capable enough in forecasting different market conditions (at least with relatively high probability). I reveal for the first time that some fund strategies with specific fundamental characteristics within specific market conditions can even deliver negative alpha to investors. Another use of the findings could be by fund administrators to use more flexible performance fee policies that can capture in a better way hedge fund managers' performance.

I have investigated hedge funds that focus mainly in the North America region because I use U.S. business cycles. An interesting investigation would be focusing on the European and Asia-Pacific regions, however, the definition of the business cycles in these regions would be questionable. One more limitation is that I do not use lookback straddles that are appropriate for CTAs, due to data unavailability in the early 1990s. Hence, a CTA-only mixed level examination using lookback straddles would also be of interest, even if shorter period of time is used. Last but not least, there is a need to examine hedge fund behaviour for Emerging Market Strategies at mixed level, within a similar approach.

5 Chapter: Persistence and mixed trading strategies

This chapter (paper) examines the impact of multiple business cycles and different market conditions on hedge fund strategies in terms of persistence and how investors can utilize this. Similar to the previous chapters it has its own structure with introduction, methodology, empirical analysis and conclusion sections (a version of this paper is to be submitted to a journal).

I examine US hedge funds' performance persistence and mixed-trading strategies across both different economic and market conditions for 1990-2014. I use parametric and non-parametric models and I examine hedge fund persistence in various aspects. During "good" times there is smoothness in hedge fund (risk-adjusted) returns whereas during "bad" times this smoothness disappears. With respect to the market benchmark, with a few exceptions, there is no performance persistence. Concerning the persistence within each strategy group, for "good" times I find persistence up to one year whereas for "bad" times it lasts up to six months. There is strong evidence that the persistence is driven mainly by the top performers, and recessions are harsher than down regimes for hedge fund persistence. Finally, I construct mixed trading strategies and I introduce the zero investment portfolio "momentrarian" strategy that can bring conditional high excess returns to investors.

5.1 Introduction

Investors very often rely on hedge fund past performance expecting that it is stable over time and that some fund managers outperform their peers. There is strong evidence that there is at least short term persistence (e.g. Agarwal and Naik, 2000a; Harri, and Brosen, 2004; Eling, 2009; Joenvaara, Kosowiski, and Tolonen, 2012; Hentati-Kaffel and Peretti, 2015). However there are studies (e.g. Jagannathan, Malakhov, and Novikov, 2010; Ammann, Huber, and Schumid, 2013) that challenge the above studies showing that there is long term persistence (over a year). Nevertheless, further research is needed to verify the results of these recent studies. There is evidence (Bares, Gibson, and Gyger, 2003; Eling, 2009) that some non-directional strategies (e.g. Merger Arbitrage, Convertible Arbitrage strategies) present more persistence than directional strategies (e.g. Long Only and Short Bias strategies). Details concerning the nature of the fund persistence continue to emerge, such persistence varying between different hedge fund strategies and between different fund characteristics such as size (Joenvaara, Kosowski and Tolonen, 2012), age (Meredith, 2007), fees (Amenc and Martellini, 2003) and flow restrictions (Bae and Yi, 2012). Other studies (e.g. Bollen and Pool, 2006; Agarwal, Daniel, and Naik, 2011; Itzhak, Franzoni, Landlier and Moussawi, 2013) showed that illiquidity has a significant effect and the smoothing of returns is widespread as some fund managers invest in illiquid assets or manage their returns. In hedge fund studies, there are differences due to industry heterogeneity and the use of different databases, time periods and methodologies. However, there are some consistent trends and patterns that reveal useful dimensions about hedge fund behaviour.

Although the above studies are important in explaining hedge funds performance in terms of persistence, there is a need to examine hedge fund performance persistence in a more comprehensive way by making a distinction between the different types of performance and not only focusing in one only type of persistence (e.g. persistence within each strategy). Furthermore, there is a need to examine the impact of different market conditions in hedge fund performance persistence focusing on specific region(s) for more robust results. This paper uses the term multiple business cycles and different market conditions (these are not limited to only one recession/growth period or financial event) and focuses on North America funds[38] as this is the most important region for hedge funds in economic terms. Therefore, this study fills a gap in the literature. It makes a distinction between multiple business cycles and different market conditions as they do not coincide necessarily, having different implications (as presented later in the empirical analysis) in hedge fund behaviour. Furthermore I investigate hedge funds at the strategy level and it examines different types of persistence using several parametric and non-parametric tests. Another gap in the literature is the lack of the examination of different trading strategies based on persistence and spreads of top/bottom performers that investors or fund of fund managers can exploit so as to gain higher returns. This paper deals with various mixed trading strategies (investment styles) that can help fund managers achieving higher returns. I also introduce the term "momentrarian strategy" that is a combination of a momentum and contrarian strategy under specific conditions, as discussed later in section 5.2.1.

There are some important findings that contribute to the academic literature beyond those that agree with other authors above in terms of short term persistence (e.g. Harri

[38] These are funds that invest primarily in the North America region.

and Brorsen, 2004; Eling, 2009; Joenvaara, Kosowski, and Tolonen, 2012; Hentati-Kaffel, and Peretti, 2015) or that some strategies appear to be more consistent than others (e.g. Eling, 2009; Brown and Goetzmann, 2003; Hari and Brorsen, 2004): First, using a regression based parametric approach, non-directional and semi-directional strategies have on average smoother returns compared to directional strategies, however during stressful market conditions there is a negative impact on the smoothness for all hedge fund strategies. When considering risk-adjusted returns the smoothness weakens even more in all cases. Second, using CPR tests and Chi-square tests, I found that there is little or no persistence of hedge funds against the market benchmark. Only a few strategies such as Long Short, Multi-strategy, and Long Short seem to present some performance persistence against the market during “good” market conditions. Third, when examining persistence within strategies, I found that there is persistence up to one year, however, during stressful market conditions there is quarterly persistence (with a few exceptions that provide semi-annual persistence). Fourth, the persistence, on average, is attributed mainly to top performers and less to bottom performing funds. Often, there are reversals in bottom performers as fund managers are pressurized to deliver higher returns; otherwise they will go out of business. Furthermore, during stressful market conditions, the persistence is reduced dramatically for hedge fund strategies. Fifth, I created a framework of using various zero investment trading strategies that can utilize differences in return spreads between top and bottom performing funds among different strategies. I found that a momentum trading strategy is, on average, the most efficient within “good” market conditions whereas the momentrarian strategy is, on average, the most efficient during stressful market conditions.

This study makes important contributions to the literature and to investors as well. I have revealed aspects that have not been examined before. More specifically, for the first time, I make a clear distinction between different aspects of performance persistence and I examine each of these aspects, at strategy level, within multiple business cycles and different market conditions, as these two different states do not coincide necessarily, having different implications for hedge funds. For example it seems that recessions periods are, on average, fiercer in terms of hedge fund performance persistence compared with down regimes. Investors know what to expect from different strategies in terms of performance persistence. Past performance is no guide to the future; however, most investors in their capital allocation process rely on past performance. One more contribution is that, for the first time, I develop a framework of using zero investment trading strategies that utilize the differences in return spreads between top and bottom performing hedge funds. These mixed or synthetic trading strategies can be a guide to investors allowing them for potential higher returns, outperforming market returns. Last but not least, I executed a systematic database merging and cleaning process that can be considered as a guide for future studies.

Investors can benefit from the findings as they are able to know what to expect from different strategies in terms of performance persistence. Although past performance is no guide to the future, most investors in their capital allocation process, rely on funds' past records. This implies that investors expect performance to be stable over time and that some fund managers provide better performance compared to their peers. This study provides a comprehensive investigation of hedge fund performance persistence allowing investors to implement mixed trading strategies utilizing return spreads between top and bottom performers of different hedge fund strategies. Financial government authorities can benefit by better understanding hedge funds in terms of their persistence and risks, in case there is any need for closer monitoring (e.g. "unusual" hedge fund persistence) or a change in the legal framework.

The remainder of this paper is as follows: First I present the methodology used describing the theoretical framework and the data. Second, I proceed to the empirical analysis by presenting some key statistics, the regime switching model, the performance persistence analysis at strategy level, and the mixed trading strategies. Then I have some robustness tests. Lastly, I present the conclusions providing a summary of the findings and some opportunities for further research.

5.2 Methodology

This section presents the theoretical framework along with the data.

5.2.1 Theoretical framework

As in the Chapters Three and Four, the proposed model uses predefined and undefined structural breaks conditional on different states of the market. As predefined structural breaks I use the U.S. business cycles and as undefined structural breaks I use the statistical Markov switching process conditional on the different states of the market index. For more information please see Chapter Three's methodology section. Within this framework I examine hedge fund performance persistence in terms of returns and risk-adjusted returns to investors. I present the methods used in order to detect performance persistence. Afterwards, I present several trading strategies that includes a *momentrarian* trading strategy which is a combination of momentum and contrarian strategies, so the investor or fund of funds manager can have higher returns in her portfolio.

In order to examine hedge funds at a strategy level I form portfolios of hedge funds according to their strategy (total 11 strategy portfolios – see the data section of the empirical chapter one). In this study I examine hedge fund performance persistence in terms of smoothness (how constant are their raw and risk-adjusted returns), against the market benchmark and within strategy groups (hedge funds) over quarterly, semi-annual, and annual intervals. These are the most common time horizons examined in the literature. I do not use time horizons of more than a year due to limited observations during stressful market conditions[39].

5.2.1.1 Performance persistence - Methods

As Agarwal and Naik (2000a) said, in general there are two statistical approaches when examining performance persistence: two-period and multi-period approaches. In the first approach two consecutive time units are examined (e.g. months) whereas in the second approach more than two consecutive periods are examined. This is known as a Kolmogorov-Smirnov test. In this study I use the traditional two-period framework. This is because I examine persistence within multiple business cycles and market conditions and there are not enough available observations for the stressful market conditions to consider a multi-period framework.

Within the two-period framework as a nonparametric approach the contingency-table methods are based on the construction of tables of winners and losers. Winners are funds whose performance is higher than the median of all funds within the same group or benchmark, whereas losers are funds whose performance is lower than the median. Funds that are winners (WW) or losers (LL) in both time units are persistent. Funds that are winners in the first period and losers in the second are denoted WL or LW. In this

[39] The numbers of observations for recessions and down regimes are 34 and 36, respectively. Hence, at the yearly time horizon I would have only three observations.

framework I have conducted as a primary test the cross-product ratio (CPR) and as a secondary test the Chi-square statistic so as to detect the performance persistence. This is because the CPR is stricter than the Chi-square test and is able to capture the positive or negative manner of the persistence.

The cross-product ratio (CPR) test is the ratio of funds that display persistence to the funds that do not (Agarwal and Naik, 2000b).

$$CPR = (WW * LL)/(WL * LW) \tag{15}$$

The null hypothesis in this setting means that there is persistence where the CPR is equal to one. Under this, it is expected that the each of the four categories (WL, LL, WL, and LW) will have 25% of the funds under consideration. The statistical significance of the CPR can be tested using the standard error of the natural logarithm of CPR that is given by

$$\sigma_{\ln(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{LL} + \frac{1}{WL} + \frac{1}{LW}} \tag{16}$$

The resulting Z-statistic is the ratio of the natural logarithm of the CPR to the standard error of the natural logarithm.

In the Chi-square test (see Park and Staum, 1998) the observed frequency distribution of WW, LL, WL, and LW is compared to the expected frequency distribution.

$$x^2 = \frac{(WW-D1)^2}{D1} + \frac{(WL-D2)^2}{D2} + \frac{(LW-D3)^2}{D3} + \frac{(LL-D4)^2}{D4} \tag{17}$$

Where $D1 = {(WW + WL) * (WW + LW)}/{N}$

$D2 = {(WW + WL) * (WL + LL)}/{N}$

$D3 = {(LW + LL) * (WW + LW)}/{N}$ and

$D4 = {(LW + LL) * (WL + LL)}/{N}$; | N is the number of funds.

Following the chi-square distribution with one degree of freedom, a critical value X^2 (chi-square) greater than 3.84 (6.64) indicates significance at the 5% (1%) confidence level.

Within the two-period framework as a parametric approach I use the regression-based parametric model (Brown, Goetzmann, Ibbotson, 1999) where I regress funds' returns (and risk adjusted returns) during the current period against the returns (or risk adjusted returns) during the previous period. As risk adjusted measures I use the Sharpe ratio and the Information ratio. For each month, I computed the Sharpe ratio which is the portfolio return minus the risk free return divided by the standard deviation of the portfolio return. $Sharpe\ Ratio = (\ \overline{R}_p - \overline{R}_f)\ /\ \sigma_\rho$, (Sharpe, 1994). Similarly, for each month, I computed the Information ratio which is the portfolio return minus the benchmark (Wilshire 5000TRI, including dividends) return divided by the standard deviation of the excess market returns. $Information\ Ratio = \overline{(R_P - R_B)}/\sigma(R_P - R_B)$, (Goodwin, 1998). A positive significant slope coefficient indicates performance persistence. This means that a hedge fund (or group) that did well in a specific period tends to do well in the subsequent period. In other words, there are no high fluctuations in the returns. The statistical significance of the slope can be tested using the t-statistic. As I mentioned, I use the regression-based parametric model so as to examine the smoothness of returns for each hedge fund strategy.

$R_t = a + b(R_{t-1}) + \ \varepsilon_i$ where R are fund's returns (18)

Within the multi-period framework a Kolmogorov-Smirnov goodness-of-fit-test (Agarwal and Naik, 2000a) is applied, where a series of wins and losses are constructed for each fund and I compare the observed frequency distribution with the theoretical frequency distribution of more than two consecutive wins and losses. For example, under the null hypothesis of no persistence the expected probabilities of observing WWW or LLL and WWWW or LLLL is one-eighth and one-sixteenth, respectively. By using the two sample Kolmogorov-Smirnov test I check whether the observed distribution is statistically different from the theoretical distribution.

Last but not least I use the portfolio construction approach by forming initial winners P1 and losers P10 and tracking their performances for the next period denoted by P1* and P10*. I examine the relationship of P1 versus P1*, and the relationship of P10 versus

P10*. Then I examine the relationship between P1* with the average within the same strategy and the relationship of P10* with the average in the same strategy as well. I use parametric and non-parametric correlation tests such as the Pearson and the Spearman correlation tests for more robust results. The Spearman correlation test is the Pearson's correlation coefficient on the ranks of the data.

5.2.1.2 Aspects of performance persistence

Contrary to earlier studies (e.g. Harri, and Brosen, 2004; Eling, 2009; Hentati-Kaffel, and Peretti, 2015) that focus only on whether fund winners (losers) continue to be fund winners (losers), I measure three different aspects of performance persistence. The first aspect is the smoothness (uniform consistency or fluctuation from one period to the next) of the returns and risk adjusted returns for hedge funds groups at strategy level. As absolute performance is the most important element in the hedge fund industry when examining persistence, I focus more on raw returns. However, I also include risk-adjusted returns in my analysis, computing the Sharpe ratio and Information ratio cross-sectionally using funds at the strategy and fundamental level for each time period, as some strategies are more risky whereas others attempt to offer more stable returns. I use the regression based parametric model described previously.

The second aspect is measuring the out(under)performance of hedge funds returns against a specific benchmark which is the market index. In other words I try to determine whether hedge funds consistently provide higher (or lower) returns against the market index (Wilshire 5000TRI, including dividends). This is examined at a strategy level and using the CPR and Chi-square tests described in the previous section.

The third aspect is the examination of persistence at a fund level. I take into consideration funds that belong to the same strategy. The objective is to examine whether fund winners (losers) continue to be fund winners (losers) in the next period. In order to fulfil the objectives I form ranked portfolios of funds that are rebalanced every subsequent period. I follow a decile classification similar to other authors (e.g. Carhart, 1997; Capocci, 2007). Each period (quarterly, semi-yearly, yearly) all funds within a specific group (e.g. strategy) are ranked in ten equally weighted portfolios (D1 [highest]…D10 [lowest]) based on their previous period results. The portfolios are held until the next period and then rebalanced again. Funds that disappear are included in their equally weighted average until their death, then the portfolio weights are adjusted appropriately[40]. After this, I examine the spread between the first ranked and the last ranked portfolios and I implement the regression based parametric model so as to examine the smoothness of the underlying spread[41]. I then examine the relationship between initially top (bottom) ranked portfolios against the subsequent performance in the next time period of the same portfolios. Finally I compare the returns of the subsequent performances (top or bottom initially ranked portfolios) with the average of all funds within the same strategy, according to the tests mentioned in the previous section.

5.2.1.3 "Momentrarian" trading style

It is known from the academic literature that the momentum (e.g. Jegadeesh and Titman, 1993) and contrarian (e.g. De Bondt and Thaler, 1990) trading strategies produce significant excess returns to investors. In this study, I introduce the term *momentrarian* which denotes an investment style (or trading strategy) that utilizes the momentum (MOMEN-) and the contrarian (-TRARIAN) trading strategies to maximize returns. For the first time, I present a trading style that is a combination of these two trading styles that can bring conditional higher returns than just exploiting one of these strategies. Table 37 presents a framework with the possible actions when using momentum and contrarian trading strategies. These possible actions may refer to securities, financial indices or hedge funds, as in this case. I use periods of quarterly, semi-yearly, and yearly similar to my performance persistence examination. Hence, an investor when using trading strategies at the hedge fund level has the following four cases: The first case (A) is the momentum trading concerning top performers; the second case (B) is the (reverse) momentum trading concerning the bottom performers. The third case (C) is the contrarian strategy concerning the top performers; the fourth case (D) is the (reverse) contrarian strategy with the bottom performers. It is known from the literature that the momentum strategy can be a zero investment portfolio that is long past winners and short past losers. Similarly, the contrarian strategy can be a zero investment portfolio short in (early) past winners and long in (early) past losers.

[40] Due to the fact that my data length concerning the various horizons under consideration (e.g. quarterly, semi-annual, annual) does not always match, and I want to exploit as many observations as I can, I exclude data-months where the missing values are more than 50% of the total. For example, in the yearly analysis within recessions, the third year consists of ten months/observations that are available. On the contrary, in the yearly analysis within growth periods, I excluded the last five months/observations because the missing data (seven months/observations) were greater than the 50% required (12 months/observations).

[41] A positive and significant slope means that the spread is smooth, in other words the distance between top and bottom performers is not random (not having high fluctuations).

According to the literature (e.g. Jegadeesh and Titman, 1993) the momentum effect lasts for a few months (e.g. up to a year). Hence beyond this time period I expect the contrarian effect to dominate.

As can be seen from Table 37, the above trading strategies can work horizontally (e.g. implementing in parallel two separate zero investment portfolios – one momentum and the other contrarian) denoted as a horizontal *momentrarian* trading strategy. The other case is a vertical *momentrarian* strategy (using a combination of a momentum and contrarian strategy). For the vertical *momentrarian* trading strategy the implementation seems more difficult as in order to have zero investment portfolios the period should be the same for the momentum and the contrarian trading, although in different time intervals (please see the next example).

Table 37. Basic Trading Strategies

This table provides the basic trading strategies which are momentum (horizontal), contrarian (horizontal), and the momentrarian (vertical). There are two basic momentrarian strategies: high and low returns exploitation.

Momentrarian Trading (high rtns)	Momentum Trading	Hedge funds, A : High Recent Returns Action: Buy then Sell	Hedge funds, B : Low Recent returns Action: Short-Sell then Buy	Momentrarian Trading (low rtns)
	Contrarian Trading	Hedge funds, C : High Earlier Returns Action: Short-Sell then Buy	Hedge funds, D : Low Earlier Returns Action: Buy then Sell	

A simple example of a vertical *momentrarian* (involving high returns exploitation) strategy is: At time *t*, select and buy a hedge fund (A) whose returns at *t*-1 (e.g. last year) are high (compared to other funds). Also, select and short-sell another hedge fund (C) whose returns at *t*-2 (e.g. two years before) were higher (compared to other funds)[42]. At time *t*+1 (e.g. one year, ahead) sell hedge fund (A) and buy hedge fund (C). Then, at time *t*+1, I rebalance the portfolio, repeating the above initial process, and so on.

[42] In practice, when the fund manager wants to apply the momentrarian strategy (involving high returns exploitation) and has to select between e.g. two similar funds (C) whose returns are higher at t-2 (years before) compared to other funds, she can choose the fund where the performance trends are poorer at t-1, as it is a sign that the contrarian effect starts to takes place and at t+1 the fund's returns will be relatively low. This applies accordingly in the next example of the momentrarian strategy (involving low returns exploitation) when considering two similar (D) funds. In this case the fund manager should choose the fund whose performance trends are better at t-1, as it is a sign that the contrarian effect start to takes place and at t+1 fund's returns will be relatively high. Last but not least, my framework covers many variations of the above strategies with different time periods of forming/holding portfolios that an investor can choose. However for simplicity reasons we focus on specific equal forming/holding horizons of portfolios for momentum strategies (being in accordance with my fund persistence analysis) and one year forming with holding periods of one, two and three years for the contrarian and momentrarian strategies .

A similar example could be used in the other vertical momentrarian (involving low return exploitation). At time *t*, select and short-sell a hedge fund (B) whose returns at *t*-1 (e.g. last year) are low (compared to other funds). Also, select and buy another hedge fund (D) whose returns at *t*-2 (e.g. 2 years before) are low (compared to other funds). At time *t*+1 (e.g. one year, ahead) buy hedge fund (B) and sell hedge fund (D). Afterwards, at time *t*+1, I rebalance the portfolio, repeating the above initial process, and so on.

In section 5.3.3 I take into consideration the above framework, revealing the *momentrarian* trading styles that can bring substantially higher returns to investors. I implement this strategy along with the momentum and the contrarian trading strategies. Moreover, I implement these trading strategies at different business cycles or market conditions for even higher investor returns. Later, in order to test the study for sufficient and robustness, I take into consideration fund redemption fees (lockups), and I perform a sub-period analysis with a holdback period.

5.2.2 Data

As in the Chapters Three and Four, in the analysis I combine and use three hedge fund databases (one with live/dead funds, one with live funds and one with dead funds) from two database vendors. These are BarclayHedge and EurekaHedge covering the period from January 1990 to March 2014. For more details about the database merging and cleaning processes, and the reported strategies please see Chapter Three. In this chapter I use hedge funds' raw returns investigating funds' performance persistence and how investors can explicit these differences between hedge fund strategies. The reader is reminded that I have selected funds that invest primarily in the North America region due to the use of U.S. business cycles.

In order to assure data quality and integrity I excluded the returns of the first 12 months so as to deal with the instant history bias. Regarding the outliers I applied the "winsorized" technique and deal the zeros or null values according to specific rules. For more details about all these process please see Chapter Three's, data section. The mapping between the database strategies is the same as that adopted in Chapter Three.

It is important to make the point that non-parametric techniques are useful in the presence of a few datapoints. This data requirement is particularly relevant when analyzing hedge fund returns where usually only monthly returns are available, for example, if 120 monthly returns are examined, which are then reduced even further to 12 yearly and 6 biyearly datapoints. The use of the non-parametric teckniques is also important where returns do not follow a normal distribution (Eling, 2009). The use of correlation-based techniques may be problematic in the presence of serial correlation and the absence of normality of fund returns. This is also a problem with regression-based tests, however, there are modified statistics available for autocorralated data (e.g. the Newey-West statistic) that I have used in the appendix. Beyond this, the dataset used in this study is long enough (to my knowledge the longest ever used in a scholarly study) hence the above issues are mitigated. Additional discussion about the assumptions needed for the parameter-based techniques used can be found in chapter 3, section 3.3.1.

5.3 Empirical analysis

In this section I proceed from basic statistics about hedge fund strategies and market classification to broader categories of the hedge fund strategies, and give details of the regime switches that I used.

5.3.1 Basic statistics and regimes

The basic statistics for the raw returns for each of the 11 hedge fund strategies are presented in the Chapter Three's basic statistics section. I followed the same approach as there by classifying the hedge fund strategies into directional, semi-directional, and non-directional strategies. This is based on the correlation of each strategy with the market index as is represented by the Wilshire 5000TRI, including dividends. The correlation of each strategy and its classification are presented in Chapter Three's – basic statistics section.

I remind the reader that in the analysis I took into consideration different U.S. business cycles and market conditions. There are three official U.S. business cycles from January 1990 to March 2014. The growth periods are 01/1990-07/1990, 04/1991-03/2001, 12/2001-12/2007 and 07/2009-03/2014 and the recession periods are 08/1990-03/1991, 04/2001-11/2001 and 01/2008-06/2009. Similarly to the Chapter Three, I used the Markov Switching process so as to determine the regimes that based on the mean and volatility of the Wilshire 5000TRI. The two regimes are: up regimes 01/1990-06/1990, 11/1990-10/2000, 10/2002-05/2008 and 03/2009-03/2014 and down regimes 07/1990-

10/1990, 11/2000-09/2002 and 06/2008-02/2009. The average monthly MAI (excess risk free) return for down regimes is -3.69% whereas for recessions it is -1.03%.

5.3.2 Performance persistence

In this section I examine hedge funds' performance persistence at strategy level within multiple business cycles and different market conditions. I first examine the smoothness of the returns, then the persistence with respect to the market index, and finally the persistence within each strategy. I examine the smoothness at quarterly, semi-annual, and annual horizons by computing the average return within each time period.

5.3.2.1 Smoothness of returns

5.3.2.1.1 Growth/Recession periods

Table 38 Panel A presents the results for the growth period under examination using the regression based parametric method. Concerning the raw returns, the majority of the hedge funds strategies present smoothness in their returns. On average non-directional (except for the CTA strategy) and semi-directional strategies have more consistent returns than the directional strategies (except for the Short Bias strategy). Regarding the Sharpe ratio, the situation is almost the same as for raw returns. However, some strategies such as Other, Global Macro and CTA suffer more compared to the others. On average, non-directional (except CTA) and semi-directional strategies (except Global Macro) have more consistent returns than directional strategies (except Short Bias). Regarding the information ratio, almost all hedge fund strategies have poor results in term of smoothness. One exception is the Long Short strategy that presents consistency at semi-annual and annual horizons.

Table 38 Panel B presents the results during recession periods. No hedge fund strategies present consistency in their raw returns with a few exceptions such as Long Only and Market Neutral that present significant consistency at annual horizons. Regarding the Sharpe ratio and the Information ratio all hedge funds have little consistency. There are a few exceptions such as CTA and Long Bias that provide some consistency at semi-annual horizons.

Table 38. Hedge Fund Smoothness at Strategy Level – Growth/Recession Periods

This table shows the results of the regression-based parametric model (equation 18) for raw returns (RR), the Sharpe ratio (SR), and the Information ratio (IR), during growth periods (Panel A) and recessions (Panel B). A positive and significant slope coefficient indicates performance persistence. This suggests that a hedge fund (or group) that did well in a specific period tend to do well in the subsequent period and vice-versa. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed t-statistic test. For space reasons, I present only coefficients followed by the t-statistics in parentheses.

	RR - Time Horizon			SR - Time Horizon			IR - Time Horizon		
Strategy	Quarterly	Semi-Annual	Annual	Quarterly	Semi-Annual	Annual	Quarterly	Semi-Annual	Annual
Panel A: growth period									
Short Bias	-0.114	0.060	-0.082	0.168	0.198	0.634**	0.109	0.198	0.720**
	(-1.077)	(0.393)	(-0.351)	(1.575)	(1.360)	(3.609)	(1.004)	(1.355)	(4.567)
Long Only	0.241*	0.474**	0.553*	0.222*	0.444**	0.619**	0.054	(2.273)	(2.110)
	(2.268)	(3.422)	(2.765)	(2.026)	(3.117)	(3.341)	(0.488)	0.366*	0.384
Sector	0.279**	0.543**	0.453*	0.323**	0.519**	0.529*	0.097	0.366*	0.384
	(2.665)	(4.165)	(2.248)	(3.124)	(3.843)	(2.701)	(0.913)	(2.576)	(0.129)
Long Short	0.322**	0.532**	0.597**	0.299**	0.462**	0.509*	0.265*	0.296	0.570*
	(3.112)	(4.028)	(3.235)	(2.862)	(3.283)	(2.476)	(2.484)	(1.986)	(2.744)
Event Driven	0.578**	0.661**	0.805**	0.604**	0.649**	0.748**	0.102	0.178	0.289
	(6.467)	(5.646)	(5.983)	(6.897)	(5.414)	(4.764)	(0.932)	(1.147)	(1.258)
Multi-Strategy	0.712**	0.763**	0.760**	0.518**	0.612**	0.582**	-0.250*	-0.214**	-0.005
	(9.315)	(7.622)	(5.310)	(5.496)	(4.945)	(4.091)	(-2.364)	(-4.790)	(-0.059)
Other	0.786**	0.850**	0.843**	-0.001	0.596**	0.606**	-0.120	0.147	0.380
	(11.892)	(10.490)	(7.138)	(-0.007)	(8.723)	(9.019)	(-0.948)	(0.764)	(1.330)
Global Macro	0.411**	0.571**	0.524**	0.340**	0.457**	0.366	0.111	0.298	0.191
	(4.146)	(4.499)	(2.990)	(3.093)	(3.121)	(1.619)	(0.963)	(1.897)	(0.804)
Relative Value	0.718**	0.796**	0.871**	0.675**	0.735**	0.840**	0.015	0.227	0.311
	(9.425)	(8.301)	(7.732)	(8.310)	(6.755)	(6.314)	(0.132)	(1.478)	(1.288)
Market Neutral	0.744**	0.771**	0.758**	0.472**	0.419**	0.620**	0.029	0.317*	0.472
	(10.181)	(7.827)	(5.257)	(4.885)	(2.885)	(3.368)	(0.264)	(2.107)	(2.079)
CTA	0.185	0.448**	0.708**	0.030	0.080	0.382	-0.007	0.085	0.445
	(1.766)	(3.342)	(4.530)	(0.286)	(0.547)	(1.851)	(-0.063)	(0.557)	(1.869)
Panel B: recession period									
Short Bias	0.073	-0.533	0.357	0.285	0.433	-0.001	0.329	0.393*	-0.002
	(0.251)	(-1.129)	(0.258)	(0.927)	(1.196)	(-0.075)	(1.058)	(3.456)	(-0.164)
Long Only	0.080	-0.748	3.451*	0.057	-0.065	-0.748	0.007	-0.184	-0.030
	(0.255)	(-1.705)	(4.788)	(0.168)	(-0.119)	(-1.128)	(0.084)	(-1.568)	(-0.070)
Sector	0.176	-0.437	-0.125	0.196	-0.194	-0.216	-0.038	-0.421	0.846
	(0.511)	(-0.775)	(-0.227)	(0.597)	(-0.335)	(-1.267)	(-0.122)	(-0.950)	(1.126)
Long Short	0.141	-0.712	-0.090	0.062	-0.825	-0.224	0.106	-0.489	1.853
	(0.413)	(-1.346)	(-0.136)	(0.193)	(-1.599)	(-0.490)	(0.302)	(-0.985)	(1.622)
Event Driven	0.206	-0.822	0.116	0.260	-0.686	-0.326	0.077	-0.362	0.041
	(0.541)	(-1.478)	(0.096)	(0.746)	(-1.106)	(-0.514)	(0.236)	(-0.824)	(0.038)
Multi-Strategy	0.138	-0.4551	-0.006	0.181	-0.576	0.243	-0.283	-0.717	0.527
	(0.381)	(-0.709)	(-0.065)	(0.492)	(-0.779)	(0.352)	(-1.014)	(-1.500)	(0.414)
Other	0.276	-0.039	0.282	-0.254	0.332	0.899	0.120	0.032	0.671
	(0.831)	(-0.075)	(1.043)	(-0.716)	(0.448)	(0.976)	(0.314)	(0.059)	(1.746)
Global Macro	0.129	0.844	0.824	0.124	0.589	1.075	0.167	0.974	1.529
	(0.381)	(2.216)	(5.812)	(0.318)	(0.713)	(1.125)	(0.449)	(1.238)	(7.158)
Relative Value	0.028	-0.666	0.215	0.024	-0.570	1.253	-0.053	-0.352	0.929

Table 38. Hedge Fund Smoothness at Strategy Level – Growth/Recession Periods (continued)

	(0.085)	(-1.190)	(0.546)	(0.090)	(-1.144)	(9.045)	(-0.151)	(-0.658)	(0.836)
Market Neutral	0.183	-0.177	0.704*	-0.149	-0.569	1.716	-0.025	-0.663	0.360
	(0.977)	(-0.726)	(3.499)	(-0.554)	(-1.163)	(0.382)	(-0.083)	(-1.422)	(0.222)
CTA	0.004	0.747	0.909	0.011	0.940*	1.036	0.027	-0.433	0.156
	-0.018	(2.523)	(2.917)	(0.044)	(4.531)	(2.532)	(0.082)	(-0.814)	(0.134)

5.3.2.1.2 Up/Down regimes

Table 39 Panel A shows that during up regimes almost all hedge fund strategies (except Short Bias and CTAs) display consistency in their returns for all horizons. Moreover, on average, non-directional and semi-directional strategies have higher returns consistency for the underlying time horizons compared to the directional strategies. Regarding the Sharpe ratio, CTA, Others and Global Macro strategies show the least persistence. Concerning the Information ratio, similar to the growth periods, hardly any hedge fund strategies display persistence.

Table 39 Panel B presents the results during down regimes. Almost no hedge fund strategies show raw returns consistency. One exception is the Market Neutral Strategy that is consistent in all time horizons, and CTA that is, but only on a quarterly basis. As far as the Sharpe ratio is concerned almost no hedge fund strategies provide smooth returns. There are some exceptions such as the Short Bias and CTA strategy that provides return consistency on quarterly basis and the Market Neutral that provide on yearly basis. Information ratio results during down regimes are poor in terms of smoothness. However, there are a few strategies such as Sector, Long Short, Event Driven that present consistency at a semi-annual period whereas other strategies such as Short Bias, Global Macro and CTA present consistency on quarterly horizons.

Table 39. Hedge Fund Smoothness at Strategy Level – Up Regimes

This table shows the results of the regression-based parametric model (equation 18) for raw returns (RR), the Sharpe ratio (SR), and the Information ratio (IR), during up (Panel A) and down (Panel B) regimes. A positive and significant slope coefficient indicates performance persistence. This suggests that a hedge fund (or group) that did well in a specific period tend to do well in the subsequent period and vice-versa. * denotes significance at $P < 0.05$ and ** denotes significance at $P < 0.01$ using a two-tailed t-statistic test. For space reasons, I present only coefficients followed by the t-statistics in parentheses.

	Time Horizon - RR			Time Horizon - SR			Time Horizon - IR		
Strategy	Quarterly	Semi-Annual	Annual	Quarterly	Semi-Annual	Annual	Quarterly	Semi-Annual	Annual
Panel A: up regime									
Short Bias	0.112	-0.135	-0.244	0.163	0.042	0.185	0.199	0.071	0.260
	(1.067)	(-0.894)	(-1.095)	(1.507)	(0.267)	(1.009)	(1.852)	(0.452)	(1.501)
Long Only	0.371**	0.409**	0.539*	0.257*	0.504**	0.648**	0.020	0.223	0.093
	(3.639)	(2.863)	(2.710)	(2.388)	(3.705)	(3.498)	(0.227)	(1.743)	(0.475)
Sector	0.425**	0.511**	0.615**	0.343**	0.538**	0.689**	-0.035	0.126	0.196
	(4.282)	(3.818)	(3.849)	(3.325)	(4.054)	(4.335)	(-0.330)	(0.831)	(0.786)
Long Short	0.407**	0.516**	0.611**	0.278*	0.506**	0.562**	0.017	0.253	0.298
	(4.059)	(3.872)	(3.577)	(2.635)	(3.740)	(2.908)	(0.155)	(1.697)	(1.214)
Event Driven	0.604**	0.589**	0.636**	0.577**	0.641**	0.658**	-0.066	0.152	0.307
	(6.897)	(4.673)	(3.656)	(6.438)	(5.333)	(3.764)	(-0.602)	(0.988)	(1.331)
Multi-Strategy	0.721**	0.708**	0.726**	0.662**	0.691**	0.662**	0.085	0.138**	0.004
	(9.505)	(6.420)	(4.959)	(7.975)	(5.993)	(3.984)	(0.774)	(3.683)	(0.066)
Other	0.717**	0.865**	0.862**	0.002	0.615**	0.627**	-0.143	-0.119	0.631
	(9.492)	(11.162)	(7.959)	(0.033)	(9.739)	(9.295)	(-1.117)	(-0.598)	(1.785)
Global Macro	0.397**	0.478**	0.560**	0.340**	0.465**	0.360	0.118	0.292	0.144
	(3.950)	(3.520)	(3.007)	(3.050)	(3.146)	(1.541)	(1.008)	(1.826)	(0.579)
Relative Value	0.729**	0.691**	0.759**	0.724**	0.751**	0.793**	-0.099	0.134	0.327
	(9.661)	(6.068)	(5.676)	(9.481)	(7.077)	(5.621)	(-0.907)	(0.867)	(1.253)
Market Neutral	0.616**	0.713**	0.840**	0.408**	0.431**	0.645**	0.142	0.252	0.330
	(7.127)	(6.598)	(6.537)	(4.055)	(3.031)	(3.477)	(1.307)	(1.667)	(1.571)
CTA	0.128	0.563**	0.594**	-0.001	0.141	-0.046	0.124	0.085	0.003
	(1.204)	(4.634)	(3.304)	(-0.002)	(0.975)	(-0.205)	(1.170)	(0.552)	(0.012)
Panel B: down regime									
Short Bias	0.364	0.419	0.600	0.487**	0.007	0.127	0.512**	0.056	0.160
	(1.582)	(1.170)	(0.634)	(3.348)	(0.059)	(0.491)	(3.193)	(0.380)	(0.441)
Long Only	0.208	0.277	0.225	0.156	0.348	0.924	0.439	0.379	1.076
	(0.773)	(0.487)	(0.103)	(0.504)	(0.784)	(0.377)	(1.252)	(0.611)	(9.627)
Sector	0.008	0.757	1.401	-0.080	0.352	0.940	0.630	1.119*	1.384
	(0.027)	(1.260)	(0.757)	(-0.307)	(0.922)	(0.887)	(1.858)	(3.961)	(1.119)
Long Short	0.174	0.681	0.148	0.187	0.440	0.221	0.518	1.294**	1.512
	(0.600)	(1.064)	(0.034)	(0.672)	(0.982)	(0.104)	(1.597)	(5.616)	(3.716)
Event Driven	0.301	1.293	-3.749	0.404	0.579	-5.262	0.023	0.925**	0.930
	(1.005)	(1.373)	(-0.722)	(1.455)	(0.958)	(-8.776)	(0.070)	(4.757)	(9.132)
Multi-Strategy	0.004	1.011	-0.291	0.124	0.133	0.125	0.202	0.176	0.316
	(0.012)	(1.458)	(-0.183)	(1.046)	(1.143)	(0.430)	(1.577)	(1.074)	(0.922)
Other	-0.180	0.301	0.133	0.127	0.186	-0.819	0.626	0.339	1.035
	(-0.605)	(0.586)	(0.193)	(0.379)	(0.321)	(-0.870)	(1.870)	(0.649)	(7.618)
Global Macro	-0.094	0.383	0.479	0.169	0.415	1.613	1.184*	0.540	1.642
	(-0.513)	(1.946)	(9.891)	(0.443)	(0.741)	(5.200)	(2.382)	(1.077)	(2.190)
Relative Value	-0.024	-0.126	-1.770	0.296	-0.088	-0.678	0.272	1.109**	1.429
	(-0.081)	(-0.221)	(-3.297)	(1.418)	(-0.364)	(-4.336)	(0.822)	(7.079)	(11.340)

Table 39. Hedge Fund Smoothness at Strategy Level – Up Regimes (continued)

Market Neutral	0.535*	0.508*	0.515**	0.190	0.077	0.406*	0.260	0.583	0.825
	(2.660)	(4.179)	(9.120)	(0.885)	(0.470)	(4.883)	(1.042)	(1.354)	(0.776)
CTA	0.521*	0.267	0.359	0.393*	0.193	0.175	0.579*	0.660	0.648
	(3.097)	(1.497)	(0.962)	(2.387)	(1.085)	(0.376)	(2.495)	(2.074)	(0.686)

5.3.2.1.3 Summary

To sum up, during "good" market conditions almost all hedge fund strategies present returns consistency on quarterly, semi-annual and annual horizons. This situation weakens when I take into consideration risk-adjusted returns, although they are still mostly significant. When I take into consideration stressful market conditions hardly any hedge fund strategies present returns smoothness. Furthermore recession periods have a greater negative impact on hedge fund strategies' smoothness compared to down regimes. This is because down regimes (that are characterized by low market returns with high volatility) affect a lot of funds' performance in terms of poor but relatively consistent returns. On average, non-directional and semi-directional strategies present higher consistency in their returns. From the above it seems that during "good" times fund managers display return consistency (or massage their returns more efficiently) compared to stressful market conditions as it is more difficult to have smooth returns. The findings are close to the literature such as Getmansky, Lo and Makarov (2004) and Eling (2009) who observed serial correlation for hedge fund strategies and especially for those that invest in illiquid assets[43].

5.3.2.2 Persistence against the market benchmark

This section examines hedge funds' raw returns persistence against the market benchmark (Wilshire 5000TRI, including dividends). In other words it examines whether hedge funds are able to outperform (or underperform) the market consistently. I use three time horizons: annual, semi-annual, and quarterly. In order to consider persistence the CPR test and the Chi-square test are used. The CPR should be

[43] I have tested for autocorrelation for one, two, four, six, and twelve months and some strategies such as Relative Value, and Market Neutral present autocorrelation even at the 12-month horizon. The results are not presented here for space reasons but are available in the appendix.

significantly greater than one if it is to conclude that there is performance persistence[44]. Depending on the ratio WW/LL I discuss out- or under-performance versus the market.

5.3.2.2.1 Growth/Recession periods

Table 40 Panel A using the CPR test shows that only a few strategies such as Long Short (annual), Multi-strategy (semi-annually), and Long Short (quarterly) are able to present performance persistence against the market (although underperforming). The Chi-square test examines the difference in the observed versus the expected frequencies[45]. Using this test, Short Bias (annual, semi-annual, quarterly), Market Neutral (annual, semi-annual, quarterly), and Relative Value (annual) present persistence versus the market index. Although there are some strategies that perform better than the markets, nevertheless using two different tests these results are not significant. In other words both tests show that none of the strategies present persistence with respect to the market (in a positive or negative manner)[46].

During recession periods, due to the fact that there are relatively few observations, I use descriptive statistics as presented in Table 40 Panel B concerning the performance persistence of the strategies against the market benchmark. Similar to the growth period, I use three time horizons: annual, semi-annual, and quarterly. Concerning the annual period all strategies present two or three wins against zero or one loss in terms of frequencies. However, during the semi-annual period non-persistence is more common among all hedge fund strategies compared to persistence. The same applies for the quarterly horizon for all hedge fund strategies. An exception is the Long Only strategy that shows six cases of persistence (WW and LL) against four of non-persistence (WL and LW). Hence, during recessions hedge funds display almost no persistence against the market benchmark.

[44] After I have computed the CPR, I examine whether it is greater than one. If it is less than one, this means instantly that there is no persistence; hence I do not proceed further to hypothesis tests. The CPR test is stricter than the Chi-square test.
[45] A drawback of the Chi-square test in this case is that unlike the CPR test, it cannot capture the proportion of winners and losers. Hence, I consider the CPR test more powerful. However, I believe that it is better to use more than one test, for more robust results.
[46] An exception is the Multi Strategy that presents weakly significant persistence for the annual and semi-annual time horizon using both tests.

Table 40. Persistence against Benchmark - Growth/Recessions

This table shows the results for the persistence during growth (Panel A) and recessions (Panel B). Regarding the growth periods, Panel A shows the results of CPR and the chi-square statistics. A significant CPR statistic indicates persistence whereas a WW/LL greater (less) than one indicates outperformance (underperformance) against the market index (Wilshire 5000TRI, including dividends). A chi-square less than 0.05 indicates significant persistence against the market index. For CPR, * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed statistic test. At an annual horizon I use the t-statistic (due to the low number of observations) whereas at the semi-annual and quarterly horizon I use the z-statistic. Regarding the recessions, Panel B shows only descriptive statistics due to the low number of available observations.

Panel A: growth periods

	annual, (t-stat)			semi - annual, (z-stat)			quarterly, (z-stat)		
Strategy	CPR	WW/LL	x^2	CPR	WW/LL	x^2	CPR	WW/LL	x^2
Short Bias	2.33	0.07	22.00**	2.86	0.21	23.33**	1.01	0.31	14.15**
Long Only	5.00	1.80	4.80	2.39	1.89	5.43	1.66	1.29	2.29
Sector	3.50	1.17	2.00	2.14	1.27	2.00	2.03	1.17	3.05
Long Short	9.33*	0.88	5.20	3.04	0.59	5.81	2.47*	0.86	4.65
Event Driven	3.00	0.44	4.40	0.68	-	0.48	1.15	1.00	0.13
Multi-Strategy	8.33	0.50	7.60	4.86*	0.71	7.33	1.66	0.78	2.29
Other	1.50	0.83	0.40	2.14	0.79	2.00	1.14	0.83	0.51
Global Macro	2.50	0.30	6.80	1.33	0.35	6.19	1.35	0.70	2.11
Relative Value	0.69	-	10.80*	1.17	0.26	10.19*	0.82	-	6.06
Market Neutral	3.75	0.07	26.80**	1.86	0.12	31.33**	0.94	-	25.54**
CTA	1.50	0.83	0.40	0.64	-	1.62	0.96	-	7.75

Panel B: recession periods

	annual		semi- annual				quarterly			
Strategy	W	L	WW	LL	WL	LW	WW	LL	WL	LW
Short Bias	2	1	2	0	2	1	4	1	3	2
Long Only	2	1	1	0	2	2	4	2	2	2
Sector	3	0	2	0	2	1	5	0	3	2
Long Short	2	1	2	0	2	1	4	1	3	2
Event Driven	2	1	0	0	3	2	4	1	3	2
Multi-Strategy	2	1	0	0	3	2	4	1	3	2
Other	3	0	2	0	2	1	4	1	3	2
Global Macro	2	1	2	0	2	1	4	1	3	2
Relative Value	2	1	2	1	1	1	4	1	3	2
Market Neutral	2	1	2	0	2	1	4	1	3	2
CTA	2	1	2	0	2	1	4	1	3	2

5.3.2.2.2 Up/Down regimes

Table 41 Panel A shows hedge fund returns persistence against the market benchmark during up regimes. Using the CPR test, none of the strategies show persistence against the benchmark, over all time horizons. As I have already mentioned, the Chi-square test examines the difference of the observed versus the expected frequencies. Some strategies such as Short Bias, Global Macro, or Market Neutral show significant persistence over these time horizons but only using the X^2 test. However, it is mentioned that there is no confirmation from the two tests of performance persistence. Hence it can be concluded that no strategies present persistence against the market benchmark.

For the down regimes, we have relatively few observations, so similar to recessions we use descriptive statistics. Table 41 Panel B shows that all strategies, annually, present three wins against zero losses in terms of frequencies. Similar results apply for the semi–annual period. During the quarterly time horizon, all hedge fund strategies also present persistence in term of wins against losses. During recessions hedge funds do present some persistence against the market benchmark but we are unable to state whether this is statistically significant.

Table 41. Persistence against Benchmark – Up/Down Regimes

This table shows the results for the persistence during up (Panel A) and down (Panel B) regimes. Regarding the up regimes, Panel A shows the results of CPR and the chi-square statistics. A significant CPR statistic indicates persistence whereas a WW/LL greater (less) than one indicates outperformance (underperformance) against the market index (Wilshire 5000TRI, including dividends). A chi-square less than 0.05 indicates significant persistence against the market index. For CPR, * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed statistic test. At annual horizon I used the t-statistic (due to low number of observations) whereas at the semi-annual and quarterly horizon I used the z-statistic. Regarding the down regimes, Panel B shows only descriptive figures due to the low number of available observations.

Panel A: up regime

	annual (t-stat)			semi - annual (t-stat)			quarterly (z-stat)		
Strategy	CPR	WW/LL	x^2	CPR	WW/LL	x^2	CPR	WW/LL	x^2
Short Bias	0.75	-	12.71**	0.19	-	18.67**	0.78	-	20.48**
Long Only	0.44	-	0.80	1.47	0.92	0.48	0.56	-	1.81
Sector	3.50	0.86	2.00	1.78	1.00	0.86	0.99	-	0.38
Long Short	0.84	-	1.60	1.58	0.32	9.62*	1.00	-	4.10
Event Driven	2.00	0.50	2.40	1.67	0.60	2.57	0.50	-	5.14
Multi-Strategy	3.67	0.27	9.60*	2.08	0.37	9.24*	1.40	0.64	3.14
Other	0.44	-	0.80	0.69	-	3.14	1.20	0.83	0.57
Global Macro	0.40	-	7.76*	1.17	0.19	15.33**	0.67	-	10.57*
Relative Value	1.69	0.33	4.40	0.45	-	6.19	0.68	-	13.71**
Market Neutral	0.69	-	10.80*	0.26	-	23.14**	0.45	-	20.10**
CTA	0.16	-	3.60	0.82	-	3.90	0.71	-	9.67*

Panel B: down regime

	annual		semi- annual				quarterly			
Strategy	W	L	WW	LL	WL	LW	WW	LL	WL	LW
Short Bias	3	0	5	0	0	0	7	0	2	2
Long Only	3	0	4	0	1	0	8	0	1	2
Sector	3	0	5	0	0	0	8	1	1	1
Long Short	3	0	5	0	0	0	7	0	2	2
Event Driven	3	0	5	0	0	0	7	0	2	2
Multi-Strategy	3	0	5	0	0	0	7	0	2	2
Other	3	0	5	0	0	0	7	0	2	2
Global Macro	3	0	5	0	0	0	6	1	2	2
Relative Value	3	0	5	0	0	0	7	0	2	2
Market Neutral	3	0	5	0	0	0	6	1	2	2
CTA	3	0	5	0	0	0	6	1	2	2

To sum up, during "good" time conditions for some strategies (e.g. Long Short and Multi -Strategy) there is weak evidence that there is persistence with respect to the market within the underlying time horizons. For all the other strategies it is clear that there is no persistence. However, during stressful market conditions, there is some evidence that strategies present some persistence against the market benchmark. Unfortunately there are relatively few available observations so it is not possible calculate statistical significance. Recessions affect hedge fund persistence against the market benchmark more fiercely than down regimes as funds continue to outperform the market during down regimes. The reader is reminded that I am referring to raw returns, only. To my knowledge, I am the first to examine hedge funds returns against the market index.

5.3.2.3 Persistence within each strategy

In this section I proceed further and examine hedge fund performance persistence within each of the 11 strategies. The objective is to examine whether fund winners (losers) continue to be fund winners (losers) in the next time period (in terms of raw returns). Hence I form ranked portfolios of funds that I rebalance every subsequent period (quarterly, semi-annually, and annually). I then take the spread between the first ranked and the last ranked portfolios and implement the regression based parametric model so as to examine the smoothness of the underlying spread. I present the results of whether top performers continue to be top performers and bottom performers continue to be bottom performers.

5.3.2.3.1 Growth periods

For quarterly times, Table 42 Panel A compares the performance of the top performers (P1*) or losers (P10*) with that of the average of all hedge funds. It is important to clarify the distinction between P1 versus P1* and P10 versus P10*. P1 are the ex-ante best performer portfolios and more specifically funds that I formed based on best past performance (e.g. quarterly, semi-annual, annual). P1* are ex-post portfolios and more specifically the previous P1 after one time period (e.g. quarterly, semi-annual, annual). Similar rules apply to P10.

The monthly spread between top performers P1* and the average of all funds is positive for more than half hedge fund strategies and significant[47] as well. Short Bias, Sector, Global Macro, Market Neutral, and CTAs strategies have positive but insignificant spreads. The highest is from Relative Value (0.88%, monthly) and the lowest from Long Short (0.49%, monthly). Concerning the bottom performers P10* for all hedge fund strategies the spread is negative and in most cases significant. Short Bias and CTA

[47] Significantly different from zero. I used a two-tailed t-test at 0.05 and 0.01 levels.

strategies have positive spread but are insignificant. The highest (in terms of absolute value - negative) and most significant spread is from the Other strategy (-0.51%, monthly) and the lowest (in terms of absolute value - negative) is from Event Driven (-0.16%, monthly). I compare the ex-ante best performers portfolios (P1) with that of ex-post (P1*); For the Other and Relative strategies there is positive and significant correlation (using the Spearman and Pearson statistics). This means that the persistence for these two strategies (their spreads are the highest) is driven by the top performers. In other words, the top performers are performing extremely well. I also compare the ex-ante bottom performers' portfolios (P10) with that of ex-post (P10); there is significant negative correlation for Global Macro and Relative Value strategies. This means that, despite the reversals, the bottom performers continue to be poor performers, especially for the Relative Value strategy.

Panel B examines whether top performers continue to be top performers and bottom performers continue to be bottom performers on a semiannual basis. In other words I examine P1* and P10*. The majority of the hedge fund strategies demonstrate significant persistence for top performers. The exception is the Short Bias, Long Only, Global Macro, and the CTA strategies. The highest significant spread of the top performers P1* and the average of all funds within the specific strategy is Others (1.01%, monthly) and the lowest is for the Market Neutral strategy (0.37%, monthly). Regarding the bottom performers (P10*), there are many strategies that have significant spreads compared to the average within the specific strategy. The highest (in absolute values - negative) spread is from the Other strategy (-0.96%, monthly) and the lowest (in absolute values - negative) is from the Market Neutral strategy (-0.36%, monthly). When compare the P1 with the P1* portfolios the Other and the Relative Value have positive and significant correlations meaning that, especially for the Other strategy, top performers continue to perform extremely well. Comparing the P10 and P10* in most cases there are negative correlations although in the Relative Value strategy it is significantly different from zero. This means that there are reversals within poorly performing funds.

Table 42 Panel C examines persistence on an annual basis. Concerning the top performers (P1* hedge funds), their spreads in relation to the average funds within the same strategy are positive for almost all hedge funds strategies. The only exception is from Market Neutral and the CTA strategies although this (negative) difference is not significantly different from zero. For the rest, the highest significant spread is from Short Bias (1.01%, monthly) and the lowest from the Long Only strategy (0.44%, monthly). Regarding the worst performing funds, their spreads in relation to the average funds within the same strategy is negative, although only for the Relative Value strategy is it significantly different from zero (-0.43%, monthly). When comparing the P1 with the P1* portfolios the Long only strategy has significant negative correlations, meaning that although P1* perform well above the average, there is reversal when compared with the P1. Similarly, comparing the P10 and P10* there are no significant correlations within bottom performers.

Table 42. Persistence within Strategies – Winners/Losers – Growth Periods

This table shows average (avg) monthly returns of spreads (spd) between top P1 versus P1*, P10 versus P10* performers, spreads between P* versus the average, and P10* versus the average. These are for all hedge fund strategies on a quarterly (Panel A), semi-annual (Panel B), and annual (Panel C) basis during growth periods. * denotes significance at P < 0.05 and ** denotes significance at P <0.01 (two-tailed tests). P1 and P10 are ex-ante best performer and worst performer portfolios, respectively. P1* and P10* are ex-post portfolios of P1 and P10, respectively. Spearman (‘Spear’) and Pearson (‘Pear’) represent the relevant correlation coefficients so as to examine whether top (bottom) performers continue to be top (bottom) performers.

Panel A: Quarterly

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	3.71%	-0.014	-0.125	Spr. P1-P1*	3.32%	0.090	-0.070	Spr. P1-P1*	5.22%	0.036	-0.162	Spr. P1-P1*	4.03%	0.125	-0.113
Spr. P10-P10*	-4.09%	-0.145	-0.206	Spr. P10-P10*	-2.99%	-0.067	-0.099	Spr. P10-P10*	-4.59%	0.123	0.041	Spr. P10-P10*	-3.90%	0.024	-0.133
Spr. P1*-Avg	0.52%			Spr. P1*-Avg	0.65%**			Spr. P1*-Avg	0.28%			Spr. P1*-Avg	0.49%*		
Spr. P10*-Avg	0.14%			Spr. P10*-Avg	-0.40%*			Spr. P10*-Avg	-0.39%			Spr. P10*-Avg	-0.28%**		
Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	2.63%	0.185	-0.034	Spr. P1-P1*	2.80%	0.126	0.144	Spr. P1-P1*	2.91%	0.353**	0.237	Spr. P1-P1*	3.90%	-0.069	-0.128
Spr. P10-P10*	-2.52%	0.001	0.004	Spr. P10-P10*	-2.60%	0.063	-0.172	Spr. P10-P10*	-2.94%	-0.04	-0.139	Spr. P10-P10*	-3.57%	-0.187	-0.315*
Spr. P1*-Avg	0.62%**			Spr. P1*-Avg	0.66%*			Spr. P1*-Avg	0.85%**			Spr. P1*-Avg	0.16%		
Spr. P10*-Avg	-0.16%**			Spr. P10*-Avg	-0.28%			Spr. P10*-Avg	-0.51%*			Spr. P10*-Avg	-0.07%		
Relative	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear				
Spr. P1-P1*	1.90%	0.307**	0.309**	Spr. P1-P1*	2.30%	0.153	-0.084	Spr. P1-P1*	5.72%	-0.011	-0.073				
Spr. P10-P10*	-2.16%	-0.161	-0.292**	Spr. P10-P10*	-2.18%	-0.007	-0.04	Spr. P10-P10*	-5.51%	-0.164	-0.201				
Spr. P1*-Avg	0.88%**			Spr. P1*-Avg	0.15%			Spr. P1*-Avg	0.32%						
Spr. P10*-Avg	-0.29%*			Spr. P10*-Avg	-0.20%			Spr. P10*-Avg	0.26%						

Panel B: Semi-Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	2.75%	0.170	0.321	Spr. P1-P1*	2.87%	0.157	0.070	Spr. P1-P1*	4.19%	-0.038	-0.047	Spr. P1-P1*	3.21%	-0.093	-0.18
Spr. P10-P10*	-2.94%	-0.010	-0.196	Spr. P10-P10*	-2.50%	-0.089	-0.071	Spr. P10-P10*	-3.64%	0.098	0.243	Spr. P10-P10*	-3.04%	-0.006	0.058
Spr. P1*-Avg	0.84%			Spr. P1*- Avg	0.38%			Spr. P1*- Avg	0.28%			Spr. P1*- Avg	0.48%*		
Spr. P10*- Avg	-0.19%			Spr. P10*- Avg	-0.47%*			Spr. P10*- Avg	-0.69%			Spr. P10*- Avg	-0.40%*		

Table 42. Persistence within Strategies – Winners/Losers – Growth Periods (continued)

Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	2.13%	0.028	-0.280	Spr. P1-P1*	1.93%	0.121	0.093	Spr. P1-P1*	2.24%	0.221	0.403*	Spr. P1-P1*	2.61%	0.162	0.148
Spr. P10-P10*	-1.65%	-0.165	-0.152	Spr. P10-P10*	-2.22%	0.191	0.173	Spr. P10-P10*	-1.82%	0.071	0.136	Spr. P10-P10*	-3.04%	0.029	-0.238
Spr. P1*- Avg	0.62%**			Spr. P1*- Avg	0.9%**			Spr. P1*- Avg	1.01%**			Spr. P1*- Avg	0.47%		
Spr. P10*- Avg	-0.55%**			Spr. P10*- Avg	-0.17%			Spr. P10*- Avg	-0.96%**			Spr. P10*- Avg	0.14%		

Relative Value	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear
Spr. P1-P1*	1.62%	0.395**	0.371*	Spr. P1-P1*	1.62%	0.298	0.062	Spr. P1-P1*	4.47%	-0.140	-0.202
Spr. P10-P10*	-1.74%	-0.048	-0.342*	Spr. P10-P10*	-1.47%	0.014	-0.069	Spr. P10-P10*	-4.09%	0.163	0.042
Spr. P1*- Avg	0.76%**			Spr. P1*- Avg	0.37%*			Spr. P1*- Avg	0.30%		
Spr.	-0.33%			Spr. P10*- Avg	-0.36%*			Spr. P10*- Avg	0.28%		

Panel C: Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	2.42%	0.086	0.002	Spr. P1-P1*	2.27%	-0.519*	-0.575**	Spr. P1-P1*	3.15%	-0.217	-0.271	Spr. P1-P1*	2.67%	-0.426	-0.276
Spr. P10-P10*	-3.04%	-0.060	0.055	Spr. P10-P10*	-2.21%	0.005	-0.219	Spr. P10-P10*	-3.06%	0.060	-0.369	Spr. P10-P10*	-2.67%	0.052	-0.312
Spr. P1*-Avg	1.01%*			Spr. P1*-Avg	0.44%*			Spr. P1*-Avg	0.59%			Spr. P1*-Avg	0.29%		
Spr. P10*- Avg	0.41%			Spr. P10*- Avg	-0.47%			Spr. P10*- Avg	-0.35%			Spr. P10*- Avg	-0.17%		

Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	1.90%	0.048	0.044	Spr. P1-P1*	1.98%	-0.074	0.072	Spr. P1-P1*	2.33%	0.050	0.016	Spr. P1-P1*	2.77%	-0.318	-0.244
Spr. P10-P10*	-1.72%	0.200	-0.128	Spr. P10-P10*	-2.00%	-0.164	-0.234	Spr. P10-P10*	-1.70%	0.222	0.220	Spr. P10-P10*	-2.40%	0.318	-0.277
Spr. P1*- Avg	0.46**			Spr. P1*- Avg	0.29%			Spr. P1*- Avg	0.58%			Spr. P1*- Avg	0.08%		
Spr. P10*- Avg	-0.19			Spr. P10*- Avg	0.12%			Spr. P10*- Avg	-0.68%			Spr. P10*- Avg	-0.04%		

Relative Value	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear
Spr. P1-P1*	1.57%	0.279	0.285	Spr. P1-P1*	1.95%	0.104	-0.247	Spr. P1-P1*	3.78%	0.221	-0.011
Spr. P10-P10*	-1.39%	-0.021	-0.395	Spr. P10-P10*	-1.75%	0.064	0.065	Spr. P10-P10*	-3.71%	0.108	-0.037
Spr. P1*- Avg	0.63%**			Spr. P1*- Avg	-0.26%			Spr. P1*- Avg	-0.42%		
Spr. P10*- Avg	-0.43%**			Spr. P10*- Avg	0.21%			Spr. P10*- Avg	-0.41%		

5.3.2.3.2 Recession periods

Table 43 Panel A presents the results on quarterly basis. Concerning top performing hedge funds the spreads between the top performers P1* and the average are for the majority of hedge fund strategies positive, although not significant. The only exception is for the Relative Value strategy that is weakly significant (0.98%, monthly). Similar results are for spreads between bottom performers P10* and the average which is negative in all strategies, although not significant. The only exception is for the CTA strategy with significantly positive spread (2.36%, monthly). When compare the P1 with the P1* portfolios only the Relative Value Strategy demonstrates high significant positive correlation between them. This means that top performers continue to perform extremely well. Similar results are seen when compare P10 and P10* where there are no significant correlations within bottom performers.

Panel B presents the results on a semi-annual basis. Regarding the top performers (P1*), their spreads in relation to the average within the specific strategy are for the majority of hedge fund strategies positive, although not significant. The only exception is the CTA strategy with a significantly negative spread equal to -3.60%, monthly. Similar results are seen for spreads between bottom performers P10* and the average which are negative in all strategies although not significant. The only exception is for the CTA strategy with a significantly positive spread (3.04%, monthly). This means that for P1 and P10 of the CTA strategy there is not only a lack of performance persistence but there are significant reversals when comparing these portfolios with the average fund within the same strategy. When comparing the P1 with the P1* portfolios there is no significant correlation between them, although in most cases it is positive. Similar results are seen when compare P10 and P10*, where there are no significant correlations within bottom performers. The only exception is from Market Neutral where there is a significant negative correlation, meaning that bottom performers P10* tend to reverse their performance, but still they underperform compared to the average within this strategy.

Panel C the results on an annual basis. The spread between P1* and the average of funds within the specific strategy varies between positive and negative. The largest positive is from the Long Only strategy (1.83%, monthly) and the largest negative is from the Sector and Other strategy (-2.56%, monthly). P1 and P1* spreads for all strategies are relatively high. The largest is from the Short Bias strategy (10.70%, monthly) and the smallest is from the Multi Strategy (2.56%, monthly). P10 and P10* spreads for all strategies are negative. The largest (in terms of absolute value) is from CTA (-7.31%, monthly) and the smallest is from the Multi Strategy (-0.29%, monthly). It seems that during recessions, there is no yearly performance persistence among hedge fund strategies.

Table 43. Persistence within Strategies – Winners/Losers - Recessions

This table shows average (avg) monthly returns of spreads (spd) between top P1 versus P1*, P10 versus P10* performers, spreads between P* versus the average, and P10* versus the average. These are for all hedge fund strategies, on a quarterly (Panel A), semi-annual (Panel B), and annual (Panel C) basis, during recessions. * denotes significance at P < 0.05 and ** denotes significance at P <0.01 (two-tailed tests). P1 and P10 are ex-ante best performer and worst performer portfolios, respectively. P1* and P10* are ex-post portfolios of P1 and P10, respectively. Spearman (Spear) and Pearson (Pear) represent the relevant correlation coefficients so as to examine whether top (bottom) performers continue to be top (bottom) performers. Panel C shows descriptive only statistics (due to the low number of observations).

Panel A: Quarterly

Short Bias	Return	Spearm	Pearson	**Long Only**	Return	Spearm	Pearson	**Sector**	Return	Spearm	Pearson	**Long Short**	Return	Spearm	Pearson
Spr. P1-P1*	4.32%	-0.214	-0.006	Spr. P1-P1*	9.38%	0.433	0.335	Spr. P1-P1*	8.87%	-0.200	0.004	Spr. P1-P1*	7.06%	0.225	0.229
Spr. P10-P10*	-6.13%	0.143	0.057	Spr. P10-P10*	-6.41%	-0.083	0.133	Spr. P10-P10*	-8.41%	0.173	0.101	Spr. P10-P10*	-7.51%	0.027	0.094
Spr. P1*-Avg	1.77%			Spr. P1*-Avg	-0.89%			Spr. P1*-Avg	-0.42%			Spr. P1*-Avg	0.03%		
Spr. P10*-Avg	-0.70%			Spr. P10*-Avg	-0.39%			Spr. P10*-Avg	-0.44%			Spr. P10*-Avg	-0.26%		

Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	5.42%	0.382	0.519	Spr. P1-P1*	3.93%	0.321	0.153	Spr. P1-P1*	6.41%	0.250	0.190	Spread P1-P1*	7.56%	-0.200	-0.299
Spr. P10-P10*	-3.72%			Spr. P10-P10*	-4.03%	-0.006	-0.040	Spr. P10-P10*	-6.50%	-0.567	-0.383	Spr. P10-P10*	-5.53%	-0.550	0.286
Spr. P1*-Avg	0.33%			Spr. P1*-Avg	1.21%			Spr. P1*-Avg	0.40%			Spr. P1*-Avg	0.20%		
Spr. P10*-Avg	-1.53%			Spr. P10*-Avg	-0.78%			Spr. P10*-Avg	-0.29%			Spr. P10*-Avg	-0.19%		

Relative Value	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear
Spr. P1-P1*	3.94%	0.818**	0.653*	Spr. P1-P1*	3.96%	0.418	0.332	Spr. P1-P1*	8.98%	-0.082	0.245
Spr. P10-P10*	-4.48%	-0.105	-0.309	Spr. P10-P10*	-3.06%	0.227	0.035	Spr. P10-P10*	-10.50%	-0.009	0.070
Spr. P1*-Avg	0.98%			Spr. P1*-Avg	-0.47%			Spr. P1*-Avg	-0.51%		
Spr. P10*-Avg	-0.22%			Spr. P10*-Avg	-0.48%			Spr. P10*-Avg	2.36%*		

Panel B: Semi-Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	5.29%	0.500	0.254	Spr. P1-P1*	4.72%	-0.200	0.082	Spr. P1-P1*	8.80%	0.500	0.652	Spr. P1-P1*	5.01%	0.300	0.733
Spr. P10-P10*	-7.86%	-0.900*	-0.943	Spr. P10-P10*	-8.00%	-0.800	-0.924	Spr. P10-P10*	-7.87%	-0.100	-0.519	Spr. P10-P10*	-7.83%	-0.100	-0.700
Spr. P1*-Avg	-1.81%			Spr. P1*-Avg	0.20%			Spr. P1*-Avg	-0.72%			Spr. P1*-Avg	0.28%		
Spr. P10*-Avg	-0.06%			Spr. P10*-Avg	2.76			Spr. P10*-Avg	-0.12%			Spr. P10*-Avg	1.28%		

Table 43. Persistence within Strategies – Winners/Losers – Recessions (continued)

Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	6.51%	0.700	0.740	Spr. P1-P1*	3.57%	0.500	0.288	Spr. P1-P1*	4.52%	-0.200	0.354	Spr. P1-P1*	6.50%	0.400	0.471
Spr. P10-P10*	-5.29%	-0.500	-0.745	Spr. P10-P10*	-5.44%	-0.500	-0.832	Spr. P10-P10*	-6.50%	-0.400	-0.822	Spr. P10-P10*	-6.25%	-0.200	-0.565
Spr. P1*-Avg	-1.44%			Spr. P1*-Avg	0.30%			Spr. P1*-Avg	0.64%			Spr. P1*-Avg	0.48%		
Spr. P10*-Avg	1.00%			Spr. P10*-Avg	0.72%			Spr. P10*-Avg	0.98%			Spr. P10*-Avg	1.29%		
Relative Value	Monthly	Spear	Pear	**Market Neutral**	Monthly	Spear	Pear	**CTAs**	Monthly	Spear	Pear				
Sprd P1-P1*	3.74%	0.300	0.225	Spr. P1-P1*	2.46%	0.101	0.334	Spr. P1-P1*	10.19%	0.200	0.379				
Spr. P10-P10*	-3.87%	-0.500	-0.471	Spr. P10-P10*	-2.60%	-0.900*	-0.887*	Spr. P10-P10*	-11.26%	0.700	0.764				
Spr. P1*-Avg	0.06%			Spr. P1*-Avg	0.45%			Spr. P1*-Avg	-3.60%*						
Spr. P10*-Avg	-0.91%			Spr. P10*-Avg	-0.38%			Spr. P10*-Avg	3.04%*						

Panel C: Annual

Short Bias	Return	**Long Only**	Return	**Sector**	Return	**Long Short**	Return
Spread P1-P1*	10.70%	Spread P1-P1*	3.52%	Spread P1-P1*	5.67%	Spread P1-P1*	4.40%
Spread P10-P10*	-6.68%	Spread P10-P10*	-2.60%	Spread P10-P10*	-4.77%	Spread P10-P10*	-3.93%
Spread P1*- Avg	-1.04%	Spread P1*- Avg	1.83%	Spread P1*- Avg	-0.07%	Spread P1*- Avg	0.41%
Spread P10*- Avg	1.45%	Spread P10*- Avg	-1.54%	Spread P10*- Avg	-2.56%	Spread P10*- Avg	-1.44%
Event Driven	Return	**Multi Strategy**	Return	**Other**	Return	**Global Macro**	Return
Spread P1-P1*	4.12%	Spread P1-P1*	2.56%	Spread P1-P1*	3.92%	Spread P1-P1*	4.18%
Spread P10-P10*	-2.55%	Spread P10-P10*	-0.29%	Spread P10-P10*	-1.42%	Spread P10-P10*	-3.05%
Spread P1*- Avg	-0.02%	Spread P1*- Avg	0.92%	Spread P1*- Avg	0.76%	Spread P1*- Avg	1.18%
Spread P10*- Avg	-1.41%	Spread P10*- Avg	-2.33%	Spread P10*- Avg	-2.56%	Spread P10*- Avg	-0.94%
Relative Value	Return	**Market Neutral**	Return	**CTAs**	Return		
Spread P1-P1*	2.97%	Spread P1-P1*	4.37%	Spread P1-P1*	6.97%		
Spread P10-P10*	-1.39%	Spread P10-P10*	-2.77%	Spread P10-P10*	-7.31%		
Spread P1*- Avg	1.16%	Spread P1*- Avg	-1.65%	Spread P1*- Avg	-2.27%		
Spread P10*- Avg	-4.66%	Spread P10*- Avg	0.01%	Spread P10*- Avg	1.44%		

5.3.2.3.3 Up regimes

For quarterly times Table 44 Panel A investigates whether top performers continue to be top performers and bottom performers continue to be bottom performers. Regarding the top performers (P1*), their spreads in relation to the average within the same strategy is for the majority of cases significantly positive. There are some exceptions such as Global Macro, CTAs, and Market Neutral where the spreads are not significantly different from zero. Similar results are seen for spreads between the bottom P10* performers and the average, which are negative in all strategies, although not significant. This means that the bottom performers do not differ significantly from the average hedge fund within the same strategy. When comparing the P1 with the P1* portfolios, for almost half of the strategies there is significantly positive correlation. For some strategies such as the Multi Strategy and the Relative Value this correlation is strongly significant. Similar results are seen when comparing P10 and P10*. Many strategies have significantly negative correlations such as the Long Short, Other and CTA strategies, meaning that there is a reversal in bottom performers even though they perform poorly compared to the average fund in the same strategy.

Panel B presents the results on a semi-annual basis. Concerning top performers (P1*), their spreads with the average are for the majority of hedge fund strategies significantly positive. Regarding the spreads between bottom performers P10* and the average, this is negative in almost all strategies but is not significant. The only exception is for the Relative Value and the CTA strategies which are negative and positive, respectively. In the first case this means that bottom performers' funds consistently underperform the average within the Relative Value strategy, whereas in the second case bottom performers outperform the average, meaning there is a reversal. When comparing the P1 and P1* portfolios, the correlations between them are not significant except for the Other and Relative Value strategies which are significantly positive. This implies that top performer funds continue to perform extremely well. When comparing P10 and P10* only the Long Short, Global Macro, and Relative Value strategies demonstrate significantly negative correlation, meaning that there is a reversal in bottom performers even though they perform poorly compared to the average fund in the same strategy, as is case with the Relative Value strategy.

I report the results regarding persistence on an annual basis in Panel C. Concerning the top performers P1*, and their spreads with the average, for specific strategies such as the Long Only, Event Driven, Multi Strategy and Relative Value the spread is positive and significantly different from zero. Regarding the spreads between the bottom performers P10* and the average, only the Relative Value strategy presents a negative spread that is a significantly different from zero. This means that the worst performing funds consistently underperform the average within the strategy. When comparing the P1 with the P1* portfolios only the Relative Value strategy presents significant results (positive correlation). When comparing P10 and P10* only the Sector Strategy presents significant negative correlation, meaning that there is a reversal in the worst performers.

Table 44. Persistence within Strategies – Winners/Losers – Up Regimes

This table shows average (avg) monthly returns of spreads (spd) between top P1 versus P1* P10 versus P10* performers, spreads between P* versus the average, and P10* versus the average. These are for all hedge fund strategies, on quarterly (Panel A), semi-annual (Panel B) and annual basis (Panel C) during up regimes. * denotes significance at P < 0.05 and ** denotes significance at P <0.01 (two-tailed tests). P1 and P10 are ex-ante best performer and worst performer portfolios, respectively. P1* and P10* are ex-post portfolios of P1 and P10, respectively. Spearman (Spear) and Pearson (Pear) represent the relevant correlation coefficients so as to examine whether top (bottom) performers continue to be top (bottom) performers.

Panel A: Quarterly

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	3.14%	0.040	0.125	Spr. P1-P1*	3.27%	0.175	0.267*	Spr. P1-P1*	4.70%	0.348	0.201	Spr. P1-P1*	3.88%	0.165	0.254*
Spr. P10-P10*	-3.34%	-0.009	-0.007	Spr. P10-P10*	-3.15%	-0.230*	-0.188	Spr. P10-P10*	-4.76%	-0.180	-0.103	Spr. P10-P10*	-4.01%	-0.211	-0.349**
Spr. P1*-Avg	0.77%*			Spr. P1*-Avg	0.75%*			Spr. P1*-Avg	0.64%*			Spr. P1*-Avg	0.68%**		
Spr. P10*-Avg	-0.15%			Spr. P10*-Avg	-0.21%			Spr. P10*-Avg	-0.16%			Spr. P10*-Avg	-0.16%		
Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	2.73%	0.143	0.374**	Spr. P1-P1*	2.76%	0.353**	0.373**	Spr. P1-P1*	3.18%	0.143	0.068	Spr. P1-P1*	4.76%	0.141	0.165
Spr. P10-P10*	-2.56%	-0.052	-0.105	Spr. P10-P10*	-3.13%	0.083	0.118	Spr. P10-P10*	-3.57%	-0.155	-0.329**	Spr. P10-P10*	-4.65%	-0.181	-0.298**
Spr. P1*-Avg	0.7%**			Spr. P1*-Avg	0.71%**			Spr. P1*-Avg	0.87%*			Spr. P1*-Avg	-0.31%		
Spr. P10*-Avg	-0.28%			Spr. P10*-Avg	0.24%			Spr. P10*-Avg	-0.09%			Spr. P10*-Avg	0.83%*		
Relative	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear				
Spr. P1-P1*	1.96%	0.460**	0.550**	Spr. P1-P1*	2.37%	0.213	0.082	Spread P1-P1*	5.66%	-0.112	-0.100				
Spr. P10-P10*	-2.06%	-0.052	-0.012	Spr. P10-P10*	-2.21%	0.041	-0.045	Sprd P10-P10*	-5.15%	-0.318**	-0.234*				
Spr. P1*-Avg	0.97%*			Spr. P1*-Avg	0.09%			Spr. P1*-Avg	0.28%						
Spr. P10*-Avg	-0.31%			Spr. P10*-Avg	-0.11%			Spr. P10*-Avg	0.12%						

Panel B: Semi-Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	2.74%	0.197	0.038	Spr. P1-P1*	2.92%	0.023	0.102	Spr. P1-P1*	3.56%	0.088	0.098	Spr. P1-P1*	3.04%	0.079	0.145
Spr. P10-P10*	-2.87%	0.085	0.165	Spr. P10-P10*	-2.71%	-0.284	-0.368*	Spr. P10-P10*	-3.68%	-0.112	0.053	Spr. P10-P10*	-3.02%	-0.223	-0.347*
Spr. P1*-Avg	0.43%			Spr. P1*-Avg	0.36%			Spr. P1*-Avg	0.82%**			Spr. P1*-Avg	0.54%		
Spr. P10*-Avg	0.14%			Spr. P10*-Avg	0.03%			Spr. P10*-Avg	-0.27%			Spr. P10*-Avg	-0.19%		

Table 44. Persistence within Strategies – Winners/Losers – Up Regimes (continued)

Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	2.24%	-0.144	0.123	Spr. P1-P1*	2.18%	0.069	-0.139	Spr. P1-P1*	3.09%	0.428**	0.347*	Spr. P1-P1*	3.24%	-0.205	-0.139
Spr. P10-P10*	-2.28%	0.008	-0.269	Spr. P10-P10*	-2.14%	0.224	0.102	Spr. P10-P10*	-2.68%	0.115	0.094	Spr. P10-P10*	1.16%	-0.322	-0.425*
Spr. P1*-Avg	0.51*			Spr. P1*-Avg	0.52%*			Spr. P1*-Avg	0.54%*			Spr. P1*-Avg	0.21%		
Spr. P10*-Avg	-0.08			Spr. P10*-Avg	-0.03%			Spr. P10*-Avg	-0.28%			Spr. P10*-Avg	0.32%		

Relative	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear
Spr. P1-P1*	1.84%	0.467**	0.505**	Spr. P1-P1*	1.97%	0.230	0.096	Spr. P1-P1*	4.66%	0.124	0.187
Spr. P10-P10*	-1.59%	0.036	-0.308*	Spr. P10-P10*	-1.81%	0.236	0.132	Spr. P10-P10*	-4.20%	-0.094	-0.103
Spr. P1*-Avg	0.67%**			Spr. P1*-Avg	0.04%			Spr. P1*-Avg	2.14%**		
Spr. P10*-Avg	-0.38%**			Spr. P10*-Avg	-0.08%			Spr. P10*-Avg	2.53%**		

Panel C: Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	2.46%	-0.064	-0.207	Spr. P1-P1*	2.32%	-0.120	-0.003	Spr. P1-P1*	3.53%	-0.099	0.061	Spr. P1-P1*	2.81%	-0.019	0.048
Spr. P10-P10*	-3.32%	-0.130	-0.173	Spr. P10-P10*	-1.97%	-0.376	-0.410	Spr. P10-P10*	-3.28%	-0.370	-0.474*	Spr. P10-P10*	-2.71%	-0.156	-0.228
Spr. P1*-Avg	0.43%			Spr. P1*-Avg	0.54%*			Spr. P1*-Avg	0.57%			Spr. P1*-Avg	0.36%		
Spr. P10*-Avg	0.54%			Spr. P10*-Avg	-0.33%			Spr. P10*-Avg	-0.07%			Spr. P10*-Avg	-0.16%		

Event Driven	Return	Spear	Pear	**Multi**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	1.98%	-0.052	0.041	Sprd P1-P1*	1.93%	-0.114	0.036	Spr. P1-P1*	2.96%	0.286	0.173	Spr. P1-P1*	3.11%	0.135	0.140
Spr. P10-P10*	-1.81%		-0.374	Spr. P10-P10*	-2.30%	0.196	0.118	Spr. P10-P10*	-2.19%	0.154	0.149	Spr. P10-P10*	-2.50%	-0.094	-0.240
Spr. P1*-Avg	0.38%**			Spr. P1*-Avg	0.46%*			Spr. P1*-Avg	0.26%			Spr. P1*-Avg	-0.07%		
Spr. P10*-Avg	-0.18%			Spr. P10*-Avg	0.18%			Spr. P10*-Avg	-0.42%			Sprd P10*-Avg	0.40%		

Relative	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear
Spr. P1-P1*	1.78%	0.640**	0.674**	Spr. P1-P1*	1.58%	-0.048	-0.040	Spr. P1-P1*	3.56%	0.065	0.024
Spr. P10-P10*	-1.41%	-0.145	-0.216	Spr. P10-P10*	-2.44%	0.011	0.013	Spr. P10-P10*	-3.49%	-0.013	-0.023
Spr. P1*-Avg	0.64%**			Spr. P1*-Avg	0.03%			Spr. P1*-Avg	0.19%		
Spr. P10*-Avg	-0.29%*			Spr. P10*-Avg	-0.04%			Spr. P10*-Avg	0.07%		

5.3.2.3.4 Down regimes

Table 45 Panel A presents the quarterly results. Regarding the top performers P1* and their spreads with the average, most hedge fund strategies present positive spreads, although they are not significant. The Relative Value strategy presents a significant spread equal to 0.76% monthly (and the Event Driven has a weakly significant positive spread). Regarding the spreads between the bottom performers P10* and the average, almost all hedge fund strategies present negative spreads, although they are not significant. When comparing the P1 with the P1* portfolios only the Long Only and Event Driven strategies present significantly positive correlations. When comparing P10 and P10* there are mixed results of positive and negative correlations, although they are not significantly different from zero.

Panel B presents the semi-annual results. Concerning the top performers P1*, and their spreads with the average, the majority of hedge fund strategies present positive spreads, although this is not significant (some strategies such as Sector, Long Short, and Relative Value provide results weakly significantly different from zero). Regarding the spreads between the bottom performers P10* and the average, almost all hedge fund strategies present negative spreads, although these are not significant (but some strategies such as Sector, Long Short, and Market Neutral present results weakly significantly different from zero). When comparing the P1 with the P1* portfolios in all cases except for the CTA strategy, there is positive correlation. For some strategies such as the Sector, Long Short and Long Only these are significantly different from zero. When comparing P10 and P10* there are mixed results of positive and negative correlations, although they are not significantly different from zero. However, the Other and the Market Neutral strategies present results significantly different from zero.

Panel C shows that the spread between P1* and the average of funds within the specific strategy varies from positive to negative. The largest positive is for the Global Macro strategy (2.59%. monthly) and the largest negative is for the Global Macro strategy (-3.64%, monthly). P1 and P1* spreads for all strategies are relatively high. The largest is from the Long Only strategy (5.01%, monthly) and the smallest is from CTA (1.82%, monthly). P10 and P10* spreads for all strategies are negative. The most negative is from CTA (-4.34%, monthly) and the least negative is from Global Macro (-0.28%, monthly).

Table 45. Persistence within Strategies – Winners/Losers – Down Regimes

This table shows average (avg) monthly returns of spreads (spd) between top P1 versus P1*, P10 versus P10* performers, spreads between P* versus the average, and P10* versus the average. These are for all hedge fund strategies, on quarterly (Panel A), semi-annual (Panel B) and annual basis (Panel C), during down regimes. * denotes significance at P < 0.05 and ** denotes significance at P <0.01 (two-tailed tests). P1 and P10 are ex-ante best performer and worst performer portfolios, respectively. P1* and P10* are ex-post portfolios of P1 and P10, respectively. Spearman and Pearson represent the relevant correlation coefficients so as to examine whether top (bottom) performers continue to be top (bottom) performers.

Panel A: Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	8.34%	-0.048	-0.049	Spr. P1-P1*	5.57%	0.636*	0.403	Spr. P1-P1*	6.37%	-0.509	-0.502	Spr. P1-P1*	5.90%	0.309	0.125
Spr. P10-P10*	-5.63%	0.001	-0.258	Spr. P10-P10*	-6.20%	-0.188	-0.081	Spr. P10-P10*	-6.67%	-0.145	-0.204	Spr. P10-P10*	-6.11%	0.036	0.001
Spr. P1*-Avg	-1.12%			Spr. P1*-Avg	0.65%			Spr. P1*-Avg	0.60%			Spr. P1*-Avg	0.36%		
Spr. P10*-Avg	-0.43%			Spr. P10*-Avg	-1.00%			Spr. P10*-Avg	-2.94%			Spr. P10*-Avg	-1.74%		

Event Driven	Return	Spear	Pear	**Multi Strategy**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	3.31%	0.618*	0.718*	Spr. P1-P1*	0.50%	0.467	0.305	Spr. P1-P1*	4.78%	0.055	-0.271	Spr. P1-P1*	5.52%	-0.167	-0.109
Spr. P10-P10*	-4.18%	0.300	0.157	Spr. P10-P10*	-3.48%	-0.309	-0.192	Spr. P10-P10*	-5.80%	-0.442	-0.345	Spr. P10-P10*	-6.98%	0.050	0.124
Spr. P1*-Ag	1.34%			Spr. P1*-Avg	0.78%			Spr. P1*-Avg	-0.30%			Spr. P1*-Avg	0.88%		
Spr. P10*-Avg	-0.87%			Spr. P10*-Avg	-1.58%			Spr. P10*-Ag	-0.20%			Spr. P10*-Avg	0.33%		

Relative	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear
Spr. P1-P1*	3.17%	0.491	0.324	Spr. P1-P1*	3.01%	0.445	0.223	Spr. P1-P1*	8.97%	0.309	0.347
Spr. P10-P10*	-4.47%	-0.227	-0.246	Spr. P10-P10*	-3.81%	0.300	0.399	Spr. P10-P10*	-6.45%	-0.564	-0.423
Spr. P1*-Avg	0.76%*			Spr. P1*-Avg	0.54%			Spr. P1*-Avg	-1.23%		
Spr. P10*-Avg	-1.01%			Spr. P10*-Avg	-0.05%			Spr. P10*-Avg	0.05%		

Panel B: Semi-Annual

Short Bias	Return	Spear	Pear	**Long Only**	Return	Spear	Pear	**Sector**	Return	Spear	Pear	**Long Short**	Return	Spear	Pear
Spr. P1-P1*	6.02%	0.200	0.033	Spr. P1-P1*	3.18%	0.900*	0.825	Spr. P1-P1*	4.10%	0.998**	0.964**	Spr. P1-P1*	0.14%	0.900*	0.902*
Spr. P10-P10*	-3.47%	0.600	-0.002	Spr. P10-P10*	-3.46%	0.400	-0.251	Spr. P10-P10*	-5.42%	-0.100	-0.024	Spr. P10-P10*	-3.91%	0.200	0.184
Spr. P1*-Avg	0.42%			Spr. P1*-Avg	-0.01%			Spr. P1*-Avg	1.80%			Spr. P1*-Avg	1.07%		
Spr. P10*-Avg	-1.14%			Spr. P10*-Avg	-2.52%*			Spr. P10*-Avg	-3.98%			Spr. P10*-Avg	-3.01%		

Table 45. Persistence within Strategies – Winners/Losers – Down Regimes (continued)

Event Driven	Return	Spear	Pear	**Multi**	Return	Spear	Pear	**Other**	Return	Spear	Pear	**Global Macro**	Return	Spear	Pear
Spr. P1-P1*	3.26%	0.600	0.412	Spr. P1-P1*	3.25%	0.700	0.713	Spr. P1-P1*	2.90%	0.600	0.435	Spr. P1-P1*	4.44%	0.300	0.669
Spr. P10-P10*	-2.38%	0.400	0.214	Spr. P10-P10*	-3.64%	-0.700	-0.029	Spr. P10-P10*	-2.27%	0.900*	0.755	Spr. P10-P10*	-3.92%	-0.100	-0.070
Spr. P1*-Avg	0.61%			Spr. P1*-Avg	0.70%			Spr. P1*-Avg	0.55%			Spr. P1*-Avg	1.69%		
Spr. P10*-Avg	-2.02%			Spr. P10*-Avg	-1.50%*			Spr. P10*-Avg	-2.44%			Spr. P10*-Avg	-1.84%		
Relative	Return	Spear	Pear	**Market Neutral**	Return	Spear	Pear	**CTAs**	Return	Spear	Pear				
Spr. P1-P1*	3.56%	0.300	0.479	Spr. P1-P1*	2.37%	0.800	0.445	Spr. P1-P1*	8.11%	-0.100	-0.315				
Spr. P10-P10*	-3.06%	-0.100	-0.327	Spr. P10-P10*	-2.94%	0.700	0.879*	Spr. P10-P10*	-7.82%	-0.100	-0.195				
Spr. P1*-Avg	0.80%			Spr. P1*-Avg	0.68%			Spr. P1*-Avg	-1.29%						
Spr. P10*-Avg	-2.14			Spr. P10*-Avg	-0.88%			Spr. P10*-Avg	-0.31%						

Panel C: Annual

Short Bias	Return	**Long Only**	Return	**Sector**	Return	**Long Short**	Return
Spread P1-P1*	2.83%	Spread P1-P1*	5.01%	Spread P1-P1*	4.02%	Spread P1-P1*	3.84%
Spread P10-P10*	-3.00%	Spread P10-P10*	-1.62%	Spread P10-P10*	-3.53%	Spread P10-P10*	-2.97%
Spread P1*-Average	1.08%	Spread P1*-Average	-0.28%	Spread P1*-Average	1.46%	Spread P1*-Average	0.85%
Spread P10*-Average	-1.68%	Spread P10*-Average	-1.82%	Spread P10*-Average	-2.94%	Spread P10*-Average	-1.91%
Event Driven	Return	**Multi Strategy**	Return	**Other**	Return	**Global Macro**	Return
Spread P1-P1*	2.48%	Spread P1-P1*	3.36%	Spread P1-P1*	3.49%	Spread P1-P1*	4.55%
Spread P10-P10*	-1.89%	Spread P10-P10*	-2.87%	Spread P10-P10*	-2.45%	Spread P10-P10*	-0.28%
Spread P1*-Average	-2.75	Spread P1*-Average	0.32%	Spread P1*-Average	-0.29%	Spread P1*-Average	2.59%
Spread P10*-Average	-2.61	Spread P10*-Average	-1.70%	Spread P10*-Average	-1.10%	Spread P10*-Average	-3.64%
Relative Value	Return	**Market Neutral**	Return	**CTAs**	Return		
Spread P1-P1*	2.50%	Spread P1-P1*	2.21%	Spread P1-P1*	1.82%		
Spread P10-P10*	-1.49%	Spread P10-P10*	-2.24%	Spread P10-P10*	-4.34%		
Spread P1*-Average	0.50%	Spread P1*-Average	0.12%	Spread P1*-Average	1.69%		
Spread P10*-Average	-1.80%	Spread P10*-Average	-0.49%	Spread P10*-Average	-0.04%		

To sum up, I examined whether top performers continue to be top performers and bottom performers continue to be bottom performers (in technical terms I examined P1* and P10*). During "good" market conditions many strategies such as the Event Driven, Relative Value and Multi Strategy funds display persistence up to one year. Some other strategies such as the Sector and Other show persistence up to half a year. Some other strategies such as Short Bias and Long Only present persistence on a quarterly basis. In most cases the persistence was driven by the top performers that continue to perform extremely well. Also, in most cases there were reversals in bottom performers. This implies that there is fierce competition among bottom performers to be at least average in terms of performance, otherwise the fund will go out of business. It is known that there are high attrition rates in the hedge fund industry; hence funds that are underperforming in one time period push their managers to do their best to reverse their performance. During stressful market conditions the persistence reduces dramatically for all hedge fund strategies. Some strategies such as Event Driven and Relative Value present quarterly persistence and some such as CTA show semi-annual persistence[48].

The results confirm earlier studies (e.g. Agarwal and Naik, 2000a; Eling, 2009; Joenvaara, Kosowski, and Tolonen, 2012; Hentati-Kaffel, and Peretti, 2015) that there is short term persistence. However, in this study I proceed further, by confirming the initial assumption that that persistence depends also on the different business cycles and the different market conditions. More specifically there is a negative impact concerning the spreads between top P1 and bottom P10 performers and their performance persistence. Also I show evidence that some non-directional strategies (e.g. Relative Value) present more persistence than directional strategies (e.g. Short Bias or Long Only). Nevertheless the difference in persistence is mainly related to the type of strategy each fund follows. There are some studies such as Kosowski, Naik and Teo (2007), Jagannathan, Malakhov and Novikov (2010), and Amman, Huber and Schmid (2013) that indicate persistence beyond one year. This study examines persistence up to one year due to the limitation of data availability, especially during stressful market

[48] I also examined the spreads between top P1 and bottom P10 performing funds across all hedge fund strategies for "good" and "bad" market conditions. During "good" times I found persistence in spreads up to an annual basis. During "bad" times I found persistence in spreads on a quarterly basis whereas for the semi-annual period many strategies such as the Short Bias, Other, Global Macro and Relative Value do not provide persistence in their spreads. For the annual period I found no persistence in spreads among hedge fund strategies. It seems that during stressful market conditions there is fiercer completion among fund managers, thus making it more difficult for sustainable outperformance against its peers. In all market conditions, on average, directional strategies present higher spreads between top P1 and bottom P10 fund performers, compared to semi or non-directional strategies. I do not provide detailed results here for space reasons but these are shown in the appendix.

conditions. This study reveals that the persistence is driven mainly by the top performers, a finding that agrees with Jagannathan, Makakhov and Norvikov (2010), as they noticed reversals in bottom performers in most cases. Other authors (e.g. Capocci, 2007) suggest that bad performance is more likely to persist than good performance. This is intuitive as, in general, it is easier to identify fund characteristics that result in poor performance (e.g. high expense ratios, high turnover ratios, high trading costs) compared to identifying the secrets of successful stock picking. However, if there were consistency in poor performance these bottom performers would soon be out of business unless they reversed their performance.

5.3.3 Mixed trading strategies

In this section I discuss trading strategies based on the persistence analysis at section 5.3.2 at the hedge fund level that an investor can exploit for potential higher returns. They are considered growth periods and recessions. This is because down regimes that are characterized by down market movements with high volatility are more difficult to predict or to realize instantly once they happen. Moreover, contrary to recessions that last for a few months, down regimes primarily consist of shocks; thus any trading strategy implementation is difficult during down regimes**.** After a brief discussion of the underlying trading strategies, in the next two sub-sections (5.3.3.1 and 5.3.3.2) I demonstrate to the reader the theoretical optimal implementation of different trading strategies, so that the reader can rationalize these strategies. It is expected that strategies with higher persistence compared to other strategies and strategies with high spreads between top and bottom performers can be used by investors for high returns. Indeed I show later that some strategies that appear to be more common in our examples (e.g. Other, Sector, Short Bias, Relative Value) in general present these characteristics. This is explained with the suggestion that these strategies may demand excessively high skills from fund managers such as investing on start-ups or private investment in public equity (Others), deep knowledge of specific sectors (Sector), better contrarian investment styles (Short Bias), or finding arbitrage opportunities (Relative Value). Subsequently, I proceed to the overall evaluation of these eight trading strategies by presenting their average performance within the different market conditions. Finally, there are some robustness tests.

5.3.3.1 Trading strategies

I begin the analysis when dealing with growth periods on quarterly, semi-annual, and annual basis. Then I proceed to recession periods. I take into consideration three basic trading strategies (based on the whole data length): (i) momentum strategy, (ii) contrarian strategy, and (iii) momentrarian strategy (see section 5.2.1 for an explanation of the latter). I inform the reader that investors select a portfolio based on the expected performance represented by the P1* and P10* which are the ex post values of P1 and P10, respectively. In other words, P1 and P1* refer to the same portfolio (e.g. top fund performers of a particular strategy) but within different time periods. Hence, an investor that wants to follow a specific trading style (e.g. momentum quarterly) selects the portfolio based on the P1* (quarterly expected performance). Similar rules apply in the case of P10 and P10*.

The zero investment momentum trading strategy consists of two sub strategies: the first is when the investor selects one hedge fund strategy (the one with the highest spread between P1* and P10*) but within the same period (quarterly, semi-annual, annual). The second sub-strategy is when the investor uses different hedge fund strategies (so that the cross sectional spread between P1* and P10* is the highest) but again within the same period. The rationale behind the momentum strategy is that fund managers (similary to stocks) will continue to perform well (badly) during relatively short periods (e.g. due to investors' short term overreaction to new information).

The contrarian (zero investment) strategy also consists of two sub strategies: the first is when the investor selects one hedge fund strategy (the one with the highest spread between P1* and P10*) for a longer period (e.g. two or three years). The second is when the investor selects different hedge fund strategies for a longer period (e.g. two or three years) as well. I use longer holding periods than the previous momentum trading strategy so as to capture the contrarian effect. The contrarian strategy is rationalized in a similar way to stocks where well (bad) performers will reverse their performance in the long run (e.g. due to investors' long term underreaction to new information, fund managers reversding their bad performance to stay in business, or fund managers are "tried up" off new ideas or there are other better-performing fund managers).

The momentrarian (zero investment) strategy is defined as an investment style (or trading strategy) that is a combination of a momentum (MOMEN-) and contrarian (-

TRARIAN) strategy by taking the appropriate long and short positions on different funds (securities or financial indices). The momentrarian strategy consists of two sub strategies: the first is the momentrarian involving high return exploitation focusing on the top performing funds' spreads; the second sub strategy is the momentrarian involving low return exploitation focusing on the worst performing funds' spreads. Both sub strategies are on an annual basis involving P1* and P10* that are held for one, two or three years (please see the trading examples in section 5.2.1). I do not take into consideration quarterly or semi-annual periods because the contrarian effect does not work in these "short" periods.

It is expected that strategies requiring very high manager skill (e.g. specializing in specific sectors, with portfolio allocations not used by other strategies and arbitrage) with high persistence and spreads between top and bottom performers could be the most appropriate selections for implanting mixed trading strategies.

5.3.3.1.1 During growth periods

Table 46 presents the monthly returns (%) for top and bottom hedge fund performers, for all hedge fund strategies during growth periods. This table is derived from table 42 presented in section 5.3.2.3.1 (persistence within strategies – winner/loser returns of P1* and P10*). Since there is short term performance persistence in hedge fund returns, investors can utilize these spreads by forming appropriate trading strategies so as to increase their returns. The analysis when forming and constructing trading strategies is based on the performance of winners and losers.

Table 46. Spreads – Winners/Losers – Growth Periods

This table shows results of spreads (spd) between P1* versus P10* (or ex-post spreads of P1 vs P10) of all hedge fund strategies, at quarterly, semi-annual, annual, two years, and three years. These are for all hedge fund strategies during growth periods.

Short Bias	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	0.62	0.92	1.00	0.43	-0.33
P10*	0.24	-0.10	0.40	1.07	-1.12
Spd P1*-P10*	0.38	1.03	0.60	-0.64	0.79

Long Only	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.93	1.64	1.71	1.33	1.76
P10*	0.89	0.79	0.79	1.46	1.07
Spd P1*-P10*	1.05	0.85	0.92	-0.13	0.69

Sector	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.57	1.55	1.88	1.30	0.51
P10*	0.90	0.58	0.94	1.34	0.97
Spd P1*-P10*	0.68	0.97	0.94	-0.04	-0.46

Long Short	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.66	1.62	1.40	1.38	1.44
P10*	0.88	0.75	0.94	1.18	0.80
Spd P1*-P10*	0.78	0.88	0.46	0.20	0.63

Event Driven	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.71	1.69	1.52	1.27	1.11
P10*	0.93	0.53	0.87	1.13	1.17
Spd P1*-P10*	0.79	1.17	0.65	0.14	-0.06

Multi Strategy	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.78	2.00	1.40	1.32	0.91
P10*	0.84	0.92	1.23	1.25	0.76
Spd P1*-P10*	0.97	1.08	0.17	0.07	0.14

Other	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.90	2.04	1.56	0.91	0.47
P10*	0.53	0.07	0.31	1.03	0.37
Spd P1*-P10*	1.37	1.97	1.25	-0.12	0.10

Global Macro	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	0.91	1.19	0.72	0.53	0.28
P10*	0.69	0.86	0.60	0.64	0.68
Spd P1*-P10*	0.22	0.34	0.12	-0.11	-0.40

Relative Value	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.78	1.65	1.51	1.15	0.93
P10*	0.61	0.57	0.46	0.90	0.63
Spd P1*-P10*	1.17	1.09	1.05	0.25	0.30

Market Neutral	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	0.70	0.94	0.31	0.81	0.58
P10*	0.36	0.21	0.77	0.61	0.82
Spd P1*-P10*	0.35	0.73	-0.46	0.19	-0.24

CTAs	Quarterly	Semi-yearly	Yearly	Two Years	Three Years
P1*	1.46	1.51	-1.54	-1.26	-0.44
P10*	1.41	1.50	-1.52	-0.93	-1.15
Spd P1*-P10*	0.05	0.02	-0.02	-0.33	0.71

5.3.3.1.1.1 Momentum and contrarian trading

Table 47 Panel A shows the momentum trading style when the investor uses only one strategy per time period (quarterly, semi-annually, and annually). Based on this, the investor should choose to invest in the strategy with the highest expected difference between top and bottom performers and more specific the Others strategy. Therefore, the investor should take long and short positions in the top and bottom performers accordingly to exploit the differences in spreads. For example, the investor for each time period, should take a long position on the best performers (P1) and a short position on the worst performers (P10). The next time period she should adjust and rebalance the portfolio accordingly. Thus, for the quarterly period the excess market return is 0.30% on a monthly basis whereas for the semi-annual and annual periods it is 0.90% and 0.18% respectively. Panel B shows the momentum trading style when the investor uses different hedge fund strategies. The investor should choose the hedge fund strategies with the highest cross strategy spread between P1 and P10. For the quarterly period, the investor by taking long and short positions in Long Only and Short Bias of top and bottom performers respectively can have an excess market return equal to 0.63% on a monthly basis. For the semi-annual period the investor by utilizing the Other and Short Bias strategies can have an expected excess market return equal to 1.06% on a monthly basis. For the yearly period by using the Sector and CTA strategies can have an expected excess market return equal to 2.33% on a monthly basis.

Table 47 Panel C shows the contrarian trading style when the investor uses only one strategy per time period (two and three years). The investor should use the contrarian strategies for two or more years between the top and bottom performers within the hedge fund strategy with the highest spreads between them. In the two year contrarian trading the Short Bias strategy is the most appropriate hedge fund strategy that the investor should exploit. However, we observe that although this is the best contrarian strategy, the investor receives lower returns than the market returns. Similar results are seen for the three year contrarian trading using the Sector strategy. However, the results here are not significant. Panel D shows the contrarian trading style where the investor utilizes more than one hedge fund strategy per time period. In this case the investor should utilize these strategies with the highest cross strategy spread. Therefore, for the two year contrarian trade, the investor by taking a long position in the bottom performing Long Only strategy taking a short position in the top performing CTA strategy can have an expected excess market return equal to 1.71% per month. For the three year contrarian strategy the expected excess market return is equal to 0.60% per month.

Table 47. Momentum and Contrarian Trading Strategies – Same/Mixed Hedge Fund Strategies – Growth Periods

This table presents the optimum momentum trading strategy during growth periods, when using one only strategy (Panel A) and different hedge fund strategies (Panel B) per time period. It also presents the optimum contrarian trading strategy during growth periods, when using one only strategy (Panel C) and different hedge fund strategies (Panel D) per time period. Return: Trading Raw Return, Exc.Mkt Rtn: is the Return minus the market return (Wil5000TRI including dividends). * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed t-statistic test. "…" denotes the same activity after each horizon (*t*+2, *t*+3, and so on). The returns are expected average monthly returns (%) from P1 and P10 portfolios.

Panel A

Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**
Quarterly	t	Buy P1 of OT	Short-sell P10 of OT	1.37**	0.30
	t+1	sell P1 of OT then rebalance	Buy P10 of OT then rebalance		
	…	…	…		
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**
Semi-annual	t	Buy P1 of OT	Short-sell P10 of OT	1.97**	0.90*
	t+1	Sell P1 of OT then rebalance	Buy P10 of OT then rebalance		
	…	…	…		
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**
Annual	t	Buy P1 of OT	Short-sell P10 of OT	1.25**	0.18
	t+1	Sell P1 of OT then rebalance	Buy P10 of OT then rebalance		
	…	…	…		

Panel B

Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**
Quarterly	t	Buy P1 of LO	Short-sell P10 of SB	1.70**	0.63
	t+1	Sell P1 of LO then rebalance	Buy P10 of SB then rebalance		
	…	…	…		
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**
Semi-annual	t	Buy P1 of OT	Short sell P10 of SB	2.14**	1.06*
	t+1	Sell P1 of OT then rebalance	Buy P10 of SB then rebalance		
	…	…	…		
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**
Annual	t	Buy P1 of SE	Short sell P10 of CT	3.40**	2.33**
	t+1	Sell P1 of SE then rebalance	Buy P10 of CT then rebalance		
	…	…	….		

Panel C

Contrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
2 Years	t	Buy P10 of SB|	Short sell P1 of SB|	0.64	-0.38
	t+1	Sell P10 of SB| then rebalance	Buy P1 of SB| then rebalance		
	…	…	…		
Contrarian				**Return**	**Exc. Mkt Rtn**
3 Years	t	Buy P10 of SE||	Short sell P1 of SE||	0.46	-0.55
	t+1	Sell P10 of SE|| then rebalance	Buy P1 of SE|| then rebalance		
	…	…	…		

Panel D

Contrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
2 Years	t	Buy P10 of LO|	Short sell P1 of CT|	2.72**	1.71**
	t+1	Sell P10 of LO| then rebalance	Buy P1 of CT| then rebalance		
	…	…	….		
Contrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
3 Years	t	Buy P10 of ED||	Short sell P1 of CT||	1.60**	0.60
	t+1	Sell P10 of ED|| then rebalance	Buy P1 of CT|| then rebalance		
	…	…	….		

5.3.3.1.1.2 High and Low Return Momentrarian trading

Table 48 Panel A presents the momentrarian trading style, involving high return exploitation, where the investor uses only one strategy per time period (first or second order). For the first order case, the investor exploits the spread between the top performer at t (long position based on previous one year portfolio performance) and top performer at t-1 (short position based on prior two years portfolio performance). The highest spread is from the Others strategy, nevertheless the investor is unable to outperform the market index as it provides a negative excess market return equal to -0.42% on a monthly basis. For the second order case the investor exploits the spread between the top performer at t (long position based on previous one year portfolio performance) and top performer as well at t-2 (short position based on prior three years, portfolio performance). For the Others strategy the expected excess market return is 0.30%, monthly. Nevertheless, the results here are not significant. Panel B presents the momentrarian trading style involving high return exploitation, where the investor uses different strategies per time period. In the first order case the investor should take a long position in Sector top performers (one year before) and a short position in CTA top performers (two years before); the excess market return delivered is 2.07% on monthly basis. For the second order the excess market return is 1.25% on monthly basis.

Table 48 Panel C shows the momentrarian trading style involving low return exploitation, where the investor uses only one strategy per time period (first and second order). In the first order case the investor exploits the spreads between bottom performers at one year before (long position) and bottom performers two years before (short position). The highest spread is from the Others strategy, nevertheless the investor is unable to outperform the market index as the excess market returns equal -0.35% on monthly basis. For the second order there are excess market returns equal to -0.69% on monthly basis. The results here are not significant. Panel C shows the momentrarian trading style involving low return exploitation, when the investor uses different strategies. In the first order case the investor receives excess market return equal to 1.79% on a monthly basis whereas in the second order case the excess market return is equal to 1.61% on a monthly basis.

Table 48. High Return Momentrarian Trading Strategy – Same/Mixed Strategies – Growth Periods

This table presents the optimum momentrarian trading strategy (involving high return exploitation) during growth periods, when using one only strategy (Panel A) and different strategies (Panel B) per time period. It also presents optimum momentrarian trading strategy (involving low return exploitation) during growth periods, when using one only strategy (Panel C) and different strategies (Panel D) per time period. Return: Trading Raw Return, Exc. Mkt Rtn: is the Return minus the market return (Wil5000TRI including dividends). "|" denotes the portfolio which selected based on high (P1) performance two years prior *t* (= 0) and "||"denotes the portfolio which selected on high (P1) performance three years prior *t*. "…" denotes the same activity after each yearly horizon (*t*+2, *t*+3, and so on). The returns are expected average monthly returns (%) from P1 portfolios. ** denotes significance at P < 0.01 using a two-tailed t-statistic test.

Panel A

Momentrarian		Actions		Return	Exc. Mkt Rtn
first order	t	Buy P1 of OT	Short sell P1 of OT|	0.65	-0.42
	t+1	Sell P1 of OT then rebalance	Buy P1 of OT| then rebalance		
	…	…	…		
Momentrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
second order	t	Buy P1 of SE	Short sell P1 of SE||	1.37	0.30
	t+1	Sell P1 of SE then rebalance	Buy P1 of SE|| then rebalance		
	…	…	…		

Panel B

Momentrarian		Actions		Return	Exc. Mkt Rtn
first order	t	Buy P1 of SE	Short sell P1 of CT|	3.14**	2.07**
	t+1	Sell P1 of SE then rebalance	Buy P1 of CT| then rebalance		
	…	…	…		
Momentrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
second order	t	Buy P1 of SE	Short sell P1 of CT||	2.32**	1.25
	t+1	Sell P1 of SE then rebalance	Buy P1 of CT|| then rebalance		
	…	…	…		

Panel C

Momentrarian		Actions		Return	Exc. Mkt Rtn
first order	t	Buy P10 of OT|	Short sell P10 of OT	0.72	-0.35
	t+1	Sell P10 of OT| then rebalance	Buy P10 of OT then rebalance		
	…	…	…		
Momentrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
second order	t	Buy P10 of CT||	Short sell P10 CT	0.38	-0.69
	t+1	Sell P10 of CT|| then rebalance	Buy P10 of CT then rebalance		
	…	…	…		

Panel D

Momentrarian		Actions		Return	Exc. Mkt Rtn
first order	t	Buy P10 of SE|	Short sell P10 of CT	2.86**	1.79**
	t+2	Sell P10 of SE| then rebalance	Buy P10 of CT then rebalance		
	…	…	…		
Momentrarian		**Actions**		**Return**	**Exc. Mkt Rtn**
second order	t	Buy P10 of ED||	Short sell P10 of CT	2.69**	1.61**
	t+2	Sell P10 of ED|| then rebalance	Buy P10 of CT then rebalance		
	…	…	…		

Using the above examples, I calculate the average return for each of the eight different trading styles. Overall, during "good" financial conditions, the average monthly return for zero investment quarterly, semi-annual, and annual momentum strategies using one only hedge fund strategy is equal to 0.71% (significantly different from zero at P<0.01 – two tail test, [t-statistic 3.404]), 0.92% (significant different from zero at P<0.01 – two tail test, [t-statistic 4.610]), and 0.52% (significant different from zero at P<0.05 – two tail test, [t-statistic 2.451]), respectively. For the 2-year and 3-year contrarian strategies is 0.05% (not significant different from zero) and -0.20% (not significant different from zero), respectively. For the first and second order momentrarian (involving high return exploitation) is 0.21% (not significant different from zero) and 0.38% (not significant different from zero), respectively. For the first and second order momentrarian (involving low return exploitation) is 0.35% (significant different from zero at P<0.05 – two tail test, [t-statistic 2.112]) and -0.07% (not significant different from zero), respectively.

5.3.3.1.2 During recession periods

I continue the analysis during recession periods. I again take into consideration three basic trading strategies: (i) momentum strategy, (ii) contrarian strategy, and (iii) momentrarian strategy. Due to the low number of observations during recessions, I do not consider the three year contrarian and the momentrarian second order trading strategy.

Table 49 presents the monthly returns (%) for top and bottom hedge fund performers, for all hedge fund strategies during recessions. This table is derived from table 43 presented in section 5.3.2.3.2 (persistence within strategies –winners/losers returns, of P1* and P10*). Since there is short term performance persistence in hedge fund returns (at least for a quarter), investors can benefit and have higher returns even during stressful market conditions.

Table 49. Spreads – Winners/Losers – Recessions

This table shows results of spreads (spd) between top P1* versus P10* (or ex-post spreads of P1 vs P10) of all hedge fund strategies, at quarterly, semi-annual, annual, and two years. These are for all hedge fund strategies during recession periods.

Short Bias	Quarterly	Semi-yearly	Yearly	Two Years	**Long Only**	Quarterly	Semi-yearly	Yearly	Two Years	**Sector**	Quarterly	Semi-yearly	Yearly	Two Years
P1*	2.15	1.76	-1.60	7.77	P1*	-1.51	-1.45	0.38	-3.84	P1*	0.08	-0.88	-1.29	-1.38
P10*	-0.31	2.08	0.90	2.72	P10*	-1.01	1.12	-2.99	-1.74	P10*	0.06	-0.28	-3.78	-0.79
Spr P1*-P10*	2.47	-0.32	-2.50	5.05	Spr P1*-P10*	-0.49	-2.56	3.37	-2.10	Spr P1*-P10*	0.02	-0.60	2.49	-0.59
Long Short	Quarterly	Semi-yearly	Yearly	Two Years	**Event Driven**	Quarterly	Semi-yearly	Yearly	Two Years	**Multi Strategy**	Quarterly	Semi-yearly	Yearly	Two Years
P1*	0.42	0.22	-0.43	-1.48	P1*	0.36	-1.43	-0.94	-4.14	P1*	1.38	0.49	0.36	-0.27
P10*	0.12	1.22	-2.28	-1.20	P10*	-1.50	1.01	-2.33	-0.40	P10*	-0.61	0.91	-2.89	0.60
Spr P1*-P10*	0.29	-1.00	1.85	-0.28	Spr P1*-P10*	1.86	-2.45	1.39	-3.74	Spr P1*-P10*	1.99	-0.42	3.25	-0.87
Other	Quarterly	Semi-yearly	Yearly	Two Years	**Global Macro**	Quarterly	Semi-yearly	Yearly	Two Years	**Relative Value**	Quarterly	Semi-yearly	Yearly	Two Years
P1*	0.85	0.68	0.83	0.53	P1*	0.86	1.35	1.89	0.83	P1*	1.55	0.31	0.84	-4.58
P10*	0.17	1.02	-2.48	-0.95	P10*	0.47	2.16	-0.23	0.47	P10*	-0.34	-0.65	-4.10	-0.26
Spr P1*-P10*	0.68	-0.34	3.32	1.48	Spr P1*-P10*	0.39	-0.82	2.12	0.36	Spr P1*-P10*	1.89	0.96	4.94	-4.32
Market Neutral	Quarterly	Semi-yearly	Yearly	Two Years	**CTAs**	Quarterly	Semi-yearly	Yearly	Two Years					
P1*	-0.27	0.62	-1.63	-1.04	P1*	-0.18	-2.67	-1.25	0.50					
P10*	-0.27	-0.22	0.03	-0.96	P10*	2.69	3.98	2.45	2.65					
Spr P1*-P10*	0.01	0.84	-1.66	-0.08	Spr P1*-P10*	-2.87	-6.64	-3.70	-2.15					

5.3.3.1.2.1 *Momentum and contrarian trading*

Table 50 Panel A presents the momentum trading style when the investor uses only one strategy. Based on this, the investor should choose to invest in this strategy with thee higher expected difference between top and bottom performers. Therefore, for the quarterly, semi-annual and annual period the investor should take long and short positions in the top and bottom performers accordingly to exploit the differences in spreads. For the quarterly period the excess market return is 3.28% on a monthly basis whereas for the semi-annual and annual periods it is 2.67% and 5.72%, respectively. Panel B presents the momentum trading style when the investor uses different hedge fund strategies. The investor should choose the hedge fund strategies with the highest cross strategy spread between P1 and P10. For the quarterly period, the investor by taking long and short positions in Short Bias and Event Driven for the top and bottom performers respectively can have an excess market return equal to 0.38% on a monthly basis. For the semi-annual period the investor by utilizing the Short Bias and Others strategies can have an expected excess market return equal to -0.26% on monthly basis. For the yearly period by using the Global Macro and Relative Value strategies investors have an expected excess market return equal to 6.77% on monthly basis.

Table 50 Panel C shows the two year contrarian trading style when the investor uses one only strategy per time period. The Relative strategy is theoretically the most appropriate hedge fund strategy that the investor should exploit. We observe that the investor receives excess market returns equal to 5.10%, monthly. Panel D shows the contrarian trading style where the investor utilizes more than one hedge fund strategy. In this case the investor should utilize these strategies with the higher cross strategy spread. Thus the investor, by taking a long position in the worst performing Short Bias strategy and taking a short position in the top performing Relative Value strategy, can have an expected excess market return equal to 8.08% per month[49].

[49] I have to mention that this is one of the few cases with an extraordinary return if annualized, but this is only available for a small number of months in the data and is not statistically significant.

Table 50. Momentum and Contrarian Trading Strategies – Same/Mixed Hedge Fund Strategies – Recessions

This table presents the optimum momentum trading strategy during recessions, when using one only strategy (Panel A) and different hedge fund strategies (Panel B) per time period. It also presents the optimum contrarian trading strategy during recessions, when using one only strategy (Panel C) and different hedge fund strategies (Panel D) per time period. Due to the limited data availability we computed the contrarian only for two years (we cannot also calculate the statistical significance for this horizon). Return: Trading Raw Return, Exc.Mkt Rtn: is the Return minus the market return (Wil5000TRI including dividends). * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed t-statistic test. "…" denotes the same activity after each horizon (*t*+2, *t*+3, and so on). The returns are expected average monthly returns (%) from P1 and P10 portfolios.

Panel A						**Panel B**					
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**	**Momentum**		**Actions**		**Return**	**Exc. Mkt Rtn**
Quarterly	t	Buy P1 of SB	Short-sell P10 of SB	2.46	3.28	Quarterly	t	Buy P1 of SB	Short-sell P10 of ED	3.66	0.38
	t+1	sell P1 of SB then rebalance	Buy P10 of SB then rebalance				t+1	Sell P1 of SB then rebalance	Buy P10 of ED then rebalance		
	…	…	…				…	…	…		
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**	**Momentum**		**Actions**		**Return**	**Exc. Mkt Rtn**
Semi-annual	t	Buy P1 of RV	Short-sell P10 of RV	0.96	2.67	Semi-annual	t	Buy P1 of SB	Short sell P10 of RV	2.41	-0.26
	t+1	Sell P1 of RV then rebalance	Buy P10 of RV then rebalance				t+1	Sell P1 of SB then rebalance	Buy P10 of RV then rebalance		
	…	…	…				…	…	…		
Momentum		**Actions**		**Return**	**Exc. Mkt Rtn**	**Momentum**		**Actions**		**Return**	**Exc. Mkt Rtn**
Annual	t	Buy P1 of RV	Short-sell P10 of RV	4.94	5.72	Annual	t	Buy P1 of GM	Short sell P10 of RV	5.99s	6.77
	t+1	Sell P1 of RV then rebalance	Buy P10 of RV then rebalance				t+1	Sell P1 of GM then rebalance	Buy P10 of RV then rebalance		
	…	…	…				…	…	….		
Panel C						**Panel D**					
Contrarian		**Actions**		**Return**	**Exc. Mkt Rtn**	**Contrarian**		**Actions**		**Return**	**Exc. Mkt Rtn**
2 Years	t	Buy P10 of RV|	Short sell P1 of RV|	4.32	5.10	2 Years	t	Buy P10 of SB|	Short sell P1 of RV|	7.30	8.08
	t+1	Sell P10 of RV| then rebalance	Buy P1 of RV| then rebalance				t+1	Sell P10 of SB| then rebalance	Buy P1 of RV| then rebalance		
	…	…	…				…	…	….		
Contrarian				**Return**	**Exc. Mkt Rtn**	**Contrarian**		**Actions**		**Return**	**Exc. Mkt Rtn**
3 Years		-		-	-	3 Years		-		-	-
		-		-	-			-		-	-

5.3.3.1.2.2 High and Low Return Momentrarian trading

Table 51 Panel A presents the momentrarian trading style, involving high return exploitation, when the investor uses only one strategy. The investor exploits the spreads between the top performer one year before (long position) and top performer two years before (short position). The higher spread is from the Relative strategy providing the investor with 6.20% excess market returns, on monthly basis. Panel B presents the momentrarian trading style involving high return exploitation, where the investor uses different strategies. The investor should take a long position in Global Macro top performers and short positions in Relative Value top performers. The excess market return that the investor receives is 7.25% on monthly basis.

Table 51 Panel C shows the momentrarian trading style, involving low return exploitation, where the investor uses one only strategy. The investor exploits the spreads between bottom performers (long position) and bottom performers (short position). The higher spread is from the Relative Value strategy and the investor is expected to receive excess market return equal to 4.62% on monthly basis. Panel D shows the momentrarian trading style, involving low return exploitation, where the investor uses different strategies. In this case the investor should take long position in Short Bias bottom performers and short positions in Relative Value bottom performers. The excess market return that the investor receives is 7.60% on a monthly basis.

Table 51. High Return and Low Return- Momentrarian Trading Strategies – Same/Mixed Hedge Fund Strategies - Recessions

This table presents the optimum momentrarian trading strategy (involving high return exploitation) during recessions, when using one only strategy (Panel A) and different strategies (Panel B) per time period. It also presents the optimum momentrarian trading strategy (involving low return exploitation) during recessions, when using one only strategy (Panel C) and different strategies (Panel D) per time period. Return: Trading Raw Return, Excess Mkt Return: is the Return minus the market return (Wil5000TRI including dividends). "|" denotes the portfolio which selected based on high (P1) performance two years prior *t* (= 0). "…" denotes the same activity after each yearly horizon (*t*+2, *t*+3, and so on). The returns are expected average monthly returns (%) from P1 portfolios. Unfortunately, I cannot calculate the statistical significance for the momentrarian trading strategy due to the low number of available observations.

Panel A					
Momentrarian		**Actions**		**Return**	**Excess Mkt Return**
	t	Buy P1 of RV	Short sell P1 of RV|	5.43	6.20
	t+1	Sell P1 of RV then rebalance	Buy P1 of RV| then rebalance		
	…	…	…		
Panel B					
Momentrarian		**Actions**		**Return**	**Excess Mt Return**
	t	Buy P1 of GM	Short sell P1 of RV|	6.48	7.25
	t+1	Sell P1 of GM then rebalance	Buy P1 of RV| then rebalance		
	…	…	…		
Panel C					
Momentrarian		**Actions**		**Return**	**Excess Mkt Return**
	t	Buy P10 of RV|	Short sell P10 of RV	3.84	4.62
	t+1	Sell P10 of RV| then rebalance	Buy P10 of RV then rebalance		
	…	…	…		
Panel D					
Momentrarian		**Actions**		**Return**	**Excess Mt Return**
	t	Buy P10 of SB|	Short sell P10 of RV	6.82	7.60
	t+1	Sell P10 of SB| then rebalance	Buy P10 of RV then rebalance		
	…	…	…		

Based on the above examples, I computed the average return for each of the eight different trading styles. Overall, during stressful market conditions, the monthly return for the zero investment momentum strategies on quarterly, semi-annual, and annual basis (using one only hedge fund strategy) is equal to 0.50% (not significantly different from zero), -1.25% (not significantly different from zero), and 1.35% (too few observations to test for significance), respectively. For the 2-year contrarian strategy the return is 0.66% (very low number of observation to test for significance). For the 1st order momentrarian (high return exploitation) is 0.39% (too few observations to test for significance) and for the 1st order momentrarian (low return exploitation) is 1.59% (too few observations to test for significance).

To sum up, it is important to mention that the main purpose of section 5.3.3 is to demonstrate trading strategies and more specifically the momentrarian style within a specific framework. The underlying basic trading styles help investors to form their own custom trading style that can exploit the differences between top and bottom performing funds within hedge fund strategies. Although currently there are limitations concerning the short selling of hedge funds, there may be future changes in the legal framework or a regulation change where fund of fund managers can use short selling. I demonstrated examples of the optimum eight different trading strategies that an investor can theoretically use so as to maximize her returns. As hedge fund behaviour changes during stressful market conditions, I implemented these trading strategies during growth and recession periods, only. This is because down regimes are difficult to predict or to realize instantly once they happen. Furthermore, contrary to recessions that last for a few months, down regimes mainly consist of shocks; thus trading strategy implementation is difficult during down regimes**.** By using the underlying trading styles on specific hedge fund strategies which present in general higher persistence compared to other strategies, and that have high spreads between top and bottom performers as they require very high skill levels from fund managers, (e.g. Other, Sector, Relative Value) the investor can get substantial excess market returns. In general zero investment trading strategies such as momentum are more efficient during “good” time conditions, although they cannot beat the market benchmark. On the other hand, momentrarian trading strategies are more efficient during “bad” times, and they can beat the market benchmark although, due to the low number of observations, it is not possible to calculate the statistical significance.

5.3.3.2 Robustness Checks

In order to check for robustness for the average and optimal performance of the eight trading strategies, I first take into consideration the redemption fees that managers may impose on investors, and second I replicate the analysis for two different sub-periods with a holdback period to examine whether the underlying strategies can make out-of-sample profits for investors.

5.3.3.2.1 Redemption fees

In order to compute the redemption cost by implementing the above trading strategies I proceed as follows. In the dataset 40.90% of the funds contain lockup restrictions and the equally weighted average redemption fee is 3.40%[50]. The maximum redemptions that are needed for implementation are four within a year for the quarterly momentum trading strategy and the minimum is one within three years for the 3-year contrarian strategy. Hence I compute the net return by subtracting from each trading strategy's return the average monthly redemption cost of the proportional funds that belong to the category of lockup-yes funds. I define this as:

$$AvRedCost_{monthly} = P_{lock} * RedFee * RedPer/12 \qquad (19)$$

Where $AvRedCost_{month}$ is the average monthly redemption cost, P_{lock} is the proportion of funds in the sample that impose lockups, $RedFee$ is the average redemption fee for funds that impose lockups, and $RedPer$ is the redemptions per year for a given trading strategy. I divide by 12 (number of months per year) so as to standardize it.

During "good" market conditions the average monthly costs for the quarterly, semi-annual and annual momentum strategy become 0.46%, 0.23%, and 0.12%, respectively. For the 2-year and 3-year contrarian strategy the average monthly costs are 0.06%, and 0.04%, respectively. For the 1st and 2nd order momentrarian (involving high or low return exploitation) the average monthly costs become 0.06% and 0.04%, respectively. During "bad" market conditions the average monthly cost for quarterly, semi-annual, annual and momentrartian strategies are the same as the "good" conditions. For growth periods, all trading strategies except for the contrarian and the 2nd order momentrian (low return) continue to provide positive returns to investors. For recessions all trading strategies continue to provide positive returns to investors except for the semi-annual momentum strategy. Concerning the theoretical optimal eight different trading strategies the positive returns are still higher than the market benchmark in most cases

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[50] The underlying average redemption fee corresponds to those funds with explicit restrictions mentioning a specific cost.

during growth periods (exceptions are the contrarian strategy, the quarterly momentum using one strategy, and the momentrarian low return using one strategy) whereas in recessions they are all positive.

5.3.3.2.2 Out-of-sample test

All the strategies tested previously were based on the full sample period. When using a holdback period in order to test whether the underlying trading strategies make profits out-of-sample, my results generally holds. The initial historical data on which these trading strategies are tested (in-sample data) consist of half of my data length and the other half are reserved (out-of-sample) data (for “good” and “bad” times separately). During “good” market conditions the returns for all trading strategies have the same sign. Exceptions are the 3-year contrarian and the second order momentrarian (low return exploitation) strategies. I performed the out-of-sample test during “bad” times and the semi-annual momentum strategy has the same signs contrary to the quarterly momentum strategy that presents reversals from negative returns for the first half period to positive returns for the second half period. Due to limited data availability I did not examine validity beyond one year. Concerning the theoretical optimal implementation of the eight different trading strategies hardly any of the sub-cases had differences in their signs in growth periods and the same strategies in most cases were still the best ones for the sub-periods tested. During recessions the quarterly momentum trading strategy presented the same sign, contrary to the semi-annual momentum which exhibits changes from negative returns for the first half period to positive returns for the second half. Most results concerning these (half data) returns are significantly differently from zero[51].

5.4 Conclusion

In this paper I deal with two issues: hedge fund performance persistence and different hedge fund trading strategies. This is the first study that examines different aspects of performance persistence under different market conditions. Using several parametric and non-parametric tests I examine hedge fund persistence in terms of the smoothness of returns, the persistence against the market benchmark and the persistence within each group strategy. I extend my analysis to trading strategies; this is the first study that

[51] The results of the out-of-sample tests are not presented here for space reasons. These are available in the appendix.

examines momentum and contrarian strategies when dealing with hedge fund spreads. Moreover, I am the first to introduce a mixed strategies that we term the 'momentrarian' strategy that allows investors to gain greater investment returns.

I have some important conclusions that contribute significantly to the hedge fund literature, beyond those that agree with the extant literature discussed above. Concerning hedge fund performance persistence, it is found that during "good" conditions there is smoothness in returns for almost all hedge fund strategies (an exception is the CTA and the Short Bias strategy) even for one year. This smoothness weakens but is still significant when considering risk adjusted returns. Moreover, on average, non-directional and semi-directional strategies present more smoothness in their returns compared to directional strategies. During "bad" conditions no hedge fund strategies present smoothness in their returns. As far as persistence with respect to the market benchmark is concerned I find no persistence in the examined strategies, with a few exceptions such as the Multi-Strategy (semi-annually), the Long Short (annual) and Long Short (quarterly) which present some performance persistence against the market. There is no reliable evidence during stressful market conditions due to having relatively few observations in the data. Concerning the persistence within each strategy I find persistence for hedge funds during "good" times up to one year whereas during stressful market conditions there is a negative impact on fund persistence within every strategy. There is strong evidence that persistence is driven mainly by the top performers as I found reversals in bottom performers in most cases, and recessions are fiercer than down regimes in terms of fund persistence.

The conclusions regarding the mixed trading strategies are that an investor can outperform the market by having zero investment portfolio strategies that exploit the differences between top and bottom performing funds within hedge fund strategies. During "good" conditions momentum trading strategies are on average the most successful strategies, followed by momentrarian trading strategies. However, during "bad" times the momentrarian strategies are the most successful followed by the momentum strategies. In all market conditions the contrarian trading strategy comes third after the other two trading strategies. The above average results concern trading strategies that take into consideration the spreads of only one strategy. When the investor takes into consideration different hedge fund strategies, their average returns are even higher.

The results are important as they enable us to better understand hedge funds' behaviour and reveal aspects that have not been examined before. This is the first study in the literature that examines hedge fund performance persistence under different investment conditions. More specifically, I make a clear distinction between different kinds of persistence such as in terms of smoothness of (risk-adjusted) returns, persistence against the market benchmark, and persistence within each specific strategy. All these different kinds of persistence are examined using the longest dataset ever used, from 1990 to 2014. I examine persistence under different market conditions, and not isolating just one relatively short period of time containing only one financial crisis or event. Moreover, for first time, I examined mixed or synthetic trading strategies such as the momentrarian strategies, allowing investors to utilize persistence in more efficient ways.

Investors can benefit from the findings as they now know what to expect from different strategies in terms of performance persistence. Although past performance is no guide to the future, most investors rely on funds' past records in their capital allocation process. This suggests that investors expect performance to be stable over time and that some fund managers provide better performance compared to their peers. This study provides a comprehensive investigation of hedge fund performance persistence, allowing investors to implement mixed trading strategies that utilize spreads between top and bottom performers of different hedge fund strategies although currently this is not an easy task for investors or fund of fund managers due to legal and practical restrictionas on short selling. In addition, investors do not know with certainty the future state of the market when implementing these trading strategies (including the momentrarian strategies, too). Fund administrators can apply more flexible and appropriate fee polices by taking into consideration performance persistence. Financial regulators can benefit in case there is any need for closer monitoring (e.g. monitoring of hedge funds that exhibit "unusual" persistence) or change in the legal framework (as there is apparently some market inefficiency in the hedge fund industry).

One limitation is that the focus is on hedge funds that invest in the North America region, due to the use of three U.S. business cycles. There is a need to examine performance persistence using my approach for funds that invest in other regions as well. Another limitation is the limited validation of the yearly persistence during stressful market conditions due to the small number of observations. However, it seems that during these conditions persistence is at most quarterly. Concerning the application of the proposed mixed or the synthetic trading strategies, I considered lockup redemption costs; however there might be other costs (e.g. bid-ask spreads, short-selling costs) that may affect investors’ profits and are not captured. Due to limitations of data availability, especially during stressful market conditions, I also did not considered contrarian trading strategies for two or more years.

6 Chapter: Hedge fund index engineering

This chapter (paper) examines the fourth research question that has to do why there are such large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy. In the literature review, I found that there is no universal hedge fund classification scheme and authors do not consider index construction issues (instead many authors use them just as “consumers”). As with the previous chapters this is an empirical study hence its structure has its own introduction, methodology, empirical analysis, and conclusion sections (a version of this paper is under review at Applied Economics journal).

I examine hedge fund index construction methodologies, by describing and analyzing the general principles and construction methods for a successful hedge fund index. I present case studies from two well-known database vendors and evaluate them using numerical examples on the same dataset. Despite the fact that they follow a similar due diligence process, there are great differences in the index engineering practices arising from different quantitative techniques, even for indices in the same hedge fund category. However, those quantitative techniques provide similar results. The differences are rather due to the use of different hedge fund universes and different inclusion criteria. This paper is the first to use actual numerical case studies to illustrate and compare how hedge fund index engineering works. Having read it the reader will have a good understanding of how hedge fund indices are formed and current issues in the area.

6.1 Introduction

This study sheds light on hedge fund index construction methodologies and in particular on the classification processes. This study is the first to compare different methodologies using the same dataset and demonstrate using real data how hedge fund indices can end up with very different constituents. The research objective is to close the gap in the literature concerning hedge fund index construction methodologies, particularly when dealing with classification issues. To this end I examine two existing hedge fund index engineering methodologies and compare them using a common database with practical examples, thereby providing a better understanding of how all hedge fund indices are constructed. Through this investigation I answer the research question of why there are such large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy.

In general, the hedge fund index engineering methodology consists of three broad elements: the hedge fund selection process, the classification process, and the index construction process itself. During the *selection* process every database vendor imposes not only its own inclusion criteria but within the same vendor there are different inclusion criteria for different indices. The *classification* process involves allocating hedge funds to the same group (sub-index) based on their sharing similar characteristics. The characteristics derive from the fund’s behaviour in relation to a reference element (e.g. an equity index) or characteristics of the fund itself that derive from its own return behaviour, assets, and so on. The *index construction* itself is a more standard process concerned with calculating NAV (Net Asset Value) or GAV (Gross Asset Value); usually the indices are engineered in a “tree” structure, meaning that there is one main index which consists of other indices, each of them from one or more sub-indices.

Many authors such as Harri and Brorsen (2004), Ammann and Moerth (2005), Bali, Brown and Caglayan (2011), and Getmansky (2012) simply used the classification scheme provided by the database vendors. Other authors such as Agarwal and Naik (2000), Jawadi and Khanniche (2012) and Meligkotsidou and Vrontos (2014) used hedge fund indices provided by the database vendors, thus working on a strategy index level and obviating the need to consider whether those indices really were representative. Most studies on hedge funds use more than one database, due to the fact that inclusion on every database is a voluntary decision made by the fund principals. Authors who used more than one database such as Ackerman, McEnnally, and Ravenscraft (1999), Capocci and Hubner (2004), Joenvaara, Kosowski, and Tolonen (2012), and Patton and Ramadorai (2013) usually implemented a mapping between the strategies provided by the database vendors, whereas others such as Agarwal, Daniel and Naik (2004) and Kosowski, Naik and Teo (2007) made a broader classification of the database strategies provided by the database vendors. This classification consisted of mapping strategies into five groups; directional, relative value, security selection, and multi-process funds. Yet others such as Bares, Gibson, and Gyger (2003) used classification systems based on the investment process, the asset class, and the geographical period provided by the vendor. Last but not least Das (2003) used a non-hierarchical clustering algorithm on the asset class (as disclosed by fund managers), size, fees, leverage, and liquidity. However, this classification scheme does not focus on funds' strategy or style.

Overall it seems that the majority of authors have used the predefined classification schemes from the database vendors. Subsequently, some authors grouped hedge funds into broader styles or categories. However, none of those who did use the predefined classification schemes focused on the vendors' classification process itself. There is little or no examination in the extant literature of the issues arising from the various vendors' different hedge fund classification processes, and more specifically the examination of the quantitative techniques used by these vendors. Hence, in the literature there is a significant gap regarding hedge fund index construction methods. In order to fill this gap, I focus on two studies (Hedge Fund Research Inc, 2012 and Patel, Roffman, and Meziani, 2003) from two well-known database vendors, Hedge Fund Research Inc. and Standard and Poor's. These studies describe the processes and algorithms of their respective index construction methodology and form the basis of my study. They begin by presenting their vendor's selection criteria, the classification method and then the index construction process. Nevertheless, neither study provides any practical examples of their techniques, nor do they address that fact that other database vendors adopt different quantitative techniques that must end up giving different results. These issues are covered by this study. I focus on hedge fund classification processes using the same dataset because the index construction phase (calculating NAV, GAV etc.) is similar between the two vendors.

By comparing HFR's and S&P's methods using numerical examples from the same database I came to two new findings. First, both vendors use rigorous quantitative techniques, combined with qualitative processes through due diligence so as to ensure that they produce high quality representative indices. Nevertheless, these database vendors use different quantitative techniques, particularly when dealing with the classification process. Second, I show that these different quantitative techniques end up classifying hedge funds in a fairly similar way. The differences between indices' reported returns are instead mainly due to the different datasets used and the different inclusion criteria adopted by the two database vendors.

This paper contributes to the literature by filling a gap, as being the first to examine and explain the main principles and quantitative techniques used to build hedge fund indices through the use of real vendor cases. Investors are now able to better understand the nature of the hedge fund indices on offer rather than treating them as a "black box". Database vendors are helped to construct better indices, by understanding the methods of their rivals and combining new methods in their index construction methodology, by collaborating with other vendors or even specializing in certain indices. Researchers can have deeper knowledge of the hedge fund indices that use in their research. Also, some of their results can be affected had the hedge funds been allocated to different strategies. Last but not least, financial governance authorities could through collaboration with database vendors create a common hedge fund pool to help investors, as the differences in indices are mainly due to the different hedge fund universes used by the database vendors.

Following this introduction, I proceed to the HFR case and in the third section to the S&P case. Afterwards, I proceed to numerical calculations – demonstration of the two classification methods. I then compare and evaluate the two cases on a quantitative and qualitative basis. I conclude by examining some outstanding important issues concerning index construction methods in the hedge fund industry.

6.2 Hedge fund index construction: HFR case

In this section I present a detailed analysis of the hedge fund indexing methodology that is followed by Hedge Fund Research Inc. (2012). Later I present an analytical case from S&P's Hedge Fund Indexing methodology (Patel, Roffman, and Meziani 2003), following the index engineering methodology step by step. As a result, the reader will see the differences in practical terms through these comparisons.

Hedge Fund Research, Inc. (HFR) contains more than 6800 funds and funds of funds worldwide. It constructs two main types of indices: the *HFRX* and *HFRI* indices (HFR, 2012). However in February 2013 the firm also introduced the *HFRU* indices. The HFRI Monthly indices are a range of benchmarks constructed so that they are able to represent the hedge fund industry or universe by equally weighted components of funds that are being reported by their managers to the HFR database. The HFRI index category ranges from the HFRI Fund Weighted Composite index that consists of 2200 funds to particular sub-strategy classified indices. It is non-investable. The HFRX indices have various index-weighting methods (depending on each index), have different characteristics from HFRI and HFRU indices, and are investable. The newest HFRU (Euros) index category that is denominated in euros is equally-weighted, and is not investable. The HFRU composite index consists of over 600 funds. Other differences are that the index is calculated on a daily basis and finalized within five days, it has lower minimum asset size and minimum track record for inclusion. For all the above indices there is usually no cost for reporting by fund managers.

Table 52 highlights the main differences between these three categories of HFR indices. As can be seen, HFRX indices are more restricted than HFRI indices in terms of the criteria of fund inclusion and have fewer funds, a result that is logical due to the fact that this category consists of investable indices. However, the HFRU index has the least strict criteria of fund inclusion compared with HFRX and HFRI index categories. Another difference is that the HFRX category has many weighting techniques according to specific HFRX indices, whereas HFRI and HFRU are only equally-weighted. Furthermore, the HFRU index is denominated only in Euros.

Table 52. Characteristics and Differences between HFRI, HFRX and HFRU indices

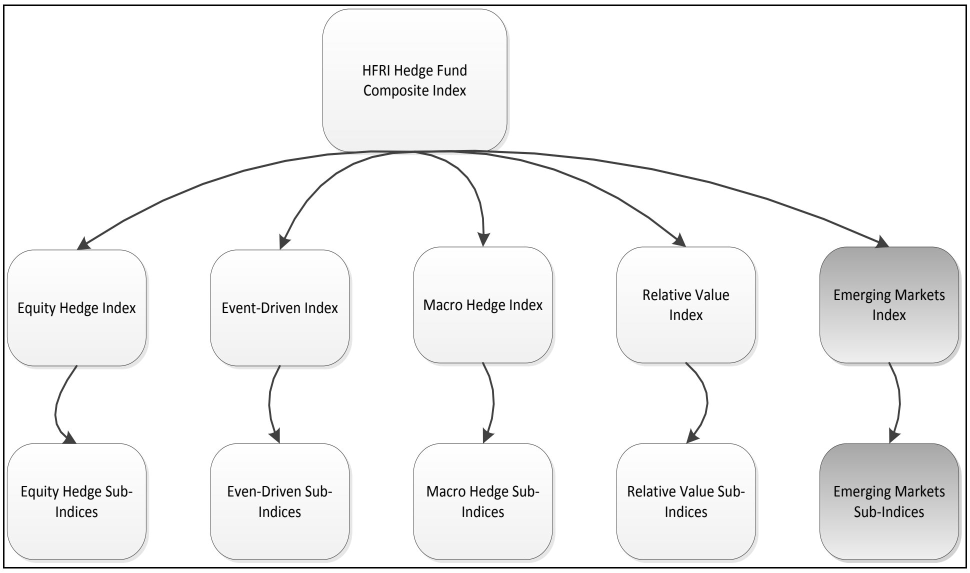
Category	HFRI Monthly Indices	HFRX Indices	HFRU Indices
Inception	Varies by index (Earliest 1990)	Varies by index (Earliest 1998)	Since 2008
Weighting	Equal-weighted	Equal-Weighted, Asset Weighted, Representative Optimization	Equal-weighted
Reporting Style	Net of all fees	Net of all fees	Net of all fees
Performance Time Series Available	Monthly	Daily or Monthly	Daily since 2011, Monthly since 2008
Index calculated	Three times per month	Daily and Monthly	Daily
Index performance finalized	Trailing four months of performance are subject to revision	Performance finalized at month-end	Trailing 5 days of performance are subject to revision
Index rebalanced	Monthly	Quarterly	Quartely
Criteria for fund inclusion	Listing in HFR Database; Reports monthly net of all fees monthly performance and assets in USD	Further to meeting HFRI criteria, fund must be open to new transparent investment and meet track record and minimum asset size requirements as listed below	Fund is UCITS compliant; Reports performance net of all fees at least bi-weekly
Minimum Asset Size and/or Track Record for fund inclusion	$50 Million minimum <u>or</u> > 12-Month Track Record	$50 Million <u>and</u> 24-Month Track Record (typical)	$10 Million EUR minimum <u>or</u> > 6-Month Track Record
Index Denomination	USD; some hedged to GBP, JPY, CHF & EUR	USD; some hedged to GBP, JPY, CHF & EUR	EUR
Investable Index	No	HFR Asset Management, LLC constructs investable products that track HFRX Indices	No
Constituents Details	Available to HFR Database subscribers	Available to HFR Database subscribers	Not available at this time
Number of Constituent Funds	Over 2200 in HFRI Fund Weighted Composite; over 600 in HFRI Fund of Funds Composite	Over 250 in total constituent universe, with over 60 of these in the HFRX Global Hedge Fund Index	Over 600 funds in the HFRU Hedge Fund Composite Index
Historical Performance	Published on HFR website and through various market data services		

Source: Hedge Fund Research Inc. (2013)

The HFRX, HFRI and HFRU indices follow almost the same quantitative and qualitative processes of hedge fund selection. However, the HFRX and HFRU indices use more up-to-date quantitative techniques regarding the weighting process (not only equal or asset weighted but also representative optimization using special algorithms). Furthermore they employ the advanced HFRX methodology (UCITS compliant) that is analyzed later in this section.

The HFRI category consists of four primary strategies. These are *Equity Hedge, Event-Driven, Macro, and Relative Value.* Each main strategy consists of many sub-strategies. In addition to the main strategies there is one more index called *Emerging Markets.* This consists of many sub-indices that are constructed according to a regional investment focus. Figure 7, depicts the structure graphically.

Figure 7. Hedge Fund Research Index Structure



Source: Modified table from Hedge Fund Research Inc. (2012)

The HFRX Global Hedge Fund Index is composed of four main strategy indices that consist of other sub-indices representing various sub-strategies (with new names from October 1st 2011). The four main strategies are: *Equity Hedge*, *Event Driven, Macro CTA,* and *Relative Value Arbitrage*. There are no differences to HFRI categories. The new HFRU index category of HFRU Hedge Fund Composite Index consists of the same four main strategies. Every strategy consists of other sub-strategies that are represented by sub-indices in the same way as for HFRI and HFRX indices.

The HFRX methodology (that is similar to HFRU) includes highly quantitative classification, cluster analysis, correlation analysis, cutting-edge optimization, and Monte Carlo simulations. This approach uses both quantitative and qualitative analysis in order to first, define whether the hedge fund is being managed with transparency and second, check whether the manager complies with the requirements of the due diligence process that is followed by Hedge Fund Research Inc. Using appropriate aggregated and weighted techniques this HFRX methodology produces the highest statistical probability that the return series would be adequately representative of the hedge fund industry. The general processes that are followed are:

(i) *Cluster Analysis*: HFR screens approximately 7000 funds in its database. Funds with at least $50M assets under management are included. Also, they must have at least two years' track record, consent to trade on a transparent basis and be open for new investment.

(ii) *Correlation Analysis*: used for grouping funds by appropriate strategies and to eliminate outliers.

(iii) *Monte Carlo Simulation*: also used for grouping funds by the most relevant strategies and to eliminate outliers.

(iv) *Due Diligence Analysis*: Selected funds from the initial screening must be transparent and pass the rigorous qualitative screening.

(v) *Strategy Weighting*: funds are weighted appropriately to maximize correlation with their group.

Each of these steps is covered in more detail below.

The first step is the construction through *initial database screening* of pure clusters that are represented by specific strategies. Each cluster is for funds using a certain strategy and will be the base for the creation of hedge fund sub-indices. So, there is an initial screening of the HFR database of open funds that (at least claim to) belong to a particular strategy class and comply with the criteria mentioned in the first section.

HFR choose one representative hedge fund in each strategy for *each* manager. It is common for successful and well-known managers to manage two or more separate hedge funds that belong to the same strategy. Therefore, if there is such a situation and the most representative hedge fund cannot determined then: (a) the fund having the longest track record will be regarded as representative (b) if the funds have the same time track record then the one with the larger assets under management is used.

The representative Hedge Fund Strategy Universe (also called the Strategy Universe-HFS) is obtained from the Global Hedge Fund Universe (HFU) that is contained in the HFR database. The funds that constitute the pure HFS are then filtered and passed only if they satisfy specific criteria such as having a minimum value of assets under management, net of fees reporting, a minimum reporting frequency, fund transparency, being open to new investments etc. If even one of these criteria is not met then the relevant formula used is equal to zero and the hedge fund does not pass on to the next stage. This process is robust, objective and all criteria must be met by each fund for inclusion. Besides this, in the due diligence process (transparency screening) HFR examine other qualitative factors through fund manager interviews, examination of financial statements and organizational structure and other important elements. This qualitative process is complementary to the quantitative process in the database screening.

At the initial database screening the self-reported strategies and sub-strategies are used. However, there are biases in self-reported data that must be eliminated. Therefore, in order to verify style purity, cluster analysis is implemented at the sub-strategy level. If a fund is an outlier then it is excluded or reclassified. Below is a detailed description of the cluster analysis.

Cluster analysis is implemented at a sub-strategy level using 24 consecutive monthly returns at the end of a prior quarter. HFR use in their methodology the Euclidian *distance* in the space of *monthly returns* as the distance or distinction measure of hedge funds. I present numerical examples in the section 6.4 of how this is implemented.

They also use Ward’s (1963) linkage rule. This rule minimizes the variance *within* clusters and maximizes it *between* the clusters at every move of the process.

Using Euclidian distances or Ward’s (1963) linkage rule is a type of cluster analysis instead of ANOVA that I present in the next section.

It was mentioned above that funds that belong to outliers may be excluded or reclassified. For that reason HFR uses the *trim parameter* within the cluster analysis that eliminates some funds, for example the six percent that are least close to the rest of the group. The remaining funds constitute the strategy pure cluster, in other words, the pure strategy index as the remaining funds after the initial classification (through distance rules and Ward's linkage rule) minus the outliers.

The next process is to perform an additional screening called *representation analysis*. This denotes how dissimilar the returns of each fund are to the respective strategy's returns (sub-strategy or region). The analysis is based on monthly returns for the last twenty four months in order that HFR can ensure that all funds have a complete available dataset. Those funds that have successfully passed *cluster analysis* and *representation analysis* are called the final *strategy pure cluster*. In each cluster all funds have equal weight.

Hedge Fund Research applies multiple representation analysis in order to calculate and rank (in ascending order) the Divergence Score (DS) for each fund. The Divergence Score measures the *dissimilarity* of a fund in relation to the cluster. Section 6.4 presents how this technique is implemented. Each fund is ranked by its return DS score according to the specific measures mentioned below.

The smaller the DS of a fund, the smaller its difference compared to the underlying cluster, hence the higher its ranking. The general formula for the Divergence Score is:

$$DS_i = Information\ Ratio\ Score_i + Beta\ Score_i + Volatility\ Score_i \qquad (20)$$

Where $IRS_i = \left(InfoRatio_{Cluster/Strategy} - InfoRatio_{i/Strategy}\right) + \left(InfoRatio_{Cluster/Substrategy} - InfoRatio_{i/Substrategy}\right) + \left(InfoRatio_{Cluster/Region} - InfoRatio_{i/Region}\right)$ (21)

The Information Ratio of fund *i* versus benchmark B is expressed by:

$$InfoRatio_{i/B} = \frac{\overline{(R_i - R_B)}}{\sigma(R_i - R_B)} \qquad (22)$$

$\overline{(R_i - R_B)}$ is the average monthly difference in returns between the fund and the benchmark for twenty four month period. The $\sigma(R_i - R_B)$ is the standard deviation of the difference in returns. The benchmarks that are used are:

Strategy = Hedge fund strategy benchmark specific to fund's strategy (i.e. Event Driven). Sub-strategy = Hedge fund sub-strategy benchmark specific to fund's strategy (e.g. Merger Arbitrage). Region = Regional equity benchmark particular to fund's investment focus (i.e. Europe).

BetaScore$_i$ in equation 20 is defined as

$$BetaScore_i = |\beta_{Cluster/Strategy} - \beta_{i/Strategy}| + |\beta_{Cluster/Sustrategy} - \beta_{i/Substrategy}| + |\beta_{Cluster/Region} - \beta_{i/Region}| \tag{23}$$

The beta of fund *i* versus benchmark *B* is expressed as:

$$|1 - \beta_{i/B}| = |1 - \rho_{i/B} * \frac{\sigma_i}{\sigma_B}| \tag{24}$$

σ_i and σ_B are the standard deviation of fund *i* and the benchmark *B* respectively. $\rho_{i/B}$ is the correlation of fund *i* with the benchmark *B* and it is expressed as:

$$\rho_{i/B} = \frac{cov(R_i,B)}{\sigma_i \sigma_B} \tag{25}$$

Where R_i denotes the returns of the fund and B the returns of the benchmark.

The Volatility Score VS_i (or return volatility) of the fund *i* in equation 12 is expressed as:

$$VS_i = \frac{|\sigma_i - \sigma_{Cluster}|}{\sigma_{Cluster}} \tag{26}$$

Where $\sigma_{Cluster}$ is the standard deviation of returns of the cluster during the evaluation period.

A high beta (correlation) and high volatility scores indicate that a fund is more directional / tactical in its classification. So, higher ranking funds are categorized as a market directional class whereas lower ranking funds are classified as being in the absolute return class. The middle group between them is not taken into consideration.

The representation analysis is the second process in the two-tier screening process and assures the pure cluster group. Accuracy is assured by means of the divergence scores.

The total number of funds that constitutes a pure strategy cluster may exceed 500. Because of the rapidly-changing nature of the hedge fund industry it is virtually impossible to maintain such a large number of funds, all providing daily transparent reporting. For that reason HFR use Monte Carlo simulations in order to construct an index with fewer funds without significantly losing representativeness. The number of funds is different from strategy to strategy and may depend upon the number of funds in each cluster, the desired accuracy level, strategy diversity and volatility. This optimization model randomly selects different sized fund samples from a certain strategy cluster and then compares the correlation between each fund sample with the whole cluster. The optimization process not only determines the number of constituents that maximize the representation of the cluster but also their optimal weights. Monte Carlo simulation is therefore employed to examine the number of funds needed to constitute a strategy index that is representative of the strategy cluster. The next step is to find the optimal weights to maximize the representation of the cluster using the Generalized Reduced Gradient quasi-Newtonian Optimization Method. The optimum number of funds depends on the weights (that should lie between certain limits) and the Divergence Score for each fund, as described above.

The underlying HFR indices compute NAV (Net Asset Value) using the actual performance of the managed account by a single hedge manager (hedge fund) that reports to the HFR database. The NAV is computed from the following formula:

$$\text{Net Asset Value}_{\text{(per share)}} = \frac{Market\ Value\ of\ Assets - Liabilities - Management\ Costs}{Shares\ Outstanding} \qquad (27)$$

The basic HFR NAV index is 1000 and represents the value of the first day of trading. HFR’s NAV index change is calculated from the percentage change from t to $t+1$, and this change depends on the weighted change of all fund-specific NAVs.

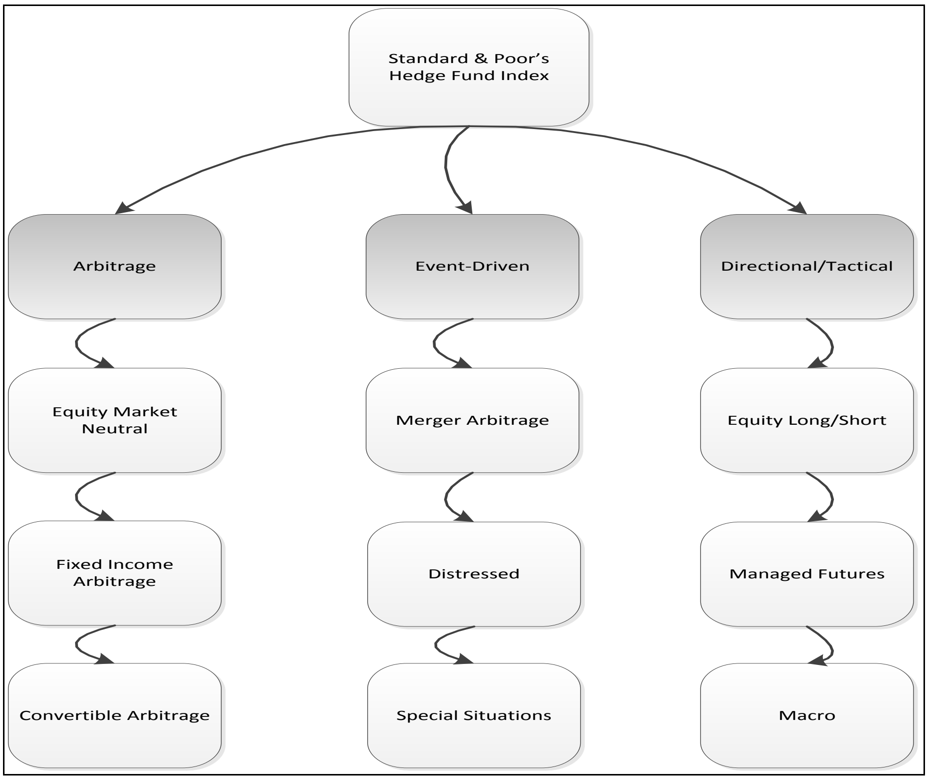
For the HFRX and HFRU indices there is an index rebalancing process implemented every quarter, whereas for HFRI indices it is every month (these are just HFR’s policies). For example, regarding HFRX indices, HFR uses the fund data available at the beginning of each period and computes the new optimal allocation weights at the beginning of the next period. Simultaneously, adjustments to the pool of funds such as additions, removals or reclassifications are taking place.

I now describe briefly how the global HFRX index, the single strategy index, and the weighted strategy index are structured. The index is organized as a tree structure. The HFRX Global Hedge Fund Index is constituted from other single strategy indices such as the Equity Hedge Fund Index, the Event Driven Hedge Fund Index, the Macro Hedge Fund Index and the Relative Value Arbitrage Hedge Fund Index. These represent the four basic categories according to HFR. The weights of each strategy are given by its assets under management in the fund universe as contained in the HFR database. I then move one level lower, to the HFRX Single (broader) Strategy Indices. Each index is represented by one of the above four categories. Each single (broader) strategy index is composed by the eligible sub-strategy indices that underlie that strategy. Hence, every index is a combination of one or more sub-indices with specific weights, either equal or percentage as described in the optimization process above.

6.3 Hedge fund index construction: S&P case

The S&P Hedge Fund Index is composed of three hedge fund styles. Those are Arbitrage, Event-Driven, and Directional/Tactical. Each style is composed of three strategies. For the first style these are Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage. For the second style they are Merger Arbitrage, Distressed, and Special Situations. For the third style they are Equity Long/Short, Managed futures, and Macro. Figure 8, depicts the structure of the S&P Index.

Figure 8. S&P Index Structure



Source: Modified table from S&P (2012)

The index construction *equally weights* the styles and strategies, and uses a rigorous quantitative and qualitative approach so as to select the appropriate funds. The whole index engineering process considers three complementary procedures.

The *first procedure* has to do with the number of funds that is required in order to build a representative and investable index. S&P apply *stratified sampling* (presented later) and *bootstrap simulation techniques* and have concluded that a fund sample consisting of approximately thirty or forty funds corresponds sufficiently to the risk/return characteristics of a wider portfolio of funds. The *second procedure* settles on a specific universe (pool) of appropriate candidates in order to be included in the index. This process begins by examining the strategy consistency of each fund through screening the fund sample for self-reporting bias and inconsistencies. The screening process may take into consideration style classification that uses two common quantitative approaches: *Fundamental Style Analysis* and *Return-based Analysis*. The process is essential so as to produce a pool that is cohesively characterized in terms of styles and strategies. Then this pool is additionally screened according to length of track record, investment capacity and assets under management in order to confirm that it is investable. The *third procedure* is the *due diligence process*. Standard & Poor's uses the due diligence process to qualitatively analyse the candidates for the index hedge funds. This process verifies the management and investment policy, operational capabilities and management experience. Consequently, having gone through this process the remaining funds are investable and have passed the due diligence evaluation. The *fourth procedure* is to apply an equal weight of styles and strategies, providing investors with broad diversification across major hedge funds strategies. The index provider ensures that there is a completely clear and public annual announcement regarding potential construction methodology changes and index rebalances to equal weights.

It is often stated that the indexing requirements of representativeness and investability conflict. Representativeness includes a large number of non-accessible funds that are not investable. Conversely, investability requires fewer hedge funds due to the fact that for each hedge fund there are more restrictions such as due diligence, continuous monitoring and additional administration. According to S&P a portfolio of 30 or 40 randomly selected funds has a stable distribution of risk and return characteristics. However, the range of these characteristics is wide. If there are two portfolios of funds (each containing twenty randomly selected funds) there may be a large difference in risk and return characteristics due to different risk exposures. To eliminate the effect of wide distribution of returns and risks in a hedge fund portfolio, S&P used the *stratified sampling technique*[52] in order to build hedge fund portfolios with balanced risk exposures to tighten the return-risk characteristics.

The first step in the stratifying sample application is to identify the risk dimensions. S&P uses two approaches: first it examines the systematic market exposures of a particular investment doctrine and second, it statistically examines the returns history of particular investments. Under the first approach, one could allocate investments to style classifications. This is simple but may be inconsistent because hedge funds' style classifications are made by fund managers. As a result, there might be some biases or inconsistencies. Concerning the second statistical approach, it is stricter but it suffers from the typical problems when dealing with historical returns analysis (fluctuations and not being precise in predicting future returns) as well as translating the analysis into a transparent investment process.

[52] It is crucial that the strata used in stratified sampling must not overlap. A stratified random sample is better than a simple random sample because it provides greater precision and guarantees better coverage of the population, providing that the strata or groups are carefully chosen and have greater similarity according to their underlying characteristics. However, stratified random sampling has difficulty in identifying strata and it is more complex to organize and analyse the results (Crossman, 2012).

Hence these two approaches constitute pools of single-strategy funds. As mentioned before they categorize hedge funds into three general styles. Those are Arbitrage, Event-Driven, and Directional/Tactical. Every style is composed of three strategies. Consequently, there are in total nine strategies that describe almost completely the investment styles and asset classes. However, there are some strategies, for instance Long-only (in equities or fixed-income securities) that can be represented by other indices, not necessarily hedge fund indices. Furthermore, there are some strategies such as Short-only that are niche strategies that are implemented within other strategies; hence there is no need for an extra hedge fund index. These strategy-groups are not necessarily designed to be used as different sub-indices. They rather exist in order to enable S&P to construct (through individual hedge funds selection from the samples) the S&P HFI index.

The second step in stratified sampling is to investigate the cohesiveness of each of the nine samples. Due to the fact that there is no consistency in style reporting, funds from different strategy groups are mixed so that the cross-section of return dispersion is high within these strategies. Also, because there is a wide spectrum of returns there is a need for a relatively large sample of funds in order to have an appropriate level of sampling precision. To enhance strategy cohesiveness there are four quantitative screens:

(i) For each fund of S&P's database they compare two correlation distributions[53] regarding returns. The first is correlation distributions with funds in the same industry and the second is correlation distributions with funds in all *other* strategies. Then using the Kolmogorov-Smirnov Test, they test whether the two distributions are different.

(ii) The next quantitative screen, after having tested that the two distributions are different, is to examine whether the median of the correlation distribution of funds within the same strategy is *greater* than the median of the correlation distribution of funds in all *other* strategies.

(iii) The next quantitative screen is to compare the degree of (return) correlation of each individual fund within the same group with other hedge fund indices of similar strategy they want to examine.

[53] "Correlation distribution": if I have a group of hedge funds then I have a number of pair correlations, i.e. the correlation of each hedge fund's returns with the returns of each of the other hedge funds. Each hedge fund has its own distribution of pair correlations, with a mean, standard deviation etc.

(iv) The last quantitative screen is to compare the standard deviation of each fund to its peer group.

In section 6.4 I implement the above techniques with numerical examples. In order to cross-validate the statistical consistency of the nine strategy groups (quantitative screen (ii) above) S&P use *ANOVA* (analysis of variance). Its principle is to examine whether the standardized distance within groups is less than the standardised distance between groups. Section 6.4 provides an application of the ANOVA using numerical examples. Since this follows standard textbook ANOVA analysis I do not present the formulae here.

ANOVA (S&P) and correlation analysis/distance (HFR) produce similar results, i.e. they cluster funds in a similar way.

To summarize, the construction of the index is begun by calculating the aggregate score of a hedge fund followed by the four quantitative screenings above. The first two calculate whether the correlations of fund returns with other funds in the industry are different from correlations with funds in other strategies. The third statistic measures the correlation of the fund return with the proper hedge fund sub-index. The fourth statistic compares the risk of a fund to the risk of other equivalent funds as they can be observed by the historical volatility.

Some further elements should be taken into consideration. The Macro strategy is extremely diverse as it invests in equities, bonds, currencies and commodities. Hence, in the quantitative screening there is a great concentration on the fund's volatility and the lack of correlation with the other eight strategies. On the other hand, within the Event-driven style, the Special Situation strategy is very similar to Merger Arbitrage and Distressed strategies over a short period of time. For that reason there is separation of funds within the Special Situation strategy that have *low* correlation with either Distressed or Merger Arbitrage strategies over two equal sub-periods.

The above processes are designed to be accurate and robust, providing reliable results concerning the appropriate grouping of hedge funds.

To find out the number of funds that are needed in order to represent a strategy for the general index construction, a simulation is needed. For each strategy S&P run 600 simulations, that is, 100 each for samples ranging from one to six funds. They use the simulated bootstrap model for which there is repeated random resampling from the original sample, using each bootstrapped sample to compute a statistic. The resulting empirical distribution of that statistic (in this case return dispersion as the number of funds increases within a certain group-strategy) is then examined and interpreted as an approximation to the true sampling distribution. S&P found that three to five funds per strategy (each of the three broader styles consists of three strategies) is a sufficient number to express the return distribution between funds.

The appropriate number of funds chosen per strategy is based on a quantitative evaluation of the simulation results as well as the number of specialities (sub-strategies) within each strategy. S&P found that portfolios of 30 to 40 funds based on quantitative techniques sufficiently narrowed the range of risk/return characteristics, but that more funds did not narrow it significantly further. Also, stratified sampling facilitates further narrowing of the spectrum of standard deviations, returns, and correlations with well-established asset classes.

So far I have described the quantitative screening of hedge funds as well as the quantitative method used in order to have the appropriate number (a target) of funds that will constitute the S&P HFI (first and second procedures). The initial candidate pool consists of funds that have the highest quantitative scores within each strategy. The third process is *Due Diligence*. The basics of S&P's Due Diligence Process are described below. It consists of three main components and includes interviews with fund managers regarding each fund's *pure style, trading strategy and practices, infrastructure and operations*. There is a special S&P Committee that participates in the formal review of hedge funds.

(i) An initial screening of selected funds takes place with sufficiently long track records to provide a preliminary indication of their performance, taking into consideration the assets under management of these funds in order to verify their appeal to investors and the sustainability of their strategy.

(ii) A preliminary examination of the track record, strategy, operating setup, and personnel is performed. This is designed to identify the quality of management, risk and operational management, strategy implementation and capacity limits.

(iii) The Due Diligence Process is a continuous process that is able to detect any changes to how the fund is being operated and managed.

There are interviews of and questionnaires for fund managers and other key staff with periodic visits. The content that is investigated is: general questions regarding the funds, management team backgrounds, investment strategy detailed questions, risk profiles and polices, portfolio construction, systems and infrastructures, service providers, performance analysis, and intensity of strategy cohesiveness. It should be clear that S&P follow a very transparent and rigorous methodology in their due diligence process.

At the beginning of this case I referred to the fact that the S&P HFI equally weights styles and the strategies. Contrary to the capitalization-weighted indexes, equally-weighted indexes avoid favouring large funds or strategies that attract noticeable capital flows. Generally, fund-weighted or equally-weighted indices, unlike asset-weighted indices, present a broader view concerning the hedge fund universe. Any biases in favour of larger funds are eliminated because there are no changes in weights. This is particularly important for strategies that contain a relatively small number of funds.

After considering via the quantitative and qualitative process the appropriate funds as well their (equal) weights, the final process is the calculation of the index value. It is calculated through the common NAVs (Net Asset Values) formula of the underlying hedge funds.

$$\text{Net Asset Value}_{\text{(per share)}} = \frac{Market\ Value\ of\ Assets - Liabilities - Management\ Costs}{Shares\ Outstanding} \qquad (28)$$

$$\text{Gross Asset Value}_{\text{(per share)}} = \frac{Total\ Value\ of\ Assets\ (excl.liabilities\ and\ mgt.costs)}{Shares\ Outstanding} \qquad (29)$$

Thus, the composite index is computed as:

$$\text{NAV Index: } \sum_{i=1}^{F} Number\ of\ shares\ of\ fund_i \times \frac{NAV_i}{Divisor} \qquad (30)$$

$$\text{GAV Index: } \sum_{i=1}^{F} Number\ of\ shares\ of\ fund_i \times \frac{GAV_i}{Divisor} \qquad (31)$$

Where F=Number of funds in the index, *Number of shares of fund*$_i$ = number of shares allocated to the fund at the last rebalancing to initiate index participation at the appropriate weight, NAV_i = net asset value of the fund (equally weighted according to S&P), GAV_i = gross asset value of the fund and *Divisor* = initial translation factor to start index at 1000. The S&P HFI tracks a hypothetical portfolio of its components with no capital inflows or outflows, which holds the divisor constant.

As the Diligence Process is an on-going procedure, some funds may be added or removed to/from the S&P HFI if they do (or do not) meet certain criteria. These changes are actioned by the S&P Committee. A fund can be excluded from the index if it violates qualitative due diligence standards, does not conform to the reporting process, there is a significant strategy shift, there are legal and regulatory issues, major management changes, or concerns for excessive growth or redemptions. Additions can take place not only to replace other hedge funds. If there is a fund that complies with all the previously mentioned criteria and rules and it will generate a more representative group for a given strategy then it may be added in alignment with the committee perspective.

To summarize, it is clear that there are mechanisms that guarantee the alignment of superior and continuously-improved hedge fund indices. The necessary adjustments take place via the on-going due diligence process.

For an index to make sense there must be a *base*. So Standard & Poor's constructed an index as of 30 September 2002 that is called the S&P HFI Pro Forma Index. This index is equally-weighted and is rebalanced annually. It uses monthly performance data for the time period January 1998 to September 2002. The S&P HFI index uses this Pro Forma Index as a reference. It is similar to that used by HFR.

It is crucial to preserve a high level of integrity and transparency in portfolio return computations. Thus, there is independent verification of portfolio holdings. For each hedge fund within the index there is a representative managed account to monitor the fund's performance information. Sometimes that information may vary from that of the hedge fund in order to ensure strategy purity. This happens because the fund manager may make an implicit shift from the strategy she had initially declared and implemented. Furthermore, a third-party administrator makes all the calculations so that the account is running in parallel with the main calculator, verifying valuation results on a daily basis. On the other hand there is another third-party partner that maintains the managed accounts. The external third parties ensure that there is no conflict of interest (e.g. index calculations and verifications) and the final results are objective.

Another important feature of the S&P hedge fund indices is timely reporting. S&P publishes on a daily basis values in the S&P HFI and executes regular performance and correlation reviews between hedge funds and their associated strategies. Net asset values are delivered via third-parties/partners to S&P that monitor their changes for any anomalies and calculate the daily index values. Due to pricing reviews there may be a time-lag of two days prior to the publication of the daily index values. After each month end, there is a final confirmation or finalization process and the monthly index values are published that cannot be changed.

6.4 HFR and S&P classification - Demonstration

This section illustrates the calculations used in implementing the HFR and S&P index engineering approaches. As in Chapter Three, I used data from two database vendors: Eurekahedge and BarclayHedge containing live and dead funds providing a long coverage (01/1990 to 03/2014). I followed a strict database cleaning and merging approach.[54] I mapped strategies between the different databases and I ended up with: *CTA, Event Driven, Global Macro, Long Only, Long Short, Market Neutral, Multi Strategy, Relative Value, Sector, Short Bias* and *Others* (includes funds that do not belong to any of the previous strategies). The Emerging Markets strategy is not included in my sample. Each portfolio of a specific strategy is represented by its average time series returns. In this section I classify these strategies in broad categories (groups).

Using numerical examples I demonstrate in practical terms the way that indices are constructed. As noted in the main body of this paper, index construction concerning the NAV or GAV calculation is the same. Nevertheless, the clustering and classification process is different between database vendors. I simulate the two different index engineering methodologies on the same dataset and then I compare the results to examine whether there are differences between them. I demonstrate that those

[54] The algorithms and processes I followed for database cleaning and merging are in the appendix.

quantitative techniques provide similar results in the index construction process. Differences in the indices between the vendors is mainly because they have different hedge fund universes (different databases) and different inclusion criteria in their due diligence process. The quantitative parts of their processes, although different, nevertheless provide similar results. In my examples the steps that I followed are:

For HFR:

1. I used part of the HFR methodology in the index engineering process that calculates the distances between those hedge fund strategies.

2. Then I implemented the Divergence Score for these hedge fund strategies.

For S&P:

1. I used part of the S&P methodology, measuring the correlations with strategies in the same category (group) and then measuring the correlations with strategies in other categories.

2. Next, I compared the (return) correlation of each individual strategy with the index in the same group.

3. I also compared the standard deviation of a strategy to its peer group.

4. I used ANOVA to examine whether the standardized distance within groups is less than the standardized distance between groups.

Table 53 shows the eleven strategies with their coding used in my examples:

Table 53. The Eleven Strategies of the Used Dataset

CTA	CT	***Market Neutral***	MN
Event Driven	ED	***Multi Strategy***	MS
Global Macro	GM	***Relative Value***	RV
Long Only	LO	***Sector***	SE
Long Short	LS	***Short Bias***	SB
Others	OT		

6.4.1 Distances between strategies (HFR)

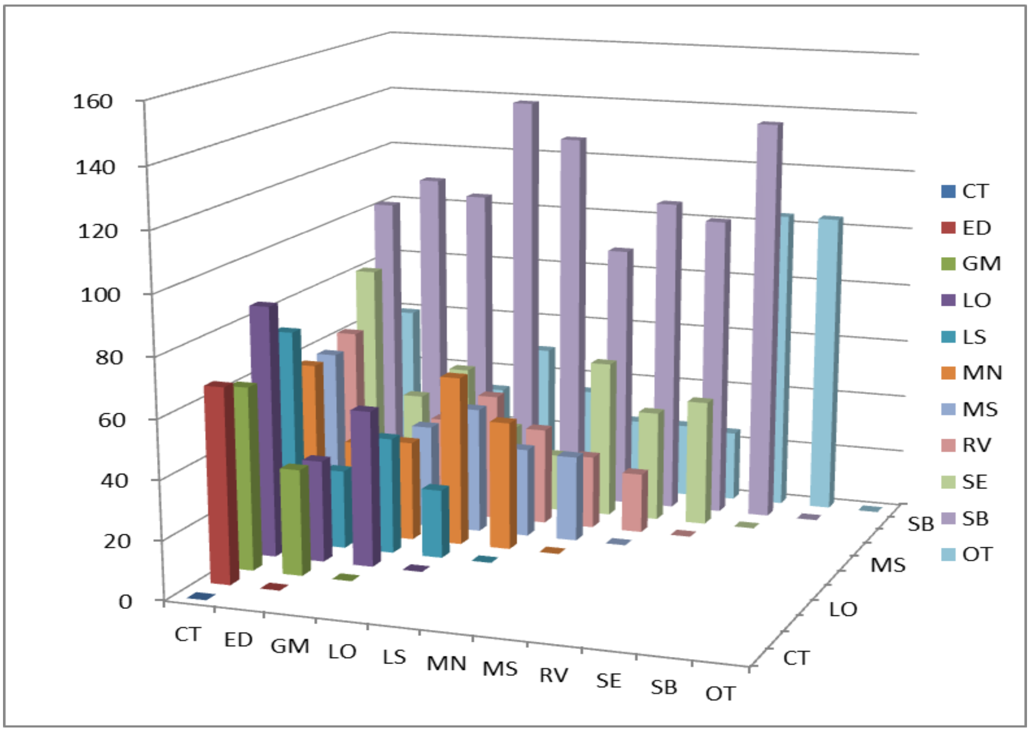
As mentioned above, I use a part of the HFR methodology and compare the distances between the eleven fund strategies. In table 54, LO, SE and LS are relatively close compared to GM, ED, and SE and even more so for SB, CT, and GM. More specifically, the average distance between LO, SE and LS is 23.850 units; for GM, ED and SE it is 40.413; and for SB, CT and GM it is 90.510 units. Hence, the SE strategy should be allocated with LO and LS and not with GM and ED. Similarly, GM is better allocated with ED and SE rather than SB and CT. Another potential group is ED, RV and MS with average distance 19.917, which is one of the lowest among the hedge fund strategies.

Table 54. Distances Between Strategies

	CT	ED	GM	LO	LS	MN	MS	RV	SE	SB	OT
CT	0.000										
ED	66.331	0.000									
GM	62.341	36.067	0.000								
LO	85.650	34.622	53.126	0.000							
LS	73.417	26.850	39.608	23.404	0.000						
MN	58.205	32.370	34.030	58.099	43.992	0.000					
MS	58.298	20.954	35.383	43.075	30.461	29.395	0.000				
RV	62.189	18.242	33.928	43.696	33.267	25.085	20.564	0.000			
SE	81.106	37.083	48.088	28.353	19.804	54.335	38.168	43.399	0.000		
SB	102.137	111.854	107.050	140.945	129.134	90.934	108.589	103.473	137.920	0.000	
OT	59.395	27.408	33.086	49.168	35.058	25.547	25.390	24.204	103.576	103.576	0.000

Figure 9 shows the distances between fund strategies graphically. I expect that fund strategies that have small distances would be allocated to the same category. The SB strategy follows an opposite direction toward the market index with negative exposures. Hence, I would expect SB to have a large distance compared to the other strategies. Figure 9 confirms this.

Figure 9. Distances Between Strategies



The above process is implemented by HFR for every fund (in pairs) with 24 months' returns so as to discover the distances between them. Some funds have a small distance between them, hence they should form a group or an index.

6.4.2 Correlations (S&P)

Following the S&P methodology, I measure the correlations of strategies in the same group (category) and then measure the correlations of strategies in other groups.

Table 55 presents all correlations between strategies. Some correlations between strategies are high, indicating a similar group; Other correlations between strategies are low, indicating strategies that belong to different groups. For example (I use the same strategies with the previous demonstration regarding distances) LO, SE, LS have an average correlation among them equal to 0.917; the strategies GM, ED, SE have 0.563

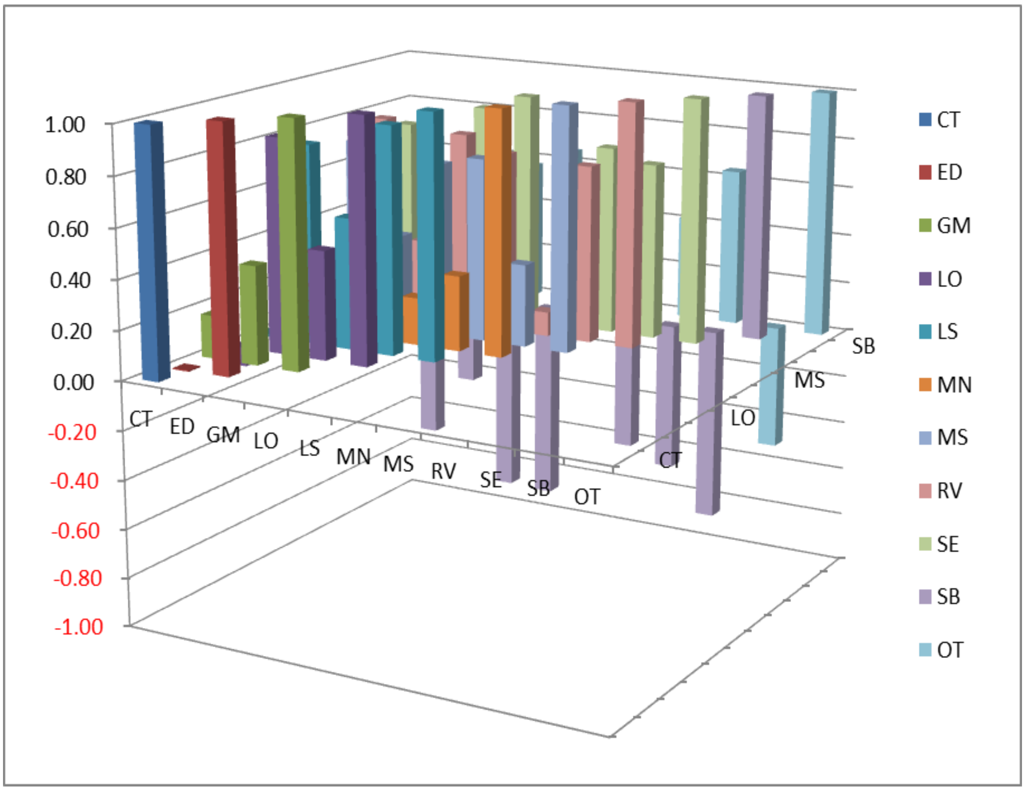
and the strategies SB, CT, GM have -0.030. Similar to the *distance* example, the SE strategy should be allocated with LO and LS and not with GM and ED. Similarly, GM is better allocated with ED, SE rather than SB, CT. Another potential group is ED, RV, MS with average pair correlation of 0.770.

Table 55. Correlations Between Strategies

	CT	*ED*	*GM*	*LO*	*LS*	*MN*	*MS*	*RV*	*SE*	*SB*	*OT*
CT	1.000										
ED	-0.005	1.000									
GM	0.174	0.400	1.000								
LO	-0.076	0.875	0.444	1.000							
LS	0.011	0.816	0.536	0.930	1.000						
MN	0.197	0.219	0.285	0.193	0.308	1.000					
MS	0.247	0.765	0.391	0.709	0.748	0.336	1.000				
RV	-0.001	0.831	0.329	0.798	0.736	0.099	0.723	1.000			
SE	-0.018	0.776	0.514	0.879	0.943	0.280	0.765	0.715	1.000		
SB	0.112	-0.626	-0.366	-0.806	-0.811	-0.057	-0.545	-0.606	-0.790	1.000	
OT	0.144	0.531	0.393	0.572	0.651	0.276	0.548	0.421	0.640	-0.506	1.000

Figure 10 shows the correlations graphically. Hedge fund strategies that are highly positively correlated to belong to the same group. Strategies that are either uncorrelated or negatively correlated (e.g. CT and ED) I expect not to belong to the same group.

Figure 10. Correlations Between Strategies



From the analysis, so far both processes (Euclidian Distance and correlation techniques) produce similar results.

Continuing the example of S&P correlation analysis, using Table 55 I calculate the correlation distribution for strategies that belong to the same group. Thus, the correlation distribution (its standard deviation)[55] for LO, SE, LS is 0.032; for GM, ED, SE it is 0.196; and for SB, CT, GM it is 0.296. Based on the correlation distribution, it is preferable that SE should belong to the same group as LO, LS compared to the candidate group GM, ED. Similarly, GM should preferably belong to the ED, SE group compared to the CT, SB group. Similarly within the group of ED, RV, MS the distribution correlation is equal to 0.056, which is relatively low.

[55] I compute the standard deviation of the pair correlations (correlation of each fund or strategy with each of the other funds or strategies) within the group.

The correlation distribution between all strategies (both within and between groups) is: standard deviation 0.511 with mean 0.410, median 0.479, and mean to standard deviation ratio 0.803. The correlation distribution for the groups (e.g. LO, SE, LS or ER, RV, MS) as I expected, is narrower than all strategies together, having larger mean-to-standard deviation ratio.

Based on table 71, I proceed further by computing the correlation of each strategy with its group. LO has correlation with its group (SE, LS) of 0.914; SE with its group (LO, LS) of 0.923; LS with its group (LO, SE) of 0.966. ED's correlation with its group (RV, MS) is 0.852; RV's with its group (ED, MS) is 0.829; MS's with its group (ED, RV) is 0.781. We can observe, as expected, strategies are highly correlated with the group that they belong to. The same process is followed by S&P at the fund level for all individual funds with the indices that they belong to, for verification purposes.

6.4.3 Standard deviation

The next step is to compare the standard deviations of strategies that belong to the same group.

LO, SE, LS have an average standard deviation equal to 3.120 and the distribution of their standard deviation[56] is equal to 0.405; GM, ED, SE have an average standard deviation equal to 2.372 and the distribution of their standard deviation is equal to 0.773, i.e. higher than the previous group; SB, CT, GM have an average standard deviation equal to 3.543 and the distribution of their standard deviation is equal to 0.594, which is also higher than the first group. It is observed that strategies belonging to the same group (LO, SE, LS) have a narrower standard deviation distribution compared to the other two groups in my example (GM, ED, SE and SB, CT, GM).

The next step in the quantitative screening process is to compare the standard deviation of a strategy to its peer group: LO has standard deviation of 3.437 compared to 2.919 for its peer group (SE, LS). SE has standard deviation equal to 3.259 compared to 2.997 for its peer group (LO, LS). LS has standard deviation of 2.663 compared to 3.245 for

[56] "Distribution of their standard deviation": If I have a group of funds within a strategy then each member of this group has its own standard deviation of returns. Hence, I have many standard deviations in this group (one value for each fund). Thus, I can plot the overall distribution (of all fund-specific standard deviation values) represented by a mean, standard deviation etc. for this group. The lower the standard deviation of the overall distribution for the group (of funds or strategies) the better it is, because this group is more homogenous.

its peer group (LO, SE). Similarly, ED has standard deviation equal to 1.840 compared to 1.373 for its peer group (RV, MS). RV has standard deviation equal to 1.238 compared to 1.669 for its peer group (ED, MS). MS has standard deviation equal to 1.713 compared to 1.475 for its peer group (ED, RV). It is observed not surprisingly, that the standard deviation is similar between each strategy and its related group.

6.4.4 Analysis of variance (S&P)

In order to validate the statistical consistency of the strategy groups, S&P uses ANOVA. The basic idea is to examine whether the standardized distance within groups is less than the standardized distance between groups. In other words, this approach investigates whether the mean vectors are the same and, if not, which mean components differ significantly.

The analysis of variance is based upon a decomposition of the observations:

X_{li}		$\bar{X}$		$\bar{X}_l - \bar{X}$		$X_{li} - \bar{X}_l$
Observation **(SSobs)**	**=**	**overall sample mean** **(SSmean)**	**+**	**estimated treatment effect (SStr - between samples-)**	**+**	**Residual** **(SSres –within samples-)**

(32)

This decomposition into sums of squares allocates variability in the combined samples into mean, treatment, and residual (error) components.

Table 56 presents pair ANOVAs between funds (or strategies) in the used sample.

Table 56. Analysis of Variance

	CT	ED	GM	LO	LS	MN	MS	RV	SE	SB	OT
CT	0.000										
ED	8.907	0.000									
GM	9.124	0.001	0.000								
LO	4.971	0.570	0.626	0.000							
LS	3.677	1.138	1.217	0.097	0.000						
MN	62.813	24.413	24.058	32.442	36.096	0.000					
MS	2.162	2.293	2.403	0.577	0.200	41.670	0.000				
RV	19.200	1.953	1.853	4.632	6.073	12.558	8.477	0.000			
SE	0.161	6.675	6.863	3.345	2.300	56.621	1.144	15.848	0.000		
SB	186.275	113.716	112.948	130.384	137.610	32.750	148.303	85.867	175.494	0.000	
OT	1.267	3.455	3.590	1.218	0.627	46.236	0.119	10.602	0.526	156.812	0.000

The average pairs ANOVA of the group LO, SE, LS is 1.913. Between non-groups such as GM, ED, SE and SB, CT, GM it is much higher, equal to 4.514 and 102.783 respectively. In figure 11 there is a visual representation of the ANOVAs which is derived from Table 56. For example, the SB and SE strategies have one of the highest ANOVAs between them compared to other pair ANOVAs. On the other hand MN and ED have one of the lowest ANOVAs between them compared to other pair ANOVAs.

Figure 11. ANOVA Chart

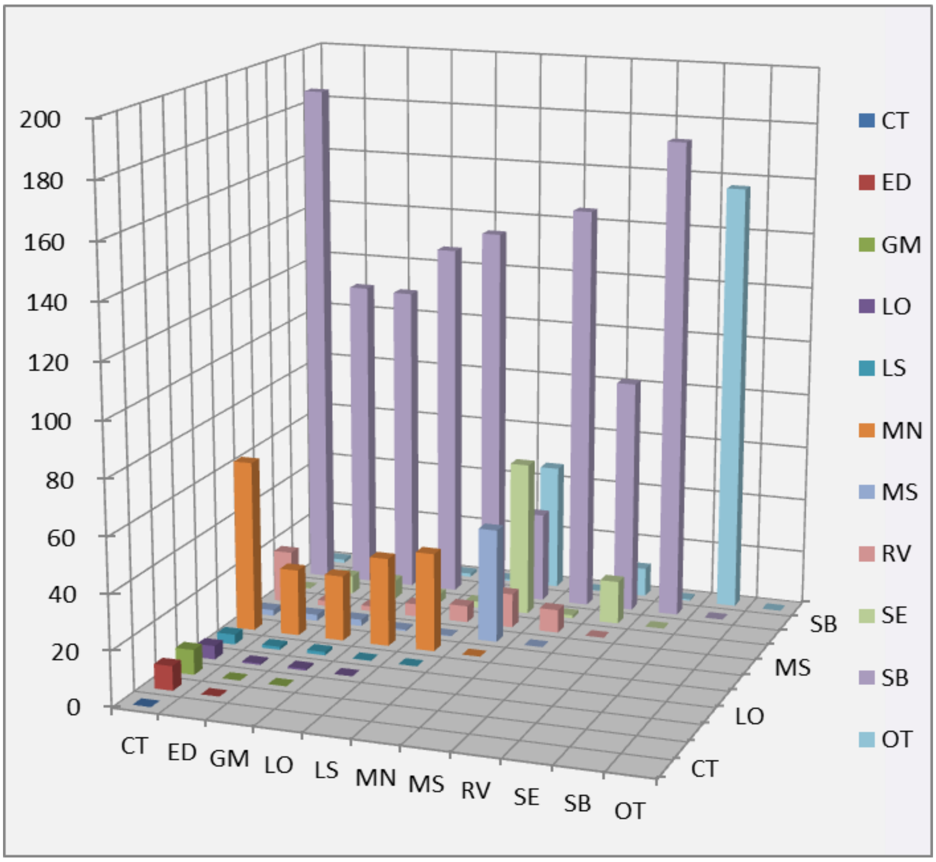


Table 57 and 58 show two example within-group ANOVA calculations. First I compute the ANOVA within group LO, SE, LS (table 57). The F-value is less than the critical value F_{crit} hence the null hypothesis that the variables are the same is not rejected. There is relatively large variance within each strategy but all these strategies behave in the same way.

Table 57. ANOVA Within Group (LO, SE, LS)

Groups	*Sum*	*Average*	*Variance*	
LO	290.77	0.999	11.813	
LS	298.3	1.025	7.093	
SE	334.89	1.151	10.620	
Source of Variation	*SS*	*MS*	*F*	*F crit*
Between Groups	3.828	1.914	0.194	3.006
Within Groups	8562.512	9.842		

Table 58 shows the results from the computation of the ANOVA between three candidate groups: (LO, SE, LS), (OT, GM, RV) and SB (it has the highest distances and opposite correlations with almost all the other strategies). The F-value is larger than the F_{crit} which means that the alternative hypothesis is accepted: the variances are not the same between these three groups.

Table 58. ANOVA Between Groups (LO, SE, LS), (OT, GM, RV) and SB

Groups	*Sum*	*Average*	*Variance*	
SB	15.3	0.053	27.004	
Group LO, SE, LS (Average)	307.987	1.058	9.178	
Group OT, GM, RV (Average)	275.98	0.948	1.401	
Source of Variation	*SS*	*MS*	*F*	*F crit*
Between Groups	177.141	88.570	7.070	3.006
Within Groups	10898.988	12.528		

I have demonstrated with the use of ANOVA that the standardized distance within the group (LO, SE, LS) is low (3.83), whereas the standardized distance between groups (LO, SE, LS), (OT, GM, RV) and SB, is considerably larger at 177.14.

I now move on to the concept of the Divergence Score as adopted by HFR.

6.4.5 Divergence score (HFR)

The divergence score (DS) measures the dissimilarity of a fund in relation to the group (cluster). It is used by HFR in their representation analysis as a second quantitative screening. The smaller the score, the better it is (less different compared to the cluster). The score for each hedge fund was defined as:

$$\text{Divergence Score (DS)} = \text{Information Ratio Score (IR)} + \text{Beta Score (BS)} + \text{Volatility Score (VS)}$$

(Note equation numbers refer to the equations already introduced in the main text.) In the example I compute the DS of LS against the group (SE, LO); then I compute the DS of the RV against the same group (SE, LO).

In the simple example I compute the information ratio of the strategy LS and the strategy RV in relation to the same candidate group.

6.4.5.1 Information Ratio:

As it was mentioned before, the Information Ratio is given by:

$$InfoRatio_{i/B} = \frac{R_i - R_B}{\sigma(R_i - R_B)}$$

$\overline{(R_i - R_B)}$ is the average monthly difference in returns between the fund and the benchmark, usually for at least 24-month period.

$\sigma(R_i - R_B)$ is the standard deviation of the difference in returns.

LS case:

Absolute average monthly difference in returns between LS and the group: 0.681

Standard Deviation of the difference of returns of LS and the group: 0.962

Hence, Information Ratio for LS is: $\frac{0.681}{0.962} = 0.708$

RV case:

Absolute average monthly difference in returns between RV and the group: 1.912

Standard Deviation of the difference of returns of RV and the group: 2.404

Hence, Information Ratio for RV is: $\frac{1.912}{2.404} = 0.795$

The above process is implemented by S&P for different levels of benchmarks i.e. strategy, sub-strategy and region.

6.4.5.2 Beta Score:

The Beta Score was defined as: $|1-\beta_{i/B}| = |1 - \rho_{i/B} * \frac{\sigma_i}{\sigma_B}|$

σ_i *and* σ_B are the standard deviation of fund *i* and the benchmark B, respectively. $\rho_{i/B}$ is the correlation (beta) of fund *i* with the benchmark B and was defined as:

$$\rho_{i/B} = \frac{cov(R_i,B)}{\sigma_i \sigma_B}$$

LS case:

Standard Deviation of Benchmark (group): 3.245

Standard Deviation of LS: 2.663

Thus, $(\sigma_\iota/\sigma_B) = \frac{2.663}{3.245} = 0.821$

Correlation of LS with the Benchmark (group): 0.966

So, the Beta Score for LS is $|1- 0.966 \times 0.821| = 0.207$

RV case:

Standard Deviation of Benchmark (group): 3.245

Standard Deviation of RV: 1.238

Thus, $(\sigma_\iota/\sigma_B) = \frac{1.238}{3.245} = 0.381$

Correlation of RV with the Benchmark (group): 0.782

So, the Beta Score for RV is $|1- 0.782 \times 0.381| = 0.702$

6.4.5.3 Volatility Score:

The Volatility Score was defined as: $VS_i = \frac{|\sigma_i - \sigma_{Cluster}|}{\sigma_{Cluster}}$

Where $\sigma_{Cluster}$ is the standard deviation of the cluster (SE, LO group in this case) and σ_i is the standard deviation of the strategy (LS or RV).

$|\sigma_i - \sigma_{Cluster}|$ for LS is $|2.663 - 3.245| = 0.582$

$|\sigma_i - \sigma_{Cluster}|$ for RV is $|1.238 - 3.245| = 2.007$

Thus, volatility score for LS is $\frac{0.582}{3.245} = 0.179$

And volatility score for RV is $\frac{2.007}{3.245} = 0.619$

Finally, I compute the Divergence Score for LS and RV:

DS	=	IR	+	BS	+	VS		
Divergence Score for LS	=	0.708	+	0.207	+	0.179	=	1.094
Divergence Score for RV	=	0.795	+	0.702	+	0.619	=	2.115

The LS strategy has a Divergence Score of 1.094, which is barely less than half that of RV (2.115). As previously mentioned, the Divergence Score denotes how much the fund is different from the benchmark (SE, LO in this case). So LS is closer to the cluster (group) than RV. I also tested LS against all the other strategies with regard to the benchmark (SE, LO group), and found that the differences in DS scores were similarly high. Thus, it can be observed that LS should be better allocated to the group (SE, LO), compared to the other strategies.

Last but not least I tested LO vs RV against the group (LS, SE) which gave Divergence Scores of 0.980 and 2.061 respectively; also SE vs RV against the group (LS, LO) which gave 0.803 and 2.063 respectively. Hence, it can be concluded that only LO should be allocated to the group LS, SE, compared to the other strategies.

To summarize, in this section I have presented parts of the HFR and S&P methodologies so as to give practical examples on how indices are constructed using their contrasting methods and particularly classification. I have demonstrated using numerical examples that the calculation of distances along with divergence scores (HFR) provides similar results to calculating correlations, standard deviation analysis and ANOVA (S&P). Strategies such as (LO, SE, LS) or (ED, RV, MS) are clustered in a similar way despite the different methods. This evidence suggests that differences of the indices between the vendors is mainly because they have different hedge fund universes and different inclusion criteria in their due diligence process.

6.5 Comparison between HFR and S&P cases

Both vendors use rigorous quantitative techniques, combined with qualitative processes through due diligence in order to ensure that they produce high quality representative indices. Nevertheless, they use some different technical quantitative methods. HFR uses cluster analysis using Ward's (1963) linkage rule (that is very similar to the ANOVA methodology) and correlation - representation analysis through the Divergence Score. On the other hand, S&P uses a stratified sampling technique considering systematic market exposures and statistically examines the returns history of the funds. Then, in order to bring out the cohesiveness and the differences among hedge funds it uses the ANOVA methodology. Both firms use simulations to find the appropriate number of funds within the index and perform due diligence analysis. HFR follows somewhat more rigorous quantitative rules concerning the initial screening process. This is because they use specific formulae and eliminate any subjectivity that a stratified method may realize. Concerning the second screening and hedge funds allocation to specific indices (strategy groups), both vendors use robust and clear techniques with several sub-processes to ensure that the construction methodology is appropriate. Ultimately, both database vendors use quantitative techniques that produce very similar results, in other words, they cluster funds in a similar way.

Furthermore, both vendors use rigorous qualitative due diligence processes with interviews, visits etc. The qualitative due diligence process is a very important element as there are some qualitative criteria that cannot be captured from the quantitative processes.

I pointed out that both index vendors use simulation techniques to construct a relatively small number of funds that are representative in a hedge fund index. However, there is one great difference concerning the weights that each fund has in the index. For S&P it is equally weighted whereas HFR use a more advanced method using an optimization process. In favour of asset-weighted indices, investors tend to allocate their money to larger companies and rebalance their portfolios' constructions according to the performance results of individual assets. Conversely, asset-weighted indices may sometimes be distorted due to large funds' performance. However, in the traditional markets there is a tendency towards capitalization weights that correspond better to investors' preferences (they invest their money in larger companies).

Regarding the index structure and index calculations, both vendors use a 'tree' framework. The general principles of the NAV calculations are the same and both use a base index equal to 100 or 1000, hence enabling them to compute index changes in a meaningful way. Concerning the computation of the Net Asset Value (NAV) the formula is similar with the same principles and compounding rules.

Nevertheless, it must be stated that between these two index construction methodologies there is almost a decade of age difference between them (2003 for S&P and 2012 for HFR). However, the purpose is not to favour one or the other. It is rather to demonstrate and present to the reader detailed index engineering construction processes in a practical way.

Index transparency is derived from three important characteristics: representativeness, investability and minimization of bias. There are several major private database vendors alongside HFR and S&P. Table 59 depicts their characteristics according to Mesirow Financial Services (2011). The weights are mostly Equal or Asset-Weighted. There are great differences between the minimum fund asset requirements, ranging from $10 million to $100 million. Moreover, the Dow Jones Credit Suisse Blue Chip takes into consideration the largest six funds in its calculation. Also, there are differences concerning funds that constitute the indices as well as regarding whether their funds are open or closed. It is noticeable that hedge funds indices that are investable have many fewer hedge funds due to their stricter constraints. Ultimately, I believe that each category index should be designed and constructed according to the needs and purposes of its users.

Table 59. Hedge Fund Index Providers

Index Provider	Funds in Universe	Funds in Index	Weight	Open / Closed Funds	Investable	Min. Fund Assets	Min. time Record	Liquidity Requirements	Rebalancing Frequency
HFRI	~ 7000+	~ 2000	Equal	Both	No	$50M	1 year	N/A	Monthly
HFRX	~ 7000+	~ 250	Complex Clustering Formula	Open	Yes	$50M	2 years	N/A	Quartely
Dow Jones Credit Suisse Hedge Fund Benchmarks	5000 tracked, ~900 meet index universe requirements	462	Asset Weighted with caps	Both	No	$50M	1 year audited	N/A	Monthly
Dow Jones Credit All Hedge	5000 tracked, ~900 meet index universe requirements	~120 Up to 25 for each of 10 sub-indices	Asset Weighted with caps and rules	Open	Yes	$100M	1 year audited	Monthly or 284 quarterly depending on strategy	Semi-Annually
Dow Jones Credit Suisse Blue Chip	5000 tracked, ~900 meet index universe requirements	60	Asset Weighted and rules	Open	Yes	Largest 6 from each sub category	1 year audited	Monthly or 284 quarterly depending on strategy	Semi-Annually
Eurekahedge	~ 9000	N/A	Equal	Both	No	None	None	N/A	Daily
Hennessee	~ 3500	1000+	Equal	Both	No	$10M	1 year	N/A	N/A

Source: Mesirow Financial Services (2011)

6.6 Issues in hedge fund index construction

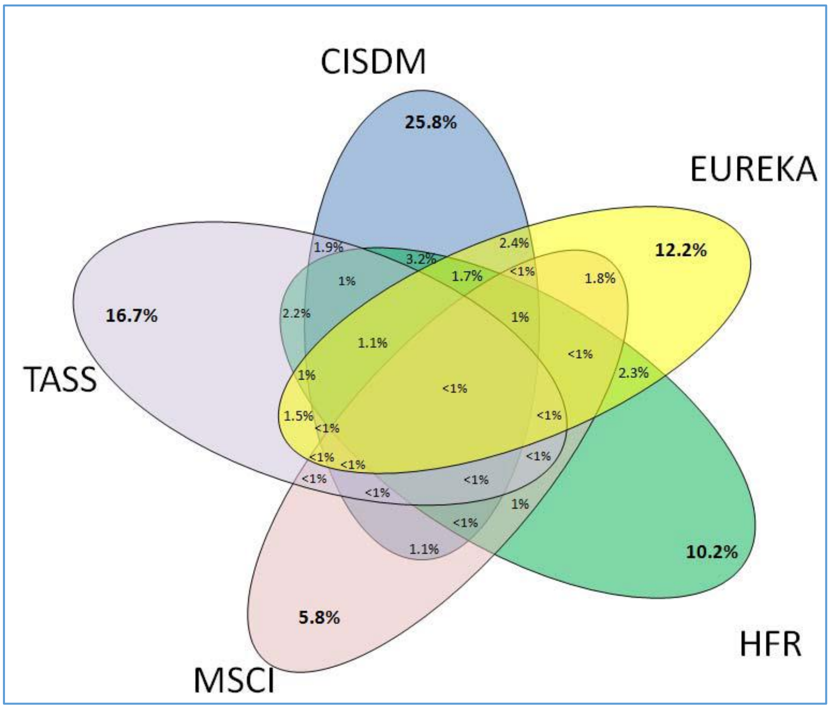
Several academic studies deal with the measurement and interpretation problems of hedge fund indices. Brittain (2001) and Schneeweis, Kazemi and Martin (2002) documented measurement and perception problems regarding existing hedge fund indices and funds subject to different market conditions respectively. Brooks and Kat (2002) showed that hedge funds are not such attractive investments if skewness and kurtosis are taken into consideration (for funds and indices). Fung and Hsieh (2002d) examined the survivorship and selection bias that are inherited from databases to benchmarks that are hedge fund indices.

However, Amenc and Martellini (2003) were the first who examined in a systematic way the differences between hedge fund indices and their lack of success in accurate measuring. The results of their performance comparison between hedge fund index providers were striking. For example, in specific time intervals, concerning the long-short equity strategy (1998-2000), Zurich Capital Market reported +20.48% return whereas EACM reported -1.56%. For the Short-Selling strategy (1998-2000), EACM reported -3.09% whereas Yan Hedge reported -24.3%. For the Global Macro strategy (1997-2000), HF Net reported +12.00% whereas Van Hedge reported -5.80%. So there are large differences and sometimes the signs are different. They also examined the correlations between these indices (average and lowest correlation). It is common sense that similar indices should be highly correlated with each other. But Amenc and Martellini found that some indices were not highly correlated. For example some strategies like Equity Market Neutral, Fixed Income Arbitrage and Global Macro had average correlations (the same strategy over time) of 0.428, 0.541 and 0.559 respectively. The Long/Short Strategy had average correlation of 0.458 with the lowest correlation being -0.190.

As I have shown in the previous two sections, hedge fund indices are built from different data sets, in keeping with different selection criteria and style allocation, and use different construction methodologies. Consequently, investors would be unwise to rely on only one index. For that reason they should follow different approaches that eliminate these disadvantages. These are (i) the pure indexes (also named ‘index of indices’) proposed by Amenc and Martellini (2003) and adopted by various institutions such as EDHEC and (ii) fund of funds indices that according to Fung and Hsieh (2002d) better estimate and deliver hedge fund industry performance. I discuss these below.

Regarding the unrepresentative nature of hedge fund indices, because hedge fund reporting is voluntary Agarwal, Daniel and Naik (2011) showed that less than one percent of hedge funds report to all known databases as presented in figure 12.

Figure 12. The Hedge Fund Universe



Source: Agarwal, Daniel and Naik (2011)

Amenc and Martellini (2003) proposed *pure indices or index of indices* as an alternative indexing approach. Instead of using one index for a given strategy, they proposed that investors should use pure indices that are combinations of relevant competitive indices. One simple method could be the construction of equally-weighted portfolios of all competing indices. However, Amenc and Martellini explored a statistical approach using Kalman filter techniques for the estimation of an observable factor from competing index return observations. Moreover, as the pure indices can be considered to be a portfolio of existing indices they proposed using the portfolio approach. In particular they suggested using Principal Components Analysis (PCA) to derive the 'best possible one-dimensional summary' of a group of competing indices and exploiting minimum variance analysis to extract the 'least biased portfolio' from a group of competitive indices.

Amenc and Martellini (2003) derived two theorems concerning the appropriateness of indexing indices. Firstly, an index of indices is consistently more representative than any competing index it is based upon. Secondly, an index of indices is consistently less biased than the average of the set of indices it is extracted from. Therefore the aim of the 'index of indices' methodology is to engineer a benchmark with better stability and representativeness than individual market indices. This approach gives to the 'index of indices' characteristics similar to portfolio properties, allowing investors to allocate their resources to alternative asset classes.

Goltz, Vaissie and Martellini (2007) examined the performance of a two-stage methodology dependent on factor analysis techniques to produce *factor replicating portfolios* that may be accounted as investable and representative indices for many different hedge fund strategies. They found that a chosen portfolio of funds sufficiently represents the returns characteristics of a large set of funds in the universe, excluding the case of Equity Market Neutral strategies.

I cover below a short case from the EDHEC Risk and Management Research Centre regarding the methodology of building pure indices, or indices of indices (Goltz *et al.,* 2007). It is known that there is non-representativeness and bias that hedge fund indices inherit from the database vendors. The immediate effect of this is the large difference in results between many hedge fund indices for the same strategy.

EDHEC use factor analysis to derive the best possible 'one-dimensional summary' of a group of competing indices in order to design 'pure style' indices. Their main objective is to find the portfolio weights that make the combination of the competitive indices embody the highest possible fraction of the information contained in the data from the various competing indexes. In other words, they use *Principal Component Analysis* (PCA) of the competing indices to create a pure style index. The first component typically captures a high proportion of cross-sectional variation, since indices of competing styles tend to be at least partially positively correlated. PCA's target is to justify the behavior of observed variables exploiting a smaller set of unobserved implied variables. The first principal component can be presumed as the 'best one dimensional summary' of a set of competing indices, as it accounts for the largest fraction of the information they contain. The formula is:

$$max_w \frac{\lambda_l}{\sum_{i=1}^{N} \lambda_i} \tag{33}$$

Where λ_i is the eigenvalue linked to the *i*th principal component.

A simple normalization can be implemented to get an index that can be considered as a portfolio of competing indices. In order to construct the alternative indices, EDHEC first eliminated strategies for which there are fewer than four indices. They concluded that for statistical reasons it is better to have at least four competing indices. Then, they eliminated strategies with very narrow concentration (e.g. the health care sector). The second step is to select the indices that are going to be included in the alternative indices. The competing indices must be public and have transparent style classifications. Furthermore, the candidate indices must rely on a broad database, and post their performances in a timely manner. Also, the competing indices must have a sufficient length of historical data (at least from 1994). Table 60 depicts seven index providers (with their weights) along with thirteen style classification EDHEC indices. As is shown, each alternative index represents a specific strategy and consists of some indices from other database vendors with a specific weight tailored to that EDHEC alternative index.

Table 60. EDHEC Indices and their Constituent Weights as of 2013Q2

EDHEC Alternative Indexes	CSFB	Hennessee	HFR	HF Net	Barclay	CISDM	Greenwitch
Convertible Arbitrage	16.5%	16.5%	16.5%	16.9%	16.9%	16.7%	-
CTA Global	33.2%	-	-	33.5%	33.3%	-	-
Distressed Securities	14.4%	14.3%	14.6%	14.4%	14.6%	14.3%	13.4%
Emerging Markets	16.8%	16.6%	17.0%	16.2%	16.9%	-	16.5%
Equity Market Neutral	12.9%	12.9%	15.1%	15.0%	14.8%	14.2%	15.1%
Event Driven	16.7%	16.6%	16.9%	16.9%	16.8%	16.1%	-
Fixed Income Arbitrage	16.7%	14.0%	-	17.5%	17.6%	17.0%	17.2%
Funds of Funds	-	-	33.3%	33.3%	33.3%	-	-
Global Macro	14.3%	12.7%	15.2%	15.0%	15.1%	14.2%	13.5%
Long / Short Equity	20.0%	-	20.0%	20.1%	19.9%	20.0%	-
Merger Arbitrage	16.3%	15.5%	17.9%	15.5%	16.9%	17.9%	-
Relative Value	-	24.3%	25.5%	25.6%	-	-	24.6%
Short Selling	16.7%	16.7%	16.3%	17.0%	16.8%	-	16.5%

Constructed table. Data source: EDHEC 2013

The EDHEC indices are rebalanced every three months and the EDHEC Index Advisory Board decides on the inclusion or exclusion of every individual hedge fund index. The criteria that are taken into consideration are: the accessible history, the clarity of the construction methodology, its representativeness, the completeness, the stability of the composition, and the consistency with which the data/index is published.

Another alternative approach regarding measuring and benchmarking hedge fund universe, that is distinct from competitive indices or an index of indices, is the Fund of Hedge Funds (FoFs). FoFs have an extra management layer and have greater diversification that can benefit investors. On the other hand they have two layers of management fees. Fung and Hsieh (2002d) proposed the simple idea of FoFs as benchmarks that constitute a most direct way to evaluate hedge fund performance. It captures the investment experience of hedge fund investors themselves. Fung and Hsieh (2004) examined several biases such as selection biases, survivorship biases and instant history biases. These biases can be eliminated when using FoFs. Regarding the selection biases, even if a hedge fund ceases reporting to databases, a FoF may include this hedge fund in its portfolio. Moreover, a FoF may contain a hedge fund that has never reported to any database. Concerning survivorship bias, even if a hedge fund stops operations or goes into bankruptcy, this fund remains in the historical return of the FoF. As far as history biases are concerned, these are reduced due to the fact that the past returns of a fund that has just joined a FoF are not included. Consequently, FoFs give a sufficiently qualitative representation of the hedge fund universe for investors.

To conclude, several studies have dealt with the problems of measuring and interpreting of indices (e.g. Brittain, 2001, Schneeweis, Kazemi and Martin, 2002), the attractiveness of investing in hedge fund indices (e.g. Brooks and Kat, 2002) or survivorship and selection biases in these indices (Fung and Hsieh, 2002d). Amenc and Martellini (2003) highlighted the major numerical differences in hedge fund indices from different vendors even though they are supposed to be measuring the same strategy. Various approaches have been proposed to improve the situation. First, Fung and Hsieh (2002d) proposed the use of Fund of Funds (FoFs) indices that can eliminate selection, survivorship, and instant history biases. These constitute a direct way to evaluate hedge fund performance because FoFs can capture the investment experience of hedge fund investors themselves. Second is the alternative indexing approach proposed by Amenc and Martellini (2003) (EDHEC institute) with the use of pure or index of indices that are more representative and less biased compared to any competing index. The third solution is from Goltz, Vaissie and Martellini (2007) who used factor replicating portfolios that counted as investable and representative indices for many different hedge fund strategies. All these solutions give the indices characteristics similar to those of portfolios, allowing investors to allocate their resources to alternative asset classes. However none of these studies were directly concerned with understanding hedge fund index construction methodologies, nor do they answer why there are large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy. Also, they make no attempt to propose best practice when classifying hedge funds based on characteristics such as their own returns behaviour or assets.

6.7 Conclusion

This study is the first to present and analyze in an integrated and practical way hedge fund index engineering processes and comparisons. I have reviewed the hedge fund index engineering process and particularly classification in detail. I have demonstrated the methods followed by two database vendors as examples that use rigorous quantitative techniques, and also qualitative processes through the due diligence process, in order to ensure that they produce high quality representative indices. The section 6.4 presents numerical examples emulating their quantitative processes using real data.

The findings are that, even though database vendors use different methods or quantitative approaches, they are able to cluster hedge funds in a somewhat similar way. This implies that the differences between the index vendors are primarily due to different datasets and different selection criteria. However, further research is needed in that direction, as I present below. It is almost inevitable that indices in the same category have great differences. This is because the vendors use different datasets, have different selection criteria and use different quantitative techniques. This was demonstrated by Amenc and Martellini (2003).

Investors may well be confused about which benchmark measurement is the appropriate one to choose. This is an important choice in order to evaluate either their investments or hedge funds managers' performance. Two solutions are the construction of an index of indices (EDHEC institute) or fund of funds indices. Another solution might be the concept of 'customized indices'. An example is the customized benchmark service provided by the ERI Scientific Beta - EDHEC Institute (2013).

Further research is needed towards the reproduction of this study using multiple datasets and focusing at the fund level. By implementing various classification techniques on hedge funds, a researcher could have more robust results on the efficiency and the similarities of the quantitative methods used by the underlying vendors. This extension could include the use of further quantitative techniques beyond those used by the database vendors. It was a surprise to me is that so little statistical work has been done to determine the best methods for different end users. Another expansion would be the evaluation and identification of the ‘best’ possible construction methods or practices (industry standards - protocols) that are appropriate to the hedge fund index composition process. This could include either evaluating specific quantitative techniques within the construction process according to predefined criteria, or evaluating currently-available indices against other benchmarks such as an index of indices or fund of funds index.

Last but not least, database vendors and researchers should take into consideration two issues: first, there are hedge funds with a great difference in length of history, making the classification process questionable; therefore, vendors should use hedge funds with at least 24 months of data for classification purposes. Second, many hedge funds operate in different times and market conditions. Hedge funds’ performances change due to different market conditions; hence there should be a standardizing process (e.g. based on hedge fund excess returns or correlation against a market benchmark) in order to capture this issue. As a result, database vendors and researchers will be able to construct more efficient and representative indices helping investors understand the performance profiles of different strategies.

7 Chapter: Conclusion

7.1 Introduction

This doctoral thesis examines hedge fund return attribution for different hedge fund strategies under changing market conditions. This thesis is important because it covers gaps in the literature that created confusion to investors and researchers. There was no a clear picture of hedge funds' behaviour under changing market conditions, in a holistic approach. Previous studies had important inefficiencies in terms of over-simplistic models for all hedge fund strategies and/or different market conditions, using several macro factors that did not necessarily present the state of the market or the economy, focusing only on the internal structure of hedge funds returns, or using some factors (e.g. general commodity factors) that did not represent accuracy their sub components. Beyond the confusion that the investors faced in their decision investment process, there was also a lack of understanding of the behaviour of hedge funds' returns in other aspects such as at the fundamental or mixed level within different market conditions.

Regarding the performance persistence, there was no clear distinction between different aspects of persistence. Neither was there a distinction between "good" or "bad" times. Examining persistence only within each strategy group of without taking into consideration other aspects did not provide deep knowledge and did not help investors much. Furthermore, until now investors have had no guidance on how they can exploit differences in persistence of hedge funds so as to gain conditional higher returns. In terms of the hedge fund index construction and classification issues, although investors were using several indices as benchmarks in their portfolios (simply as "consumers"), nevertheless, they knew almost nothing how they were practically constructed. There was a gap in the literature of why there were differences in hedge fund indices from vendors even if they supposed that they represented the same strategy. The benchmark selection in general is not a trivial process and may change the portfolio and asset allocation decision process of the investor.

I remind the reader the research questions that are examined in this study:

1. *How and what is the impact of the (multiple) business cycles and different market conditions on hedge fund strategies in terms of performance (alphas and exposures)?*

2. How and what is the impact of the (multiple) business cycles and different market conditions on hedge funds at the fundamental and mixed level in terms of performance (alphas and exposures)?

3. What is the impact of multiple business cycles and different market conditions on hedge fund performance persistence at strategy level and how investors can exploit persistence?

4. Why there are such large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy?

Based on the previous questions, the research objectives are, first, to understand and explain the return generating process under changing market conditions at a strategy level, second, understand and explain the return generating process under changing market conditions at a fundamental and mixed level, third, to examine hedge fund performance persistence and its exploitation by investors, and fourth, to examine the differences between hedge fund indices and more specific the classification problem of the hedge funds.

7.2 Findings

The main empirical findings are chapter specific and are summarized within the respective empirical chapters. In this section I provide a synthesis of these findings so as to answer the research questions in a homogeneous way. In other words, I discuss the findings in an integrated way so as to capture the "big" picture of this doctoral thesis. As I have already mentioned, this doctoral thesis examines hedge fund return attribution for different hedge fund strategies under changing market conditions. All four research questions are related and the results within each research question can be explained with regards to the other questions as well. Moreover, section 7.3 mentions the contributions of this thesis.

7.2.1 Performance at strategy level

7.2.1.1 Main results

In the third chapter that deals with hedge fund performance attribution at the strategy level, I found that almost no hedge fund strategies provide significant alphas to investors during stressful market conditions. It seems that at such times fund managers try to minimize their risks. Indeed, when I examine funds' exposures during "bad" times, hedge funds reduce both the number of their exposures to different asset classes and their portfolio allocations while some strategies even reverse their exposures. The opposite happens during "good" times as fund managers focus more on returns trying to exploit upward market movements even at the cost of increasing their systematic risk. As expected, directional strategies share more common exposures under all conditions compared to non-directional strategies due to their nature. During stressful market conditions fund managers switch from equity asset classes to commodity asset classes as the later asset classes seem to be more inelastic and economic activity is not the main driver of their prices. I have also found that down regimes are harsher than recessions as they consist mainly from down market movement with high volatility, being difficult to predict by fund managers.

7.2.1.2 Connecting performance findings with the literature

The findings of this study agree with other authors (e.g. Bali, Brown and Caglayan, 2011, Jawadi and Khanniche, 2012 and Giannikis and Vrontos, 2011) that hedge fund strategies are dynamic in terms of exposures and returns. First, the proposed model agrees with the literature that returns and factor exposures change over time, as I found major switches of hedge fund returns occurred during stressful market conditions (as modelled by Jawadi, Khannich, 2012). Moreover, there is partial agreement with Bollen and Whaley (2009) since I found only one of their two samples, containing spikes of exposures' switching appears during under stressful market conditions, although they examined funds during the period 1994 to 2005, allowing for a single shift in the parameters of the funds. Second, different strategies have different exposures due to their nature. Third, there are some common risk factors such as the market, credit, the term spread and commodities that are shared between many hedge fund strategies (Billio, Getmansky and Pelizzon, 2012) and there are some other factors such as default spread and VIX that are economically important (Avramov, Baras, and Kosowski, 2013). My findings agree with Meligkotsidou and Vrontos (2014) that the market index and the spread of small cap minus large cap were the most significant factors in hedge fund returns.

Fourth, there are changes in portfolio allocations that are more intense than changes in exposures to asset classes, as Patton and Ramadorai (2013) found. There is partial agreement with Ibbotson, Chen and Zhu (2011) as only a few strategies add significant value to investors during bear market conditions because fund managers are concerned more about risk. Nonetheless, they examined alpha and exposures only during the 2008 financial crisis. There is also agreement with Brown (2012) that traditional systematic factors such as equities or credit impose significant exposures on hedge funds although the author took into consideration performance before fees. Last but not least, as Agarwal and Naik (2004) found, I find that many hedge fund strategies exhibited significant exposures to Fama and French's (1993) three-factor model and Carhart's (1997) momentum factor. As mentioned before, my findings regarding (i) the absence of alpha (ii) the switching toward commodities during stressful market conditions, (iii) common sharing exposures for directional strategies, (iv) the high negative impact of the down regimes on hedge funds (see the findings section for more details) influence the further understanding or application knowledge in the area of hedge fund. Under this holistic approach there is a clear understanding of the relationship between hedge fund strategies and changing market conditions. This additional knowledge can be the basis of an extended examination of hedge funds for forecasting purposes.

7.2.2 Performance at fundamental-mixed level

7.2.2.1 Main results

In the fourth chapter that examines fund performance at a fundamental and mixed level I found that irrespective of the fundamental factors, hedge funds, on average, deliver significant excess returns to investors, contrary to bad times when they try to minimize their systematic risk delivering no significant alpha. These results are in alignment with the third chapter concerning the return/risk performance of hedge funds in changing market conditions. The interesting thing is that none of the fundamental factors (hedge fund characteristics) is able to assist in providing excess returns for hedge funds. On the contrary, some hedge fund strategies are able to deliver excess returns even during stressful market conditions. Also, on average, all funds irrespective of their characteristics try to minimize their systematic risk during stressful market conditions. I found that small funds suffer more than large as the latter funds seem to have more resources and being able to absorb shocks. Young funds outperform old ones for all conditions as young fund managers seems to have higher pressure than old ones to deliver higher performance. An interesting finding is that funds that do not impose restrictions (and survive) outperform funds with lockups. I rationalize this as fund managers feeling the pressure of not having the "safety" of redemption restrictions are more innovative and do better than their peers. I also found that some strategies with specific characteristics even deliver significant negative alpha to investors conditional on stressful market conditions. Indeed, as I found in the third chapter that almost no hedge fund strategies provide significant alpha during stressful market conditions, it is rational that fund strategies with specific characteristics (such as no lockups Long Only and young Multi Strategy – see chapter 3) may struggle even more. This is because in the first case there are no redemption restrictions so as to protect fund managers who have mainly long positions; in the second case as Multi Strategy needs special skills (e.g. exploiting other strategies or investing in other markets) there may be no managerial experience in doing this.

7.2.2.2 Connecting the above findings with the literature

The results concerning the relationship between size and performance agree with other authors such as Agarwal, Daniel, and Naik, 2004; Ammann, and Moerth, 2005; Meredith, 2007; Joenvaara, Kosowski, and Tolonen, 2012 that there is a negative correlation, on average. These results are in alignment with commercial studies (e.g. Pertrac Corporation, 2012), as well. Getmansky (2012) found that there is a positive and concave correlation and suggested that there is an optimal size of assets under management. A few studies are exceptions that found no relationship, such as Gregoriou and Rouah (2002) or a negative relationship such as Koh, Koh, and Teo (2003), but the differences are mainly due to the use of different samples and methods. According to my findings, although this negative relationship holds for "good" times, during "bad" times this is questionable as small funds seem to suffer more than large. Concerning the relationship between age and performance this study again agree with the literature (such as Amenc and Martelini, 2003; Meredith, 2007; Frumkin, and Vandegrif, 2009; Pertrac Corporation, 2012) that there is a negative relationship, on average. One exception is the study from Schneeweis, Kazemi and Martin (2002) that showed a positive relation taking into consideration funds with the same starting point. In this study I found that this holds for "good" and "bad" times.

Regarding the relationship of the lockup restrictions and performance this study agrees with other authors (such as Aragon, 2007; Joenvaara, Kosowski, and Tolonen, 2012) that there is a positive relationship, although, only during "good" times. During "bad" times, funds without lockup restrictions (that survive) outperform funds with lockups. I explain this as fund managers becoming more innovative with respect to their peers, under the pressure of not having the "safety" of redemption restrictions. This study extends the previous knowledge in terms of hedge fund performance and fund characteristics, providing a deeper understanding of this relationship as I find that it is not necessarily linear when changing market conditions are taken into consideration. Moreover, scholars should not take for granted that hedge funds always provide superior returns to investors. This is because I found that there are some cases (e.g. Long Only funds with no redemption restrictions and the Multi Strategy young funds) that that provide significant negative excess returns to investors, conditional on stressful market conditions.

7.2.3 Persistence and mixed trading strategies

7.2.3.1 Main results

The fifth chapter's findings are connected with those in the third one, as in general, hedge funds seem to suffer during stressful market conditions not only in terms of excess returns delivered to investors but also in terms of performance persistence. During "good" times there is smoothness in hedge fund (risk-adjusted) returns. On the contrary, during "bad" times this smoothness disappears. With respect to the market benchmark, with a few exceptions, there is no performance persistence. Regarding the persistence within each strategy group, for "good" times I found persistence up to one year whereas for "bad" times I found it for up to six months. In addition, there is strong evidence that the persistence is driven mainly by the top performers. This implies that there is fierce competition among bottom performers to be at least average in terms of performance; otherwise the fund will go out of business. An interesting aspect is that, contrary to the third chapter, recessions are harsher than down regimes. I rationalize this as hedge funds during down regimes producing very low (but steady) returns compared to recessions, when funds deliver low but sometimes relatively high (thus unsteady) returns.

7.2.3.2 Connecting persistence's findings with the literature

The results confirm earlier studies (such as Agarwal and Naik, 2000a; Eling, 2009; Joenvaara, Kosowski, and Tolonen, 2012; Hentati-Kaffel, and Peretti, 2015) that there is short term persistence. However, I proceed further, by confirming my initial assumption that persistence depends also on the different business cycles and the different market conditions. More specifically, there is a negative impact concerning the spreads between hedge fund top and bottom performers and their performance persistence. Also I showed evidence that some non-directional strategies (e.g. Relative Value) present more persistence than directional strategies (e.g. Short Bias or Long Only). Nevertheless the difference in persistence is mainly related to the type of strategy each fund follows. There are some studies such as Kosowski, Naik and Teo (2007), Jagannathan, Malakhov and Novikov (2010), and Ammann, Huber and Schmid (2013) that indicated persistence beyond one year. However this study only examined persistence up to one year due to the limitation of data availability, especially during stressful market conditions.

This study revealed that the persistence is driven mainly by the top performers, a finding that agrees with Jagannathan, Makakhov and Norvikov (2010), as there are reversals in bottom performers in most cases. Other authors (e.g. Capocci, 2007) suggest that bad performance is more likely to persist than good performance. This is intuitive as, in general, it is easier to identify fund characteristics that result in poor performance compared to identifying the "formula" for successful stock picking. Nevertheless, if there was consistently poor performance these bottom performers would soon be out of business unless they reversed their performance. This study extended the previous knowledge so that it provided a clear distinction between the different aspects of persistence. It is known now that hedge fund performance persistence changes depending on market conditions. By introducing a new framework and the "momentrarian" trading strategy there is now a new trading strategy that can be exploited not only in the hedge fund area but in the investment in general (e.g. stock trading).

7.2.4 Hedge fund classification

7.2.4.1 Main results

The sixth chapter examined hedge fund index construction methodologies by presenting case studies from two well-known database vendors and evaluated them using numerical examples on the same dataset. The vendors use different classification techniques, however those quantitative techniques provide similar results. The differences are rather due to the use of different hedge fund universes and different inclusion criteria. I have found that the investor should worry more about different universes that database vendors use than the index construction itself.

7.2.4.2 Connection with the literature

I examined and answered the research question of why there are such large differences between hedge fund indices from different vendors, even when they are supposed to represent the same strategy. It was a surprise to me that so far no or little work has been done in this direction. Amenc and Martellini (2003) were the first who examined in a systematic way the differences between hedge fund indices and their lack of success in accurate measuring, proposing the use of index of indices. My findings showed that the differences are mainly due to the use of different datasets rather than the use of different classification techniques. Based on the new knowledge provided, researchers should pay a lot more attention to the data that they use and the classification of the hedge funds as this can lead to distortions in empirical hedge fund research. Moreover, researchers now have a deeper understanding of the index constructions methods (in practical way), not just be “consumers” of the indices provided by the database vendors. As discussed later, I provide the basis for further academic research dealing with the identification and evaluation of the “best” possible construction practices in order to benefit investors.

7.3 Knowledge contribution

In this section I discuss the contribution and implication of the above synthesis with respect the research questions and how they may encroach on existing theories or understanding.

The novelty of this PhD thesis lies in the fact that it provides the first examination of hedge funds within multiple U.S. business cycles and different market conditions, using a holistic approach, so as to have a comprehensive explanation of hedge fund performance. Furthermore, unlike many previous studies, instead of only one general commodity factor, I use several specific ones. This is essential as commodities cannot be considered to behave in the same way in the market, as proposed by Bhardwaj and Dunsby (2014). I use a commodity factor related to the agriculture/food industry that to my knowledge has not been examined before. This study uses a custom piece-wise parsimonious model which can accurately identify changes in asset and portfolio allocations per strategy within different conditions, helping investors in their decision process as it enables them to know what to expect from different strategies, especially during multiple stressful financial conditions with different attributes. In addition, I perform a systematic database merging and cleaning approach that can be used as a benchmark for future studies since this is not a trivial process.

Another novelty of this doctoral thesis is that it examines hedge funds at the fundamental level and at the mixed level in a holistic approach under both multiple business cycles and different market conditions. The hedge fund performance investigation under this approach with different aspects revealed useful findings on hedge fund behaviour. Thus investors are assisted in their investment decision processes as they now know how these different aspects are related and what to expect from hedge funds. An extension of this is the analysis of ranking favorable economic states from the most desirable state to the least desirable that gives investor a deeper understanding of the association between funds' performance, fundamental and mixed level characteristics, and market conditions.

Beyond the above, this study is significant for the literature and to investors as well concerning performance persistence and trading strategies. I have revealed aspects that have not been examined before. More specifically, for the first time, I make a clear distinction between different aspects of performance persistence and I examine each of these aspects, at strategy level, within multiple business cycles and different market conditions, as these two different states do not coincide necessarily, having different implications for hedge funds (e.g. recessions periods are, on average, fiercer in terms of hedge fund performance persistence compared with down regimes). Investors know what to foresee from different strategies in terms of performance persistence. Past performance does not guarantee the same results for the future; however, most investors in their capital allocation process rely on past performance. One more contribution is that, for the first time, I develop a framework of using zero investment trading strategies that utilize the differences in spreads between top and bottom performing hedge funds. These mixed or synthetic trading strategies can be a guide to investors allowing them for potential higher returns, outperforming market returns.

Lastly, this study contributes to the literature by filling an additional gap as, for the first time, I examine and explain the main principles and quantitative techniques used to build hedge fund indices through the use of real vendor cases. By providing a deeper understanding of how hedge fund indices and sub-indices are formed, the findings can benefit groups such as investors, database vendors and financial governance authorities.

The findings provide the basis for further academic research dealing with the identification and evaluation of the “best” possible construction practices in order to benefit investors.

7.4 Managerial implications

The findings from this thesis affect investors’ practices and policies. More specifically, concerning the third and fourth chapters, investors and fund of funds managers are helped in their investment decision process as now they know what to expect when dealing with hedge fund strategies under changing market conditions (this enables them to select hedge fund strategies that do not suffer a lot during “bad” times and select hedge fund strategies that exploit a lot the upward market movement during “good” times). However, this study assumes that investors are able (at least to some extent) to predict the next state of the market as this forecasting would be out of the scope of this Thesis. They are able to know what will be the implications on the asset and portfolio allocations of hedge funds (this enables active investors to have more risk hedging opportunities within equity and commodity asset classes in their portfolios). They have a clear understanding of the different ”forms” of changing market conditions and what are their exact implications, as growth and up regimes, recessions and down regimes do not necessarily coincide and they have different implications on hedge funds. This is because these states have different attributes and characteristics as has been already discussed. At the fundamental and mixed level, investors know also what to expect from funds with different characteristics and what is the impact of changing market conditions on funds behaviour when they take into consideration funds’ strategy and individual characteristics. They are now more conscious because, contrary to what was believed, investors may not receive what they pay for, but sometimes, they may lose money (e.g. hedge fund strategies with conditional negative excess returns). Fund administrators can benefit by applying more flexible fee policies that more accurately reflect fund managers’ performance under changing market conditions (e.g. high watermarks during “good” times) and government authorities to understand the implication of hedge fund strategies for the financial system.

Concerning the fifth chapter, investors can have a clear picture about hedge fund performance persistence and its different aspects. Now, investors are familiar with what to expect from different strategies in terms of performance persistence and although past performance is no guide to the future, still most investors in their capital allocation process rely on past performance. This study allows investors to implement mixed trading strategies utilizing spreads between top and bottom performers of different hedge fund strategies, although currently there are some constraints in implementing the short selling in hedge funds. However, these mixed trading strategies can be used in other markets as well. As with the previous cases, fund administrators can apply more appropriate and flexible fee polices by taking into consideration performance persistence. Fund managers should be rewarded for performance persistence. Last but not least, financial government authorities can benefit by better understanding of hedge funds in terms of their persistence and risks, in case there is any need for change in the legal framework or closer monitoring (e.g. monitoring of hedge funds that exhibit “unusual” persistence).

Regarding the sixth chapter that deals with hedge fund index engineering, investors now have a deeper understanding of how indices are constructed in a practical way. They may feel more confident about choosing the right index benchmark for their investments (e.g. knowing their needs, how each index is constructed and what exactly shows helps them for the “right” decision). This is important as the selection of the right benchmark is not a trivial process and may affect the asset class and portfolio allocation decisions. This study can help database vendors to construct better indices by understanding the methods of their rivals and combining new methods in their index construction methodology, by collaborating with other vendors or even specializing in certain indices. A last implication of this study would be the desirability for collaboration between financial authorities and database vendors to create a common hedge fund pool, as the differences in indices are mainly due to different hedge fund universes used by the database vendors. Moreover, most of the problems regarding the hedge fund data (e.g. fragmented datasets or different kind of biases) could be minimized.

7.5 Limitations

The main limitations of this doctoral thesis are due to the nature of the hedge fund industry heterogeneity and the problem that there is with the data, as until to date there is no universal hedge fund database. I use, as other authors, different databases, different time periods, and different methodologies. Despite these issues there are some consistent trends and patterns in hedge fund behaviour. Another limitation of this study is that it focuses on funds that invest primarily in the North America region due to the use of three U.S. business cycles. Whether similar results hold for the European and Asia-Pacific regions would be a valuable out of sample test, but the definition of business cycles in these regions may be dubious. Another limitation is the absence within my analysis of the lookback straddles that are appropriate for CTAs, due to data unavailability in the early 1990s (however in my robustness tests with post 1994 data I use these factors for comparison purposes).

Due to data unavailability (e.g. time-series of long and short position holdings or leverage ratios), leverage is not considered, though this can play a role in hedge fund performance. Another limitation is the limited validation of the yearly persistence during stressful market conditions due to the small number of observations during these conditions. Concerning the application of the proposed mixed or synthetic trading strategies, I considered in the analysis lockup redemption costs; however there might be other costs (e.g. bid-ask spreads, short-selling costs) that may affect investors' profits that are not captured. Due to the limitation of data availability, especially during stressful market conditions, I did not considered contrarian trading strategies for more than three years. Finally, another limitation regarding the hedge fund classification is that this took place on the strategy level where a more detailed analysis could be done at a hedge fund level.

A final limitation (that can be an opportunity for further research) is that the prediction of the next stage of the market is not examined in this Thesis and can be a difficult task for investors in their asset and portfolio allocation process. However once they forecast (e.g. in a probabilistic way by using currently available lead macro indicators) the next stage of the market then they can use the findings of this Thesis in their investment decision process for higher returns.

7.6 Avenues for further research

The above limitations provide opportunities for future research. More specifically, as I focused on hedge funds investing in developed markets, there is a need to examine hedge funds that invest in the emerging markets within my approach. It would be very interesting for comparison reasons to examine the differences between these broad classes of hedge funds. In addition, by having access to time-series leverage data it would be interesting to examine this aspect in hedge fund performance within my approach. There is also a need to examine the return generating mechanism within the hedge fund market microstructure. For instance, the way that the working processes in the hedge fund industry relate to transaction costs, quotes, volumes, prices and trading behavior needs to be considered. Those elements have an impact on hedge fund exposures and returns.

Another avenue for future research is the development of models for forecasting purposes using machine learning techniques. Behavioural finance and Bayesian principles would be interesting and challenging elements incorporated into these models. All these models could incorporate business cycles and different market condition sub-models for purposes of the forecasting hedge fund returns.

The trading strategy framework developed, and the introduction of the "Momentrarian" strategy which is a combination of a momentum and a contrarian strategy under different time periods, provide opportunities for further research in other markets, especially those that are dealing with systematic trading or technical analysis. This brings opportunities for researchers and practitioners to consider more sophisticated trading strategies with potential higher returns. I believe that under this framework, various trading sub-strategies could be constructed suitable for every investor operating within specific markets.

Last but not least, an avenue for further research is the investigation of classification quantitative techniques beyond those used by the database vendors. This could include the evaluation and examination of the "optimal" construction methods or practices (similar to industry standard protocols) that are suitable for the hedge fund index engineering process. This could include either evaluating currently-available indices against other benchmarks such as an index of indices or fund of funds indices, or evaluating specific quantitative techniques within the construction process according to predefined criteria.

7.7 Conclusion

The prime purpose of this PhD thesis is to understand and explain the attribution of returns of different hedge fund strategies under changing market conditions. The existing knowledge had important gaps and investors were still confused or ignorant about certain aspects of hedge fund behaviour. This confusion and ignorance was an additional burden to the general complexity that the hedge fund industry encompasses, having to do mainly with the private nature of hedge funds. This PhD thesis dealt with these gaps and has advanced the study of hedge funds having met its objectives.

I have robust findings that contribute to the theoretical knowledge having managerial implications as well. More specifically, under my holistic approach there is a clearer understanding of the relationship between hedge fund strategies' performance and changing market conditions. There is also a clear understanding of the relationship between funds' performance, hedge fund strategies, and fund specific characteristics. Persistence is examined under different aspects in a holistic approach, also developing a new framework for investment trading strategies that can be used in other areas of finance. There was also a deep investigation of the fund classification problem that accompanies the hedge fund industry. From a practical point of view, investors have a clearer understanding of specific aspects of hedge funds, they know what to foresee from different investment decisions and they can have a guide to their asset and portfolio allocation process. Fund administrators can now apply more flexible fee policies that are more accurate, reflecting fund managers' performance under changing market conditions. Financial authorities and database vendors are helped to work together so as to implement, a change in the legal framework, closer monitoring or the creation of one universal hedge fund database with the appropriate benchmark indices.

Beyond the findings that contribute to the theoretical and practical knowledge, this study opens avenues for further research. These opportunities, relate to the examination of hedge funds investing in emerging markets, the impact of the market micro-structure on hedge fund performance, the application of the mixed trading strategies in other markets, and the development of forecasting models using machine learning techniques. After having understood hedge funds' behaviour to a large extent, the next natural step (in my opinion) is to try to forecast their behaviour, providing knowledge "one step ahead" that can be better exploited by researchers and investors. Finally a promising research area is the optimization of the index construction methods, especially regarding hedge fund classification.

8 Appendices

8.1 Databases - Basic information

This thesis uses more than one database from different database vendors. In particular, I use datasets from Eurekahedge and BarclayHedge database vendors. I selected those databases because they have been used by researchers containing live and dead hedge funds with a long time coverage according to my needs. Both Eurekahedge and BarclayHedge databases contain data before 1994 which comply with my research requirements. Many database vendors (such as CISDM) provide data from 1994 and afterwards thus reducing my candidate options. The underlying databases cover the period under examination from January 1990 to March 2014. However, my specifications required coverage from January 1988 to March 2014 due to the instant bias calculations. I use a graveyard database to eliminate the survivorship bias as many funds stop reporting at some point, due to liquidation or some other reason.

Prior to merging, Eurekahedge database contained live and dead hedge funds (HF) with returns and assets under management (AUM) along with HF individual characteristics and manager details. It contained in total 13,015 hedge funds. Of these, 5,865 were considered dead funds. This database contained hedge funds and Commodity Trading Advisors (CTAs) as well. BarclayHedge database contained hedge fund information similar to the above but there were two separate datasets, one with live and another one with dead funds. The Live database contained hedge funds (only) information and counted for 3,885 funds. The BarclayHedge graveyard database contained hedge funds, Funds of Funds (FoFs), CTAs, and Multi-Asset Funds (MAFs) counting totally for 14,844 funds. Hedge funds counted 7,438 and all other types for 7,406. Overall, after the merging process, there were 31,744 (13,015+3,885+14,844) funds (of all types) with 2,418 duplicates, hence the single funds were 29,326. The overall percentage of hedge funds common between the two database vendors is 7.61% (2,418/31,744). However, it is essential to mention that the graveyard database contained FoFs, CTAs and MAFs as well, counting for 7,378 records. Hence, the actual ratio of common hedge funds (excluding the other fund types) is 9.92 % (2,418/24,366).

It is important to mention that, as with other authors (Ramadorai, 2013), I treated multiple share classes of funds as separate funds; this is to make the selection bias correction robust to the variations in liquidity restrictions, returns, and fee structures that described different share classes of the same fund. For example, different classes (or accounts) of the same hedge fund may have differences in the aggressiveness, and the fee structure or the liquidity restrictions. Even if I used the correlation technique to eliminate the second case (return variations), nevertheless there were some hedge funds with names ending LP or LTD having high correlation but different legal structures. These are issues that were taken into consideration by applying a strict fund selection process.

8.2 Database merging and cleaning processes

As I have already mentioned, I use more than one database from different database vendors. I contribute to the literature because this study is one of the few such as Patton and Ramadorai (2013), Aggarwal and Jorion (2010) or Joenvaara, Kosowski, and Tolonen, (2012) that convey a systematically merging approach that other researchers can follow. It is not trivial task to remove duplicate funds from the aggregate database due to the fact that there is no common identifier for the same hedge fund in different vendors' databases. Thus, few of the existing papers provide transparent and detailed explanations of how their database is constructed. I use a strictly systematic way according to some criteria (mentioned below) and a specific algorithm in identifying unique hedge funds.

The process and the algorithms that I followed are:

1. Database auditing: Using filters and relational logic (trying to generalize from having a mass of propositional variables to representing the same information with relations), I inspected the three datasets from the two database vendors.
2. Database pre-processing: I implemented a mapping between different database fields and I managed data in order to bring them in to the same format. These processes were concerned with transposing and reversing datasets and then consolidating them in the same file format. In the Eurekahedge database I had to split returns and AUM records so as to be compatible with the BarclayHedge format that keeps them in different work sheets.
3. Sorting-Grouping the data using "keys". The primary key was the hedge fund name; the second key was the management company and the third one the fund manager name. The combination of these three keys is mandatory as there are many funds run by the same manager company or fund manager. Also, I paid

attention to the legal structure of the fund/company name. All the above keys were parsed for punctuation, filler words or spelling errors.

4. Identifying duplicates: This process has to do with distinguishing funds that have similar names, according to the previous step, but also the same inception date. There are many cases where a fund manager may run different classes (not explicitly stated) with different inception dates. These are treated as separate funds (see the previous section about share classes).
5. The next step after identifying hedge funds having the same name and inception date is to measure correlations. There are cases where two similar funds with the same inception date appear in the dataset, and are run by the same manager having different designations such as "LP" and "Limited Partnership". In these cases, if fund returns are similar (having correlation 0.99 or higher due to reporting errors) I eliminate one of the duplicates according to the criteria mentioned below. There are a few cases where companies are set up with a master-feeder fund structure. In that case I take into consideration feeder funds with more accurate AUMs (not aggregated).
6. After having identified the duplicates, the next process is to eliminate one of them. As I merge and integrate databases from two database vendors I expect to find and examine duplicates that belong to these two different datasets. I select the fund that has the longest return track record. If the two hedge funds have the same track record, then I choose the one with the longest asset under management record (AUM). If both funds have the same AUM long record then I choose the BarclayHedge database records as it contains the most comprehensive (detailed) set of assets under management observations.

Overall, the proposed matching algorithm takes into consideration first, administrative data (e.g. hedge fund name/legal structure, management company/legal structure, manager name, inception date) and second, quantitative data (return correlations). In order to be considered as a duplicate a fund, should –simultaneously- have very similar administrative data, the same inception date and returns with 0.99 correlation or higher. If so, I proceed by eliminating one fund according to the criteria already mentioned.

I was very strict concerning the key names. If there was a major difference in name or in legal structure or domicile (e.g. LP vs LLC or offshore vs onshore) then I considered them as different funds. If there were minor differences due to spelling errors or punctuation (e.g. just a dot difference or abbreviation) then I proceed to the next step (examining inception date, correlations etc.) in order to consider whether it is a duplicate or not.

Another important matter that I examined is the issue of the *zero* or *null* values. Zero returns should reflect the accurate returns for the month. However, according to the database vendors (e.g. BarclayHedge), in some instances firms update their fund information with a zero return. In the use of the dataset I considered consecutive monthly zero returns at the start or at the end of the track record as null values. Also, in the middle of the track record, if there are more than two consecutive monthly returns equal to zero, then I consider them as null values. The same principle is applied for live and dead funds.

As I have mentioned, since I am interested in the U.S. hedge fund industry, I take into consideration hedge funds that are either based in the U.S., or outside the U.S. but investing all in the U.S. This is because of the use of multiple business cycles from the U.S. economy. Furthermore, I report CTAs (Commodity Trading Advisors) separately and I exclude from the analysis FoFs (Fund of Funds). CTAs constitute a particular category in the hedge funds industry. Some studies (e.g. Fung and Hsieh, 1997) consider them as a part of the hedge fund world, whereas others (Fung and Hsieh, 2000; Capocci and Hubner, 2004), consider them on a stand-alone basis. FoFs cause a distortion from double counting of hedge funds returns and the extra expenses due to the fact that FoFs have an extra layer of management and performance fees.

Concluding, I propose a benchmark in constructing an aggregate hedge fund database by following an approach that was based on transparent main steps that can be easily replicated even with more than two database vendors. In contrast to other studies that often describe that they "carefully" remove duplicate hedge funds without describing in detail their merging process, I detail exactly the steps and the criteria that I use in the database process. I do not take into consideration the share restriction information, the compensation structure or the strategy due to different reporting standards, the changing nature of some characteristics (for example Agarwal and Ray, 2012 document that hedge funds fees are changing), and the different strategy descriptions (no unified coding). An important issue that I am the first to take into consideration is the presence of null/zero values. Having communicated with the database vendors I applied specific criteria about when a zero reported value is actually 0% return or a null (not verified) value. This high quality, reliable hedge fund data provide extra robustness strength in this PhD thesis.

Last but not least, in the merged database, funds with correlation higher than 99% can exist. However, these funds have different administrative data (e.g. different name/legal structure) and/or different inception dates thus forming different records. These records usually represent different classes of a hedge fund kept in different accounts. Overall the proposed benchmark is a rigorous approach but an even more intense and integrated approach would require direct communication with the fund managers about the underlying issues that I mentioned before. Nevertheless, this would be an inefficient process because it would require a considerable amount of resources and time.

8.3 Hedge fund selection

In the consolidated hedge fund database, BarclayHedge's records contain different types of funds -live and dead- such as hedge funds, fund of funds, CTAs (within the graveyard DB), Multi-Asset Funds and with *Fund_Reporting_Style* equal to "Net All Fees" or "Gross" or "Net Mgt", or "Blank" that invest in one or many regions; Eurekahedge's records contain -live and dead- hedge fund type of fund, "Net All Fees" that invest also to many regions.

I examine hedge funds that focus on the North America region as I use multiple business cycles from the U.S economy. Thus, the "select" statements were based on transparent and strict criteria to avoid biases. For BarclayHedge's records, I selected those funds that had *Fund_Type* equal to "hedge funds"; they had as a *Fund_Reporting_Style* equal to "Net All Fees" and as *Fund_Geographical_Focus* equal to "North America" region and/or "Global" (but with exposures to North America – as it is denoted by another field *Fund_Exposure_North_America* with at least 50 percent exposure). For the Eurekahedge records I selected those funds with a *Geographical Mandate* equal to "Canada" and/or "North America". I also selected those funds with *Geographical Mandate* equal to "Global" but having "USA" and/or "Canada" and/or "North America" of the *Country_Focus* to the field (with at least 50 percent exposure). Due to the fact that all this fund-specific information (as with other data described later) was residing in different sheets than the "Performance All" and "AUM All" sheets, I used V-Lookup Excel conditional functions so as to find the appropriate hedge funds from these sheets and to align them with the relevant attribute data. The *key* was the *HF id*. As I have previously mentioned, multiple share classes of funds were treated as separate funds. I proceed to this so as to eliminate selection bias due to different liquidity restrictions (lockups periods), legal structure, fee structures, and returns that characterize different share classes of the same fund. This is something that has also been done by other authors such Ramadorai (2012, 2013). In the dataset I included CTAs from the EurekaHedge database because it contains live and dead CTAs. I did not select CTAs from the BarclayHedge database as my sample would be downwardly biased (there were CTAs only in the graveyard database).

8.4 Managing outliers

An important issue is the management of outliers that can affect models' results. This research is one of the few in the literature that deals with outliers in a systematic way (and not simply excluding those records above e.g. 50% on monthly basis). I used a "winsorized" technique (such as Ramadorai, 2012) and I ranked hedge funds returns (for every month) having percentiles (null values were excluded). Then these returns (extreme outliers) that were below to 0.5% were assigned value equal to that presented in the 0.5% percentile. Returns above 99.5% were assigned value equal to that represented in the 99.5% percentile. By applying this technique I did not lose information by eliminating the outliers (also making the time series non-continuous). Another typical technique such as excluding values more than 3 standard scores of *z* or standard deviations away from the mean, is not sufficient because hedge funds are skewed, as reported in the literature (e.g. Brooks and Kat, 2002) and verified by this study in this appendix.

8.5 Bias calculations

In general, hedge fund studies are subject to potential data biases. Briefly speaking, there are three kinds of biases: Self-selection/natural biases, instant history, and survivorship biases. Biases can affect performance results upwards; this is an issue that it is taken into consideration. Regarding the first bias, I did not limit this study to only one database vendor; concerning the second, I eliminated returns at the beginning of the lifetime of hedge funds; for the third bias I also took into consideration "dead" hedge funds. In Table 61, I present the results concerning the instant history and survivorship bias in the used dataset. The average monthly instant history bias for 12 months is 0.104

or 1.2% on average yearly basis. The average monthly instant history bias for 24 months is 0.167 or 2.0% on average yearly basis. Hence, my estimation of biases lies between 1.2% and 2.0%. This is close to the 1.4% of Fung and Hsieh (2000), and the 1.7% of Bali, Brown and Caglayan (2011). Regarding the survivorship biases there is an average monthly bias of 0.178 for all funds or 2.1% on yearly basis. This is close to the range of 2.2% to 2.4% (Liang, 2000, 2001), and 1.7% (Bali, Brown, and Caglayan, 2011). Any differences are attributed to the different datasets and periods under examinations by the authors.

Table 61. Instant History and Survivorship Biases

This table shows the mean-return biases, instant history for 12 and 24 months, and the survivorship biases between live and dead/live funds (monthly data). These figures are average monthly percentage rates.

	Average Return		
Total Funds (records): 6,373	Live & Dead (4,048)	Only Live (2,325)	Difference: Live & Dead - Live
All returns	1.101	1.279	-0.178
All minus first 12 months	0.997	1.201	-0.204
Diff. b/n All returns and returns without the first 12 months	0.104	0.078	
All minus first 24 months	0.934	1.134	-0.200
Diff. b/n All returns and returns without the first 12 months	0.167	0.145	

Table 62 presents the median monthly return instant history and survivorship biases. The average monthly instant history bias for 12 months is 0.079 or 0.95 % on average yearly basis. The average monthly instant history bias for 24 months is 0.127 or 1.5% on average yearly basis. Regarding the survivorship biases there is an average monthly bias of 0.171 for all funds or 2.1% on average yearly basis.

Table 62. Instant History and Survivorship Biases

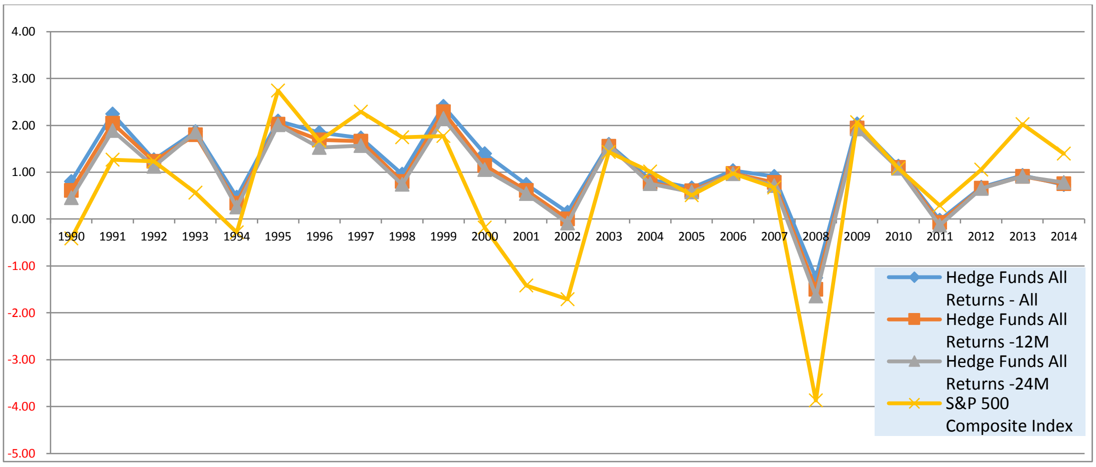
This table shows the median-return biases, instant history for 12 and 24 months and the survivorship biases between live and dead/live funds (monthly data). These figures are average monthly percentage rates.

	Median Return		
	Live & Dead	Only Live	Difference: Live & Dead - Live
All returns	1.221	1.392	-0.171
All minus first 12 months	1.142	1.350	-0.208
Diff. b/n All returns and returns without the first 12 months	0.079	0.042	
All minus first 24 months	1.094	1.225	-0.131
Diff. b/n All returns and returns without the first 12 months	0.127	0.167	

I eliminated the survivorship bias by taking into consideration live and dead funds. It is essential to mention that the word "dead" is misleading because it includes funds that are liquidated, merged/restructured, and funds that ceased reporting returns to the database vendors but may have continued operations. However, in order to be consistent, I call them "dead funds". I minimize the instant history bias by excluding the first 12 months of the dataset. Some authors (e.g. Bali, Brown, and Caglayan, 2011 or Ibbotson, Chen, and Zhu, 2011) exclude the first 12 months of returns; others like such as Ackerman, McEnnally, and Ravensceaft, (1999) exclude the first 24 or more months of returns. Others (e.g. Joenvara, Kosowski, and Tolonen, 2012) exclude the first 32 – as the average of the inception date and the date added to the database(s). In the dataset used I did not have all this information.

The annual median life of a hedge fund is almost 5.5 years which is similar to Gregoriou (2002). If I exclude 24 or more months of hedge funds returns then I lose too much information (approx. 35% of the data). This also leads to another source of biases: the truncated database bias. In Figure 13, I provide the yearly returns (all, minus 12, minus 24 months) against the S&P 500 market index. The variance for monthly returns for all hedge funds is 3.46 (or standard deviation 1.86) whereas for the S&P 500 composite index it is 22.66 (or standard deviation 4.76) (however, their difference is weakly significant – 10% significant using a t-stat two tailed test). Furthermore, as it is observed in Figure 13, the difference becomes significant during market busts such as in 2000-2001 and 2008. The market index performs much worse compared to hedge funds.

Figure 13. Hedge Fund and Market Returns



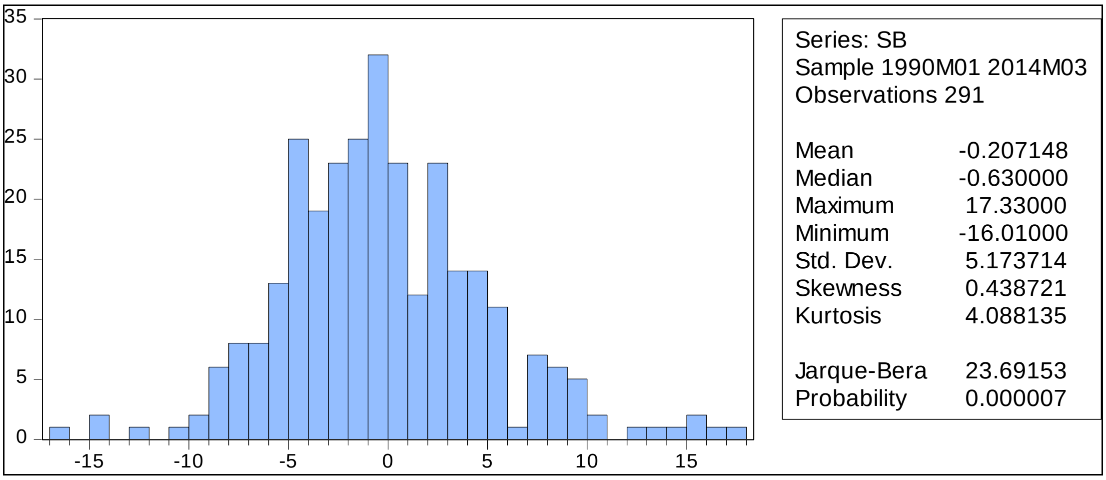
Average Hedge Fund Returns against S&P 500 Composite Index (annualized returns)

8.6 Basic statistics on fund strategies

In this appendix I provide some descriptive statistics (Figures 14 to 23) for each of the 11 representative hedge fund strategies. These are excess risk-free monthly returns (%). Most hedge fund strategies are negatively skewed except for the Short Bias, Others, Global Market, and CTA strategies. All hedge fund strategies have high kurtosis compared to that of a standard normal distribution except for Global Macro, and Market Neutral strategies that have 3.731 and 4.723 respectively. Hedge funds data are non-normal; an issue that is shared by many other authors as well. However the large number of observations do not affect the significance of the tests.

In Figure 14, the Short Bias strategy delivers a mean monthly return equal to -0.207% (0.05% for absolute returns) with standard deviation 5.174 (5.197 for absolute returns). Skewness is equal to 0.439 (0.481 for absolute returns) and kurtosis is equal to 4.088 (1.118 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 14. Short Bias Strategy



Descriptive Statistics RF Returns

In Figure 15, the Long Only strategy delivers mean monthly return equal to 0.739% (0.999% for absolute returns) with standard deviation 3.451 (3.437 for absolute returns). Skewness is equal to -1.088 (-1.089 for absolute returns) and kurtosis is equal to 6.009 (for 3.092 absolute returns). Using the Jarque-Bera test and having P < 0.01, I reject the null hypothesis that the distribution is normal.

Figure 15. Long Only Strategy

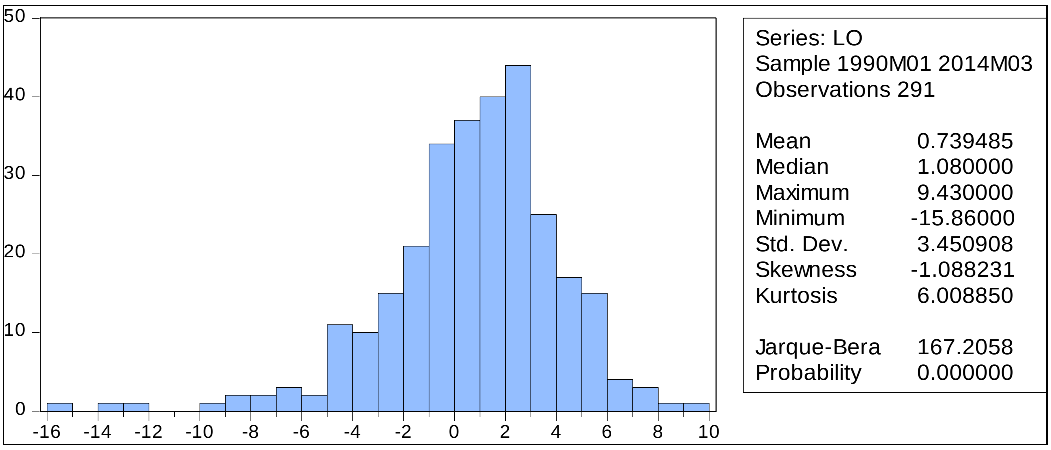


Figure 15: Descriptive Statistics of RF Returns

In Figure 16, the Sector strategy delivers mean monthly return equal to 0.891% (1.151% for absolute returns) with standard deviation 3.245 (3.259 for absolute returns). Skewness is equal to -0.628 (-0.568 for absolute returns) and kurtosis is equal to 5.103 (2.094 for absolute returns). Using the Jarque-Bera test and having P < 0.01, I reject the null hypothesis that the distribution is normal.

Figure 16. Sector Strategy

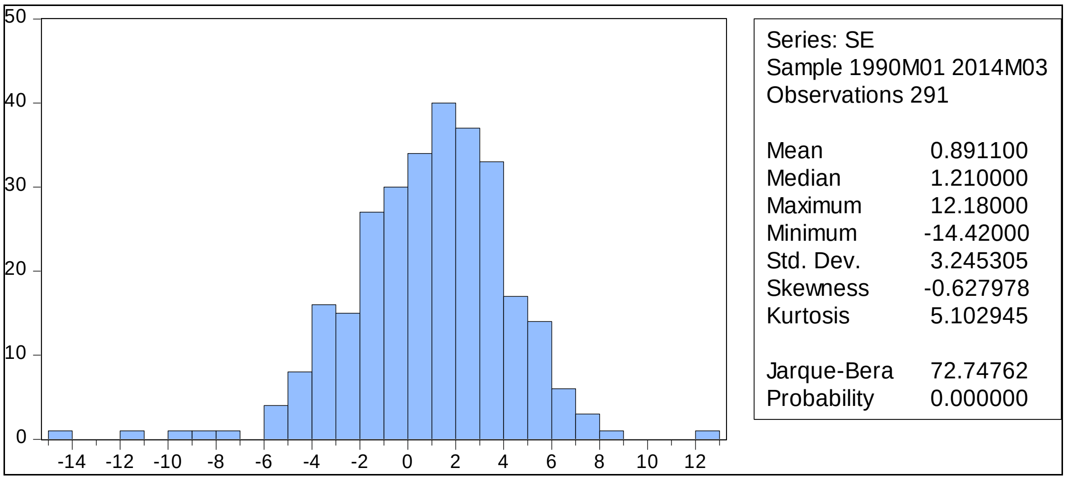


Figure 16: Descriptive Statistics of RF Returns

In Figure 17, the Long Short strategy delivers mean monthly return equal to 0.765% (1.125% for absolute returns) with standard deviation 2.650 (2.663 for absolute returns). Skewness is equal to -0.388 (-0.343 for absolute returns) and kurtosis is equal to 4.097 (1.135 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 17. Long Short Strategy

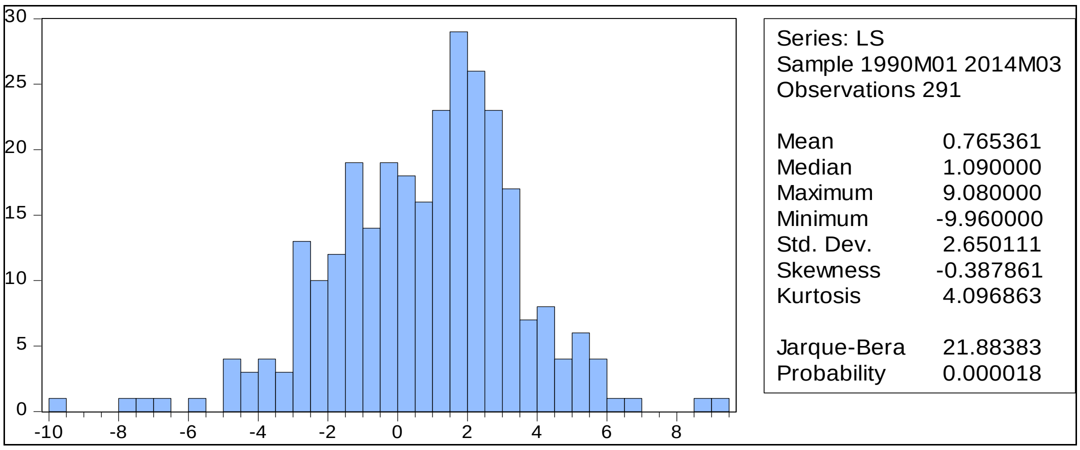


Figure 17: Descriptive Statistics of RF Returns

In Figure 18, the Event Driven strategy delivers mean monthly return equal to 0.777% (0.937% for absolute returns) with standard deviation 1.840 (1.839 for absolute returns). Skewness is equal to -1.378 (-1.475 for absolute returns) and kurtosis is equal to 8.888 (6.148 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 18. Event Driven Strategy

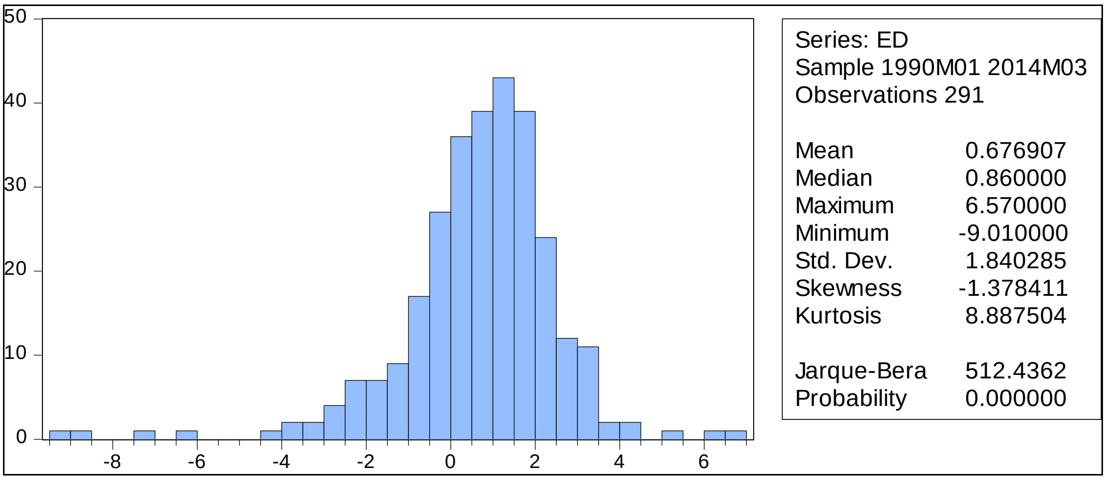


Figure 18: Descriptive Statistics of RF Returns

In Figure 19, Multi strategy delivers mean monthly return equal to 0.802 (1.062 for absolute returns) with standard deviation 1.696 (1.713 for absolute returns). Skewness is equal to -0.443 (-0.414 for absolute returns) and kurtosis is equal to 5.896 (2.977 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 19. Multi Strategy

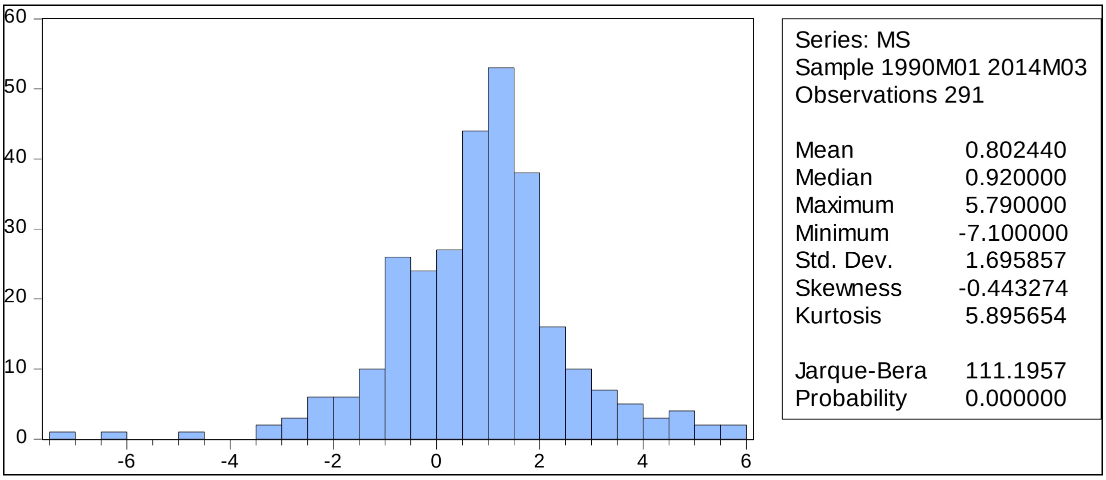


Figure 19: Descriptive Statistics of RF Returns

In Figure 20, the Others strategy delivers mean monthly return equal to 0.831% (1.349% for absolute returns) with standard deviation 1.321 (1.091 for absolute returns). Skewness is equal to 0.151 (0.202 for absolute returns) and kurtosis is equal to 4.489 (1.728 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 20. Others Strategy

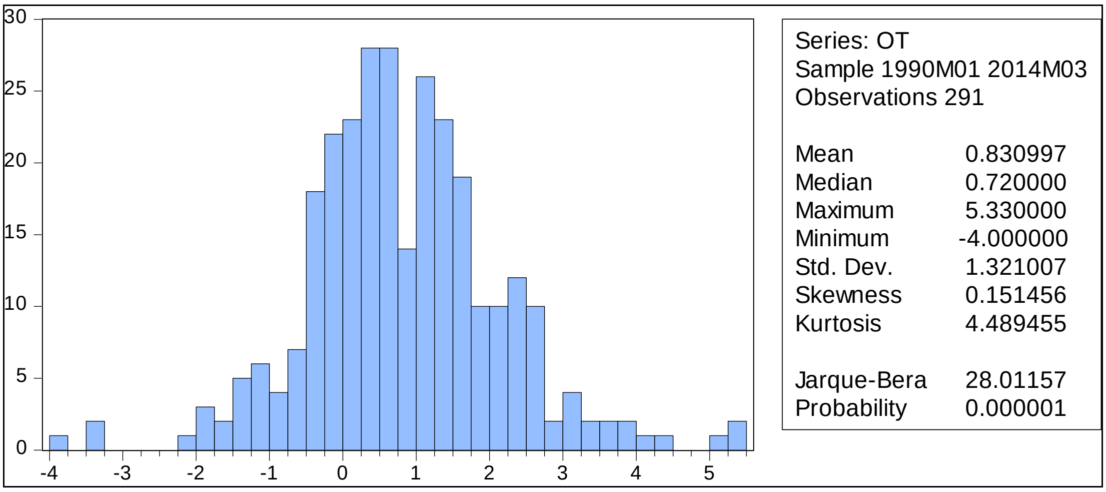


Figure 20: Descriptive Statistics of RF Returns

In Figure 21, the Global Macro strategy delivers mean monthly return equal to 0.674% (0.934% for absolute returns) with standard deviation 2.000 (2.017 for absolute returns). Skewness is equal to 0.471 (0.539 for absolute returns) and kurtosis is equal to 3.732 (0.734 for absolute returns). Using the Jarque-Bera test and having P < 0.01, I reject the null hypothesis that the distribution is normal.

Figure 21. Global Macro Strategy

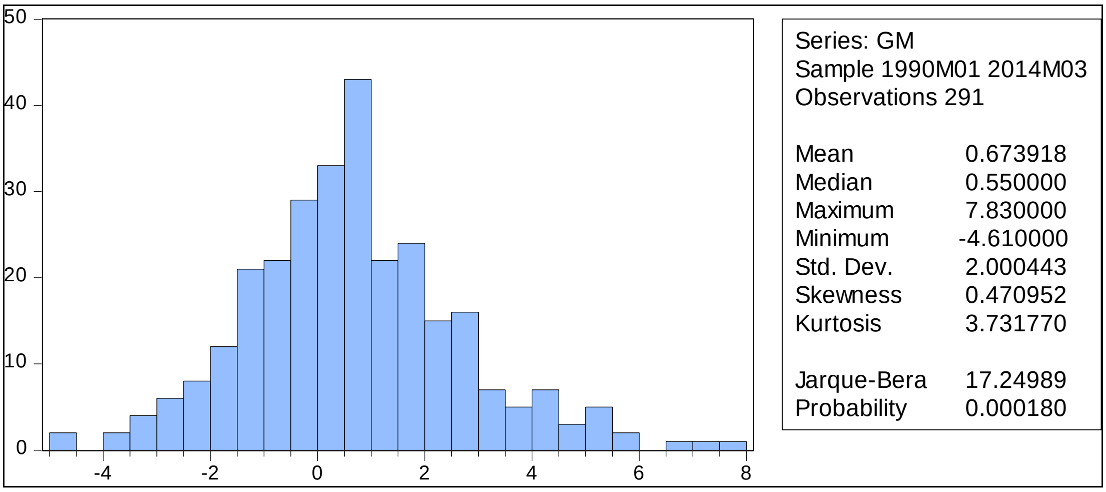


Figure 21: Descriptive Statistics of RF Returns

In Figure 22, the Relative Value strategy delivers mean monthly return equal to 0.561% (0.821% for absolute returns) with standard deviation 1.250 (1.238 for absolute returns). Skewness is equal to -1.711 (-1.728 for absolute returns) and kurtosis is equal to 11.198 (9.084 for absolute returns). Using the Jarque-Bera test and having P < 0.01, I reject the null hypothesis that the distribution is normal.

Figure 22. Relative Value Strategy

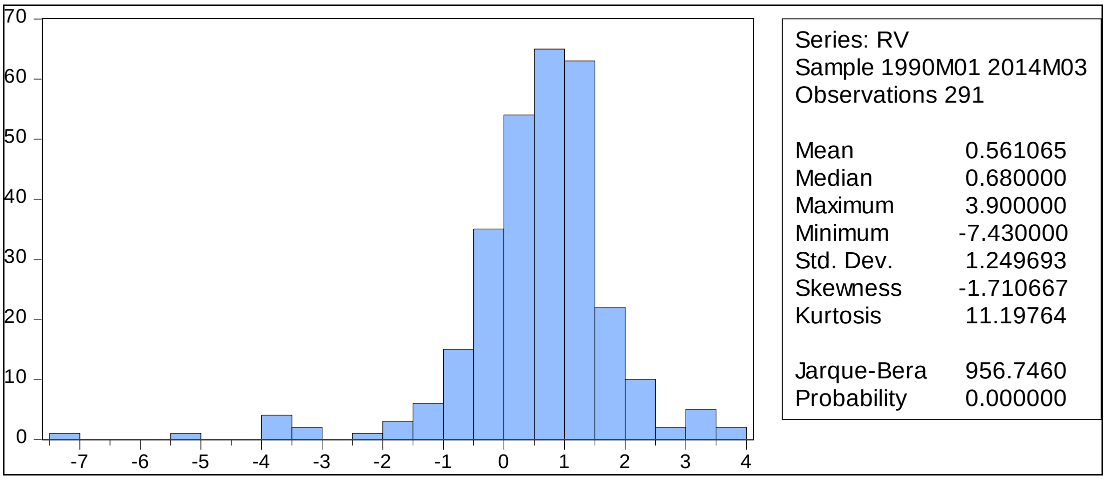


Figure 22: Descriptive Statistics of RF Returns

In Figure 23, the Market Neutral strategy delivers mean monthly return equal to 0.267% (0.525% for absolute returns) with standard deviation 0.845 (0.874 for absolute returns). Skewness is equal to -0.467 (-0.220 for absolute returns) and kurtosis is equal to 4.723 (1.361 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 23. Market Neutral Strategy

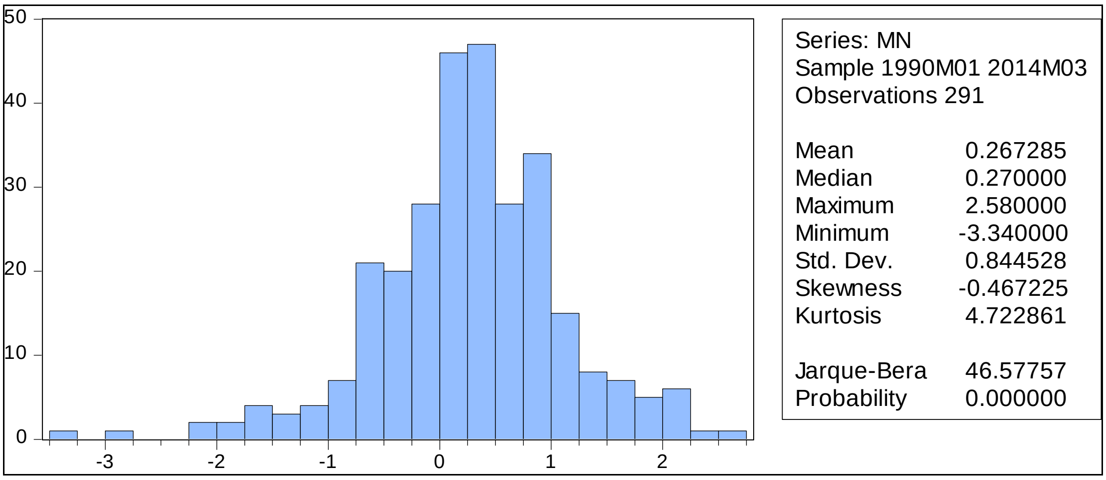


Figure 23: Descriptive Statistics of RF Returns

In Figure 24, the CTA strategy delivers mean monthly return equal to 0.924% (1.184% for absolute returns) with standard deviation 3.399 (3.415 for absolute returns). Skewness is equal to 1.191 (1.263 for absolute returns) and kurtosis is equal to 10.319 (7.442 for absolute returns). Using the Jarque-Bera test and having $P < 0.01$, I reject the null hypothesis that the distribution is normal.

Figure 24. CTA Strategy

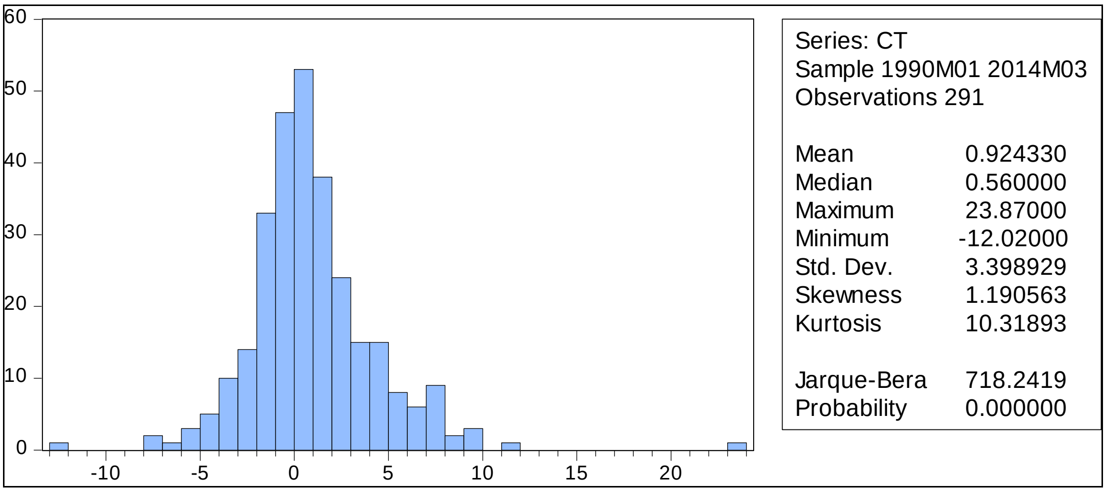


Figure 24: Descriptive Statistics of RF Returns

8.7 *Four factor (Carhart) model*

In this section I briefly present the results for the robustness tests concerning the Carhart model that includes the market factor, the size factor, the book-to-market factor, and the momentum factor. Table 63 presents the results for the growth/recessions and Table 64 presents the results for up/down regimes. For both tables all the regressors have the same sign with the proposed model and most are statistical significant. Moreover the average adjusted R squared is 0.53 which is lower than the proposed model.

Table 63. Carhart's Model Results - Growth/Recessions

This table shows the results of the Carhart model for growth (G) and recession (R) periods. The market index used is the Wilshire 5000 TRI including dividends (excess risk free returns). The risk free return is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates). Hedge funds returns are raw returns minus the risk free return. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. The left hand columns contain more directional strategies (Short Bias is extremely directional) and as I move to the right I get more strategies that are more non-directional (CTA strategy is extremely non-directional). For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent Variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTA
C (G) (excess return)	0.6236**	0.2963**	0.4255**	0.3518**	0.4994	0.6468**	0.6905**	0.4516**	0.4757**	0.1744**	0.8389**
C (R) (excess return)	-0.4160	-0.5555	0.4834	0.2213	-0.0816	0.4029	0.6076*	0.5782	0.2608	0.0635	0.7416
MAI (G)	-0.9657**	0.6783**	0.6145**	0.5391**	0.3042**	0.2252**	0.1941**	0.2457**	0.1492**	0.0721**	0.0271
MAI (R)	-0.9854**	0.6799**	0.6334**	0.4925**	0.3309**	0.2950**	0.1830**	0.0033	0.2787**	0.0165	-0.1033
SMB (G)	-0.2368**	0.2547**	0.1660**	0.1901**	0.1632**	0.0897**	-0.0225	0.0603	0.0806**	0.0090	-0.0376
SMB (R)	-0.3095	0.3565*	0.0024	0.1391	0.0019	-0.0328	0.0275	-0.0367	0.1182	-0.0756	-0.0111
HML (G)	-0.0027	0.2145**	0.0248	0.0745**	0.1774**	0.0617*	-0.0109	-0.0160	0.0708**	0.0208	-0.0210
HML (R)	0.2556	-0.1556	-0.3758**	-0.1739*	-0.0404	-0.1985*	-0.0385	-0.0738	-0.1213	-0.0696	-0.0039
MOM (G)	-0.1915**	0.0478*	0.1243**	0.1052**	-0.0035	0.0495**	0.0449**	0.0574*	0.0013	0.0781	0.1069
MOM (R)	-0.0715	-0.0094	0.0322	0.0294	-0.0306	0.0147	-0.0039	-0.0435	0.0159	0.0333	0.0143
Adj. R-squared (G)	0.6758	0.8222	0.6883	0.7987	0.6687	0.3521	0.3710	0.2484	0.4264	0.2483	0.0036
Adj. R-squared (R)	0.8118	0.8567	0.8227	0.8444	0.5203	0.4631	0.4893	0.0494	0.0494	0.0744	0.0789
Prob (F-stat) (G)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2974
Prob (F-stat) (R)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0001	0.8232	0.0000	0.1855	0.6513

Table 64. Carhart's Model Results - Up/Down Regimes

This table shows the results of the Carhart model for up (U) and down (D) regimes. The market index used is the Wilshire 5000 TRI including dividends (excess risk free returns). The risk free return is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates). Hedge funds returns are raw returns minus the risk free return. * denotes significance at $P < 0.1$, ** denotes significance at $P < 0.05$, and *** denotes significance at $P<0.01$. The left hand columns contain more directional strategies (Short Bias is extremely directional) and as I move to the right I get more strategies that are more non-directional (CTA strategy is extremely non-directional). For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant ($P<0.05$) and strongly significant ($P<0.01$) results. In the appendix I present weakly significant results ($P<0.1$) for demonstration purposes only.

Dependent Variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTA
C (U) (excess return)	0.5553**	0.2954**	0.4762**	0.3562**	0.4879**	0.6445**	0.6921**	0.4086**	0.4931**	0.1526**	0.7740*
C (D) (excess return)	0.5109	-0.4054	0.3067	0.0287	-0.0821	0.5916	0.8222**	0.8578**	0.1280	0.1963	0.8077
MAI (U)	-1.0175**	0.6792**	0.6146**	0.5504**	0.3067**	0.2287**	0.1941**	0.2394**	0.1591**	0.0744**	0.0540
MAI (D)	-0.8181**	0.6361**	0.6001**	0.4267**	0.2799**	0.2551**	0.2330**	0.1030*	0.1844**	0.0412	-0.1228
SMB (U)	-0.2587**	0.2641**	0.1802**	0.1887**	0.1687**	0.1005**	-0.0175	0.0611	0.0833**	0.0094	-0.0479
SMB (D)	-0.2831*	0.4183**	0.1801*	0.2309**	0.1216	0.0384	0.0342	-0.0071	0.1746	-0.0080	-0.0049
HML (U)	-0.0296	0.2470**	0.0812	0.0837**	0.1980**	0.0891**	0.0149	0.0080	0.0819**	0.0390*	-0.0247
HML (D)	0.1275	0.0263	-0.2653**	-0.0389	0.0571	-0.0712	-0.0683	-0.1464**	0.0071	-0.0772**	0.0062
MOM (U)	-0.1500**	0.0607**	0.1278**	0.1032**	0.0032	0.0587**	0.0374**	0.0637*	0.0058	0.0764**	0.0881
MOM (D)	-0.0928	0.0556	0.1410*	0.0656	0.0266	0.0415	0.0520	0.0189	0.0102	0.0967**	0.0326
Adj.R-squared (U)	0.6629	0.8108	0.6635	0.7834	0.6403	0.3353	0.3340	0.2034	0.4330	0.2239	0.0026
Adj.R-squared (D)	0.7839	0.8057	0.8264	0.8294	0.4111	0.3733	0.5235	0.3152	0.3682	0.3493	0.0012
Prob (F-stat) (U)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3274
Prob (F-stat) (D)	0.0000	0.0000	0.0000	0.0000	0.0004	0.0009	0.0000	0.0031	0.001	0.0015	0.4169

8.8 The custom proposed model (at strategy level) omitting pre-1994 data

Despite the fact that the used dataset contains dead funds prior to 1994, I the repeated the analysis omitting pre-1994 data. Tables 65 and 66 shows the results. The regressors have the same sign and most are statistically significant. The results still hold as most hedge fund strategies deliver significant alphas to investors during "good" times. On the contrary, during "bad" times investors do not get significant alphas as hedge fund managers focus on how to minimize their systematic risks.

Table 65. Multi-Factor Model during Growth/Recessions Periods (post-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model for growth (G) and recession (R) periods after omitting pre-1994 data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global	Relative	Market	CTA
C (G) (excess return)	0.6659***	0.2789***	1.2117***	1.3352***	0.4453***	0.8925***	1.2731***	0.1753*	0.3119***	0.5331***	0.7018***
C (R) (excess return)	0.0281	0.1974	0.3261	0.2958	0.2244	0.2684	1.7623*	-0.5661	0.4098	0.1981	0.7724*
MAI (G)	-0.8611***	0.6645***	0.5849***	0.5177***	0.3169***	0.2123***	0.2104***	0.3297***	0.1408***	0.0706***	
MAI (R)	-0.8565***	0.6398***	0.4955***	0.4270***	0.2882***				0.2469***		-0.1324*
MOM (G)	-0.1853***	0.0460**	0.0939***	0.0830***		0.0169	0.0496***			0.0639***	0.0666
MOM (R)										0.0491**	
SMB (G)	-0.2194***	0.2052***	0.1120***	0.1797***	0.1507***	0.0719***			0.0571***		
SMB (R)		0.2513*					0.1672**				
GEMI (G)	-0.0866						0.0282				
GEMI (R)							0.1429***				
COIM (G)	0.0173										
COIM (R)					0.1289**	0.1142***		-0.0404			
HML (G)		0.1557***		0.0637**	0.1671***	0.0759***			0.0548***		
HML (R)			-0.3404***	-0.1636**							
COEN (G)		0.0301***	0.0504***	0.0402***							
COEN (R)	0.0751**						0.0114	0.0217			0.0785*
COPM (G)			0.0742***	0.0318*		0.0387***		0.1004***			
COPM (R)											

Table 65. Multi-Factor Model during Growth/Recessions Periods (post-1994 period) (continued)

DEF (G)			-1.0543**	-0.7503**		-0.4416*	-0.7093***			-0.3640**	
DEF (R)											
TERM (G)				-0.2200***					0.0894**		
TERM (R)							-0.5686	0.6073*			
RLE (G)							-0.0329**				
RLE (R)											
DVIX (G)								0.0283***			
DVIX (R)						-0.0566***					
EXCH (G)											-0.3176**
EXCH (R)											
COAG (G)											
COAG (R)		0.0963**	0.1501***	0.0775**				0.1414***		0.0628***	
Adj.R-squared	0.7414	0.8550	0.7422	0.8236	0.6968	0.5275	0.5220	0.3840	0.4258	0.2740	0.0294
Adj.R-squared	0.9116	0.8908	0.8728	0.8708	0.6265	0.6220	0.7085	0.5414	0.4979	0.3247	0.1009
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0153
Prob (F-stat) (R)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000	0.0042	0.1128

Table 66. Multi-Factor Model during Up/Down Regimes (post-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model for up (U) and down (D) regimes after omitting pre-1994 data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent	Short Bias	Long	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative	Market	CTA
C (U) (excess return)	0.6636***	0.2677***	0.2903**	0.5747***	0.4466***	0.4912***	1.1139***	0.1148	-0.2027	0.1932***	0.6762***
C (D) (excess return)	-0.0068	0.0715	0.5159	0.0813	0.3109	0.5685*	0.6578***	0.6768***	0.4808*	0.1066	0.6890
MAI (U)	-0.8739***	0.6728***	0.5736***	0.5845***	0.2364***	0.2205***	0.2129***	0.3424***	0.1408***	0.0827***	
MAI (D)	-0.8093**	0.5611***	0.4880***	0.2746***	0.1677***		0.2026***	0.1144***			-0.1308*
SMB (U)	-0.2158***	0.2062***	0.0883***	0.1676***	0.1480***	0.0614***			0.0481***		
SMB (D)		0.2857***		0.1702***					0.1051*		
MOM (U)	-0.1550***	0.0425**	0.0958***	0.0842***		0.0273**		0.0383*	0.0172	0.0622***	
MOM (D)										0.0706***	
COIM (U)	0.0122										
COIM (D)					0.1932***	0.1188**			0.1716***		
GEMI (U)	-0.0914				0.0960***		0.0302				
GEMI (D)						0.0691					
HML (U)		0.1722***		0.0839***	0.1644***	0.0937***			0.0615***	0.0399**	
HML (D)			-0.2182***					-0.1236***		-0.0634**	
COEN (U)		0.0375***	0.0588***	0.0554***	0.0171**			0.0372***			
COEN (D)	0.0386			0.0350*				-0.0140			0.0296
COPM (U)			0.0838***			0.0412***		0.1069***			0.1337***
COPM (D)											

Table 66. Multi-Factor Model during Up/Down Regimes (post-1994 period) (continued)

TERM (U)				-0.2362***					0.0770*		
TERM (D)											
DVIX (U)				0.0172***				0.0368***			
DVIX (D)				-0.0311**		-0.0358**			-0.0247**		
DEF (U)							-0.4905**		0.5815***		
DEF (D)											
RLE (U)							-0.0360**				
RLE (D)											
COAG (U)											
COAG (D)		0.0957*	0.1171**							0.0487***	
EXCH (U)											
EXCH (D)							-0.1768*				
Adj.R-squared	0.7301	0.8487	0.7235	0.8148	0.7090	0.5184	0.4653	0.4235	0.4666	0.2726	0.0493
Adj.R-squared	0.8533	0.8587	0.8239	0.8552	0.5826	0.6203	0.6534	0.6832	0.6632	0.4481	0.0388
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0007
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.2141

8.9 The custom proposed model (at strategy level) with pre-1994 only data (Growth/Up)

In this appendix I implement again the proposed model by using pre-1994 data. Table 67 shows the results for the growth and up regimes. I did not implement the proposed model for recessions and down regimes as there were only 8 and 4 monthly observations, respectively. Overall there are the same qualitative results.

Table 67. Multi-Factor Model During Growth/Recessions Periods (pre-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model for growth and up regimes using pre-1994 only data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent	Short Bias	Long Only	Sector	Long Short	Event	Multi Strategy	Others	Global	Relative	Market	CTAs
C (G) (excess return)	-0.0617	0.2490	4.3993*	1.4414	0.7424**	7.9880**	3.2642	1.3176**	-0.2172	0.8826	0.8935
C (U) (excess return)	0.0123	0.0277	1.0792**	0.3720	0.6931**	1.1483**	1.6331	1.1150*	-1.0674	-0.0251	1.6114
MAI (G)	-1.3092**	0.7957**	0.7569	0.6224**	0.2179**	0.2103*	0.0006	0.1812	0.1997**	-0.0616	
MAI (U)	-1.3779**	0.6787**	0.6937**	0.5345**	0.1827**	0.2286*	-0.0298	0.0003	0.2034**	-0.0447	
MOM (G)	0.1654	-0.0903	-0.0059	0.0427		0.2994*	-0.0271			0.3395**	0.6938*
MOM (U)	0.1708	0.0749	0.0641	0.0925*		0.3370**		0.1887	0.0389	0.2665**	
SMB (G)	-0.5409*	0.5558**	0.5844**	0.4152**	0.2303**	0.2352			0.2148**		
SMB (UP)	-0.5724*	0.5371**	0.5328**	0.4192**	0.1874**	0.2792*			0.2298**		
GEMI (G)	-0.2561						0.1171*				
GEMI (U)	-0.2306				-0.0036		0.1369**				
COIM (G)	0.3979**										
COIM (U)	0.3698**										
HML (G)		0.4839**		0.0249	0.2173**	-0.1373			0.0895		
HML (U)		0.4896**		0.0039	0.2198**	-0.0786			0.1012*	-0.0628	
COEN (G)		-0.0366	0.087	0.0032							
COEN (U)		-0.0152	0.0582	-0.0024	0.0114			0.0466			
COPM (G)			0.1111	0.0534*		0.1371		0.0185			
COPM (U)			0.0948			0.1553		0.0189			0.2095
DEF (G)			-3.8958	-0.7728		-8.0536**	-2.5721			-1.2715	
DEF (D)							-0.6035		1.1674		
TERM (G)				-0.1144					0.2988*		
TERM (U)				0.031					0.2519		
RLE (G)							-0.0225				
RLE (U)							0.0324				
DVIX (G)								-0.0127			
DVIX (U)				-0.0114				-0.046			
EXCH (G)											-0.5978
EXCH (U)											

Table 67. Multi-Factor Model During Growth/Recessions Periods (pre-1994 period) (continued)

Adj.R-squared	0.7032	0.7972	0.7686	0.9404	0.5277	0.4602	0.1566	0.0123	0.6915	0.5595	0.1086
Adj.R-squared	0.7257	0.7460	0.7497	0.9239	0.4047	0.3354	0.2134	0.0355	0.6584	0.4267	0.0190
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0534	0.3378	0.0000	0.0000	0.0450
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0001	0.0008	0.0091	0.2777	0.0000	0.0000	0.3727

8.10 CTA post 1994 period

Table 68 presents the results for the post 1994 period using straddles on bonds, currencies, commodities, short term interest rates and stock indices. As well as the lookback straddles, it can be seen that COAG, COEN, and COIM were significant for this hedge fund strategy.

Table 68. CTA strategy using straddles (post-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model for growth, recessions, up and down regimes periods for the CTA strategy using post-1994 only data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). I applied my proposed model and, also including straddles on bonds, currency, commodity, short term interest rate term, and stock index (Fung and Hsieh, 2001). PTFSBD: Return of PTFS Bond lookback straddle, PTFSFX: Return of PTFS Currency Lookback Straddle, PTFSCOM: Return of PTFS Commodity Lookback Straddle, PTFSIR: Return of PTFS Short Term Interest Rate Lookback Straddle, PTFSSTK: Return of PTFS Stock Index Lookback Straddle. COEN, COIM, COAG are excess RF returns.

Growth					**Up**				
Variable	Coefficient	Std. Error	t-Statistic	Prob	Variable	Coefficient	Std. Error	t-Statistic	Prob
C	0.7885	0.1674	4.7115	0.0000	C	0.7395	0.1692	4.3709	0.0000
PTFSCOM	0.0494	0.0127	3.8735	0.0001	PTFSCOM	0.0530	0.0124	4.2772	0.0000
PTFSFX	0.0387	0.0095	4.0560	0.0001	COEN	0.0599	0.0203	2.9538	0.0035
COIM	0.1057	0.0316	3.3429	0.0010	PTFSFX	0.0343	0.0096	3.5823	0.0004
COEN	0.0597	0.0206	2.9036	0.0041	COIM	0.1011	0.0300	3.3710	0.0009
PTFSBD	0.0307	0.0116	2.6472	0.0087	PTFSBD	0.0368	0.0125	2.9365	0.0037
					DVIX	-0.0208	0.0101	-2.0465	0.0420
Adj.R-squared	0.2676				Adj.R-squared	0.3009			
F-statistic	16.7816				F-statistic	16.0641			
Prob (F-statistic)	0.0000				Prob (F-statistic)	0.0000			

Recession					**Down**				
Variable	Coefficient	Std. Error	t-Statistic	Prob	Variable	Coefficient	Std. Error	t-Statistic	Prob
C	0.8321	0.3763	2.2116	0.0372					
PTFSCOM	0.0607	0.0218	2.7904	0.0104	C	1.0397	0.4344	2.3935	0.0229
COAG	0.1117	0.0434	2.5748	0.0169					
Adj.R-squared	0.3149				Adj.R-squared	0.0000			
F-statistic	6.7465				F-statistic	-			
Prob (F-statistic)	0.0049				Prob (F-statistic)	-			

8.11 HAC/Newey-West Estimator – Strategy Level

I tested the proposed mutifactor model by using the HAC/Newey-West estimator to deal with any unknown residual autocorrelation and heteroscedasticity. The results still valid as almost all the regressors are significant different from zero. Table 69 presents the results for growth/recessions and Table 70 shows the results for up/down regimes.

Table 69. Multi-Factor Model During Growth/Recessions Periods (HAC/Newey-West estimator)

This table shows the results in terms of alphas and exposures of my multi-factor model for growth and recession periods from 01/1990 to 03/2014. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration only purposes.

Dependent	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi	Others	Global Macro	Relative	Market	CTA
C (G)	0.5741***	0.2903***	1.5764***	1.4655***	0.4965***	1.4297***	1.4816***	0.3725***	0.2545**	0.5242***	0.8174***
C (R)	-0.4633	-0.4417	0.5627**	0.3497	0.0696	0.3990	2.0808***	-1.1783*	0.3688	0.1356	0.8365***
MAI (G)	-0.8544***	0.6725***	0.5930***	0.5279***	0.3045***	0.2198***	0.1552***	0.3057***	0.1483***	0.0684***	
MAI (R)	-1.0123***	0.6094***	0.5409***	0.4663***	0.2892***				0.2839***		-0.1474***
MOM (G)	-0.1836**	0.0417	0.1020**	0.0899**		0.0429*	0.0397**			0.0760***	0.1152*
MOM (R)										0.0559**	
SMB (G)	-0.2556**	0.2502***	0.1562	0.2006***	0.1638***	0.0910**			0.0703***		
SMB (R)		0.4291***					0.1491***				
GEMI (G)	-0.1941**						0.0725***				
GEMI (R)							0.1349***				
COIM (G)	0.1126**										
COIM (R)					0.1158**	0.1096***		-0.0858**			
HML (G)		0.2077***		0.0666**	0.1774***	0.058*			0.0676***		
HML (R)			-0.3843***	-0.2013**							
COEN (G)		0.0224**	0.0436***	0.0316***							
COEN (R)	0.1302***						0.0246***	0.0735***			0.1045***
COPM (G)			0.0735***	0.0319***		0.0427**		0.0888***			
COPM (R)											
DEF (G)			-1.3262***	-0.9403***		-0.8946**	-0.8748***			-0.3826**	
DEF (R)											
TERM (G)				-0.1649***					0.1235***		
TERM (R)							-0.6613**	0.9206***			
RLE (G)							-0.0371**				
RLE (R)											
DVIX (G)								0.0214**			
DVIX (R)						-0.0613***					
EXCH (G)											-0.4015***
EXCH (R)											

Table 69. Multi-Factor Model During Growth/Recessions Periods (HAC/Newey-West estimator) (Continued)

COAG (G)											
COAG (R)		0.1118***	0.1445***	0.0781***				0.1399***		0.0600***	
Adj.R-squared (G):	0.6971	0.8250	0.7201	0.8253	0.6699	0.3757	0.4287	0.2873	0.4507	0.2576	0.0417
Adj.R-squared (R):	0.8561	0.8727	0.8830	0.8608	0.6323	0.5677	0.7258	0.5326	0.5459	0.2324	0.3261
Prob (F-stat) (G):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016
Prob (F-stat) (R):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0063	0.0008

Table 70. Multi-Factor Model During Up/Down Regimes (HAC/Newey-West estimator)

This table shows the results in terms of alphas and exposures of my multi-factor model for up and down regimes from 01/1990 to 03/2014. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration only purposes.

Dep. Var:	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi	Others	Global Macro	Relative	Market	CTA
C (U)	0.4899***	0.2880***	0.4838***	0.6267***	0.4967***	0.6387***	1.2702***	0.2971**	-0.2192	0.1528***	0.8312***
C (D)	0.3522	-0.3603	0.4854**	-0.0660	0.1778	0.5781***	0.7432***	0.8767***	0.0502	0.1579	0.8324
MAI (U)	-0.9337***	0.6690***	0.5878***	0.5737***	0.2523***	0.2256***	0.1482***	0.2846***	0.1505***	0.0751***	
MAI (D)	-0.8491***	0.5509***	0.5016***	0.3117***	0.2028***		0.1858***	0.0810***			-0.1562**
SMB (U)	-0.2704**	0.2581***	0.1428	0.1990***	0.1639***	0.0949**			0.0696***		
SMB (D)		0.4113***		0.1976***					0.1987**		
MOM (U)	-0.1431*	0.0517	0.1048***	0.0923**		0.0565**		0.0503**	0.0237*	0.0751***	
MOM D)										0.0780***	
COIM (U)	0.1067**										
COIM (D)					0.1547**	0.1175***			0.1236**		
GEMI (U)	-0.1477*				0.0561**		0.0806***				
GEMI (D)						0.0919**					
HML (U)		0.2348***		0.0856*	0.1838***	0.0852*			0.0760***	0.0347*	
HML (D)			-0.2175***					-0.1650***		-0.0702***	
COEN (U)		0.0338***	0.0468***	0.0420***	0.0187**			0.0341**			
COEN (D)	0.1091**							0.0401*			0.0676***
COPM (U)			0.0757***			0.0434**		0.0931***			0.1373***
COPM (D)											
TERM (U)				-0.1829***					0.1114**		
TERM (D)											
DVIX (U)				0.0111**				0.0176*			
DVIX (D)				-0.0253**		-0.0313***			-0.0314***		
DEF (U)							-0.5920**		0.5683**		
DEF (D)											
RLE (U)							-0.0318**				
RLE (D)											
COAG (U)											
COAG (D)		0.1131**	0.1224***							0.0445***	

Table 70. Multi-Factor Model During Up/Down Regimes (HAC/Newey-West estimator) (Continued)

EXCH (U)											
EXCH (D)							-0.2678***				
Adj.R-squared	0.6787	0.8182	0.6942	0.8082	0.6633	0.3499	0.3829	0.2761	0.4795	0.2260	0.0303
Prob (F-stat) (U):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0031
Adj.R-squared	0.8385	0.8281	0.8218	0.8429	0.5600	0.6302	0.6266	0.4938	0.5639	0.4396	0.1962
Prob (F-stat) (D):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0103

8.12 The custom proposed (fundamental) model omitting pre-1994 data

In this appendix I show the results when I implement the proposed model at the fundamental (fund specific characteristic) level. Table 71 provides the results for growth and recessions whereas Table 72 provides results for the up and down regimes. All the regressors had the same sign and were mostly statistically significant, verifying the proposed model.

Table 71. Multi-Factor Model at fundamental level during Growth/Recessions Periods (post-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model at fundamental level for growth periods and recessions after omitting pre-1994 data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (G) (excess returns)	0.9860***	0.7934***	1.7091**	0.8737**	1.0977***	0.7252***
C (R) (excess returns)	0.3208	0.3694	0.3066	0.3468	0.2640	0.3681
MAI (G)	0.4110***	0.3673***	0.3930***	0.3909***	0.4296***	0.3514***
MAI (R)	0.2518***	0.3474***	0.2944***	0.3649***	0.2669***	0.3367***
SMB (G)	0.1040***	0.1302***		0.1308***	0.1499***	0.1052***
SMB (R)						
MOM (G)	0.0649***	0.0389***	0.1029***	0.0434***	0.0418***	0.0535***
MOM (R)						
COEN (G)	0.0326***	0.0268***	0.0288**	0.0275***	0.0315***	0.0263***
COEN (R)	0.0474***		0.0435**			
DEF (G)	-0.7884***	-0.3952*	-1.4060***	-0.5604**	-0.7702***	-0.4350**
DEF (R)						
COPM (G)	0.0344**			0.0330***	0.0320**	
COPM (R)						
HML (G)		0.0880***	-0.0812**	0.0825***	0.0836***	0.0558***
HML (R)		-0.1613**	-0.2533***	-0.1381*		-0.1230*
DVIX (G)						
DVIX (R)	-0.0265**				-0.0330*	
COAG (G)						
COAG (R)	0.0578*	0.0842**	0.0526**	0.0875**	0.0816**	0.0792**
Adj.R-squared (G)	0.8105	0.7887	0.6388	0.8199	0.7801	0.8073
Adj.R-squared (R)	0.8806	0.7603	0.9161	0.7980	0.7829	0.8245
Prob (F-stat) (G)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob (F-stat) (R)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 72. Multi-Factor Model at fundamental level during Up/Down Regimes (post-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model at fundamental level for up and down regimes after omitting pre-1994 data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (U) (excess returns)	0.1646**	0.4156***	0.3010***	0.3549***	0.3877***	0.3184***
C (D) (excess returns)	0.1462	0.249	0.3592*	0.1693	0.1747	0.1666
MAI (U)	0.4763***	0.3718***	0.4032***	0.3980***	0.4281***	0.3622***
MAI (D)	0.2309***	0.1262**	0.2227***	0.1621***	0.1871***	0.1500***
COEN (U)	0.0402***	0.0349***	0.0340***	0.0344***	0.0388***	0.0329***
COEN (D)	0.0429**					
SMB (U)	0.1057***	0.1186***		0.1205***	0.1375***	0.0967***
SMB (D)	0.1175**	0.1565**	0.1424***	0.1431**	0.1882***	0.1236**
MOM (U)	0.0666***	0.0412***	0.1116***	0.0429***	0.0567***	0.0443***
MOM (D)						
COPM (U)	0.0361***			0.0357***	0.0362**	
COPM (D)						
HML (U)	0.0645**	0.0927***		0.0908***	0.0961***	0.0686***
HML (D)	-0.0648*		-0.1760***			
DVIX (U)	0.0160***					
DVIX (D)	-0.0236**	-0.0285**		-0.0254**	-0.0266*	-0.0230**
EXCH (G)						
EXCH (D)	-0.1612*					
COIM (G)						
COIM (D)		0.1342***	0.1132***	0.1226***	0.1263***	0.1019***
Adj.R-squared (U)	0.8050	0.7766	0.6060	0.8086	0.7662	0.7934
Adj.R-squared (D)	0.8765	0.7926	0.8981	0.8169	0.8244	0.8309
Prob (F-stat) (U)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob (F-stat) (D)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

8.13 The custom proposed (fundamental) model with pre 1994 only data

In this appendix I again implement the proposed model by using pre-1994 data. Table 73 shows the results for the growth and up regimes only due to limited data availability. Overall there are the same qualitative results.

Table 73. Multi-Factor Model at fundamental level during Growth/Up Periods (post-1994 period)

This table shows the results in terms of alphas and exposures of my multi-factor model at fundamental level for growth periods and up regimes using pre-1994 only data. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration purposes only.

Dependent Variable	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (G)	1.4060	1.5202**	4.5682**	1.5077***	2.4617***	0.9507
C (U)	0.5318***	0.5266**	0.9809**	0.5137***	0.8418***	0.3538***
MAI (G)	0.0706	0.5079***	0.5307***	0.4017***	0.4493***	0.3702***
MAI (U)	0.0444	0.4803***	0.5251***	0.3711***	0.3475***	0.3745***
SMB (G)	0.2759***	0.3794***		0.3456***	0.3594***	0.3325***
SMB (U)	0.2676***	0.3987***		0.3524***	0.3374***	0.3488***
MOM (G)	0.2050***	0.0282	0.0999**	0.0786***	0.0080	0.1052***
MOM (U)	0.2175***	0.0803***	0.1847***	0.1224***	0.1518***	0.1047***
COEN (G)	-0.0355	0.0123	0.0498	0.0013	-0.0097	0.0017
COEN (U)	-0.0597**	0.0169	0.0431	-0.0040	0.0018	-0.0071
DEF (G)	-0.9541	-1.0996	-4.4659	-1.0924*	-1.7741*	-0.6590
DEF (U)						
COPM (G)	0.0335			0.0310*	0.0496*	
COPM (U)	0.0092			0.0174	0.0386	
HML (G)		0.0831***	-0.0778	0.0507*	0.0125	0.0775**
HML (U)	0.0104	0.0921**		0.0644**	0.0163	0.0902***
DVIX (G)						
DVIX (U)	-0.0008					
Adj.R-squared	0.4995	0.9440	0.6994	0.9487	0.8828	0.9210
Adj.R-squared	0.4461	0.9280	0.6772	0.9226	0.7810	0.9249
Prob (F-stat) (G)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob (F-stat) (U)	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000

8.14 HAC/Newey-West Estimator – Fundamental Level

I tested the proposed multifactor model by using the HAC/Newey-West estimator to deal with any unknown residual autocorrelation and heteroscedasticity. The results still valid as almost all the regressors are significant different from zero. Table 74 presents the results for growth/recessions and Table 75 shows the results for up/down regimes.

Table 74. Multi-Factor Model During Growth/Recessions – Fundamental Level (HAC/Newey-West estimator)

This table shows the results in terms of alphas and exposures of my multi-factor model for growth and recession periods from 01/1990 to 03/2014 at fundamental level. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration only purposes.

Dep. Var:	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (G)	1.2188***	0.9055***	1.7091***	1.0016***	1.3220***	0.8228***
C (R)	0.2516	0.4043	0.3066**	0.3417	0.2463	0.3849*
MAI (G)	0.3756***	0.3828***	0.3930***	0.3937***	0.4297***	0.3554***
MAI (R)	0.2277***	0.3802***	0.2944***	0.3684***	0.2774***	0.3469***
SMB (G)	0.1266**	0.1536***		0.1523***	0.1727***	0.1284***
SMB (R)						
MOM (G)	0.0625**	0.0480**	0.1029*	0.0504**	0.0466	0.0603***
MOM (R)						
COEN (G)	0.0262***	0.0206***	0.0288***	0.0217***	0.0224**	0.0213***
COEN (R)	0.0483***		0.0435***			
DEF (G)	-0.9408***	-0.4914**	-1.4060**	-0.6521***	-0.9207***	-0.5153**
DEF (R)						
COPM (G)	0.0450***			0.0323***	0.0348***	
COPM (R)						
HML (G)		0.0941***	-0.0812	0.0841***	0.0815***	0.0642***
HML (R)		-0.1897	-0.2533***	-0.1420*		-0.1312*
DVIX (G)						
DVIX (R)	-0.0269***				-0.0344**	
COAG (G)						
COAG (R)	0.0598***	0.0855***	0.0526***	0.0914***	0.0841***	0.0811***
Adj.R-squared	0.7423	0.7902	0.6388	0.8207	0.7734	0.8069
Adj.R-squared	0.8365	0.7811	0.9161	0.8182	0.7892	0.8426
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob(F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 75. Multi-Factor Model During Up/Down Regimes – Fundamental Level (HAC/Newey-West estimator)

This table shows the results in terms of alphas and exposures of my multi-factor model for up and down regimes from 01/1990 to 03/2014 at fundamental level. Hedge funds returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05, and *** denotes significance at P<0.01. For space reasons, I do not present standard errors and t-statistics. My findings in the thesis are based on significant (P<0.05) and strongly significant (P<0.01) results. In the appendix I present weakly significant results (P<0.1) for demonstration only purposes.

Dep. Var:	Size Small	Size Large	Age Young	Age Old	Lockup-Yes	Lockup-No
C (U)	0.3133***	0.4757***	0.3010***	0.4283***	0.5073***	0.3719***
C (D)	0.2105	0.0729	0.3592**	0.0821	0.0367	0.0971
MAI (U)	0.4101***	0.3898***	0.4032***	0.3992***	0.4222***	0.3669***
MAI (D)	0.2366***	0.1487***	0.2227***	0.1747***	0.1961***	0.1649***
COEN (U)	0.0325***	0.0269***	0.0340***	0.0277***	0.0304****	0.0260***
COEN (D)	0.0434***					
SMB (U)	0.1329***	0.1507***		0.1487***	0.1645***	0.1271***
SMB (D)	0.1027***	0.1926***	0.1424***	0.1591***	0.2055***	0.1404***
MOM (U)	0.0696**	0.0515**	0.1116**	0.0521**	0.0665**	0.0528**
MOM (D)						
COPM (U)	0.0435***			0.0320***	0.0351***	
COPM (D)						
HML (U)	0.0692*	0.1001***		0.0950***	0.0952**	0.0798***
HML (D)	-0.0699		-0.1760***			
DVIX (U)	0.0102*					
DVIX (D)	-0.0211***	-0.0315***		-0.0278***	-0.0344***	-0.0229**
EXCH (U)						
EXCH (D)	-0.1927**					
COIM (U)						
COIM (D)		0.0974	0.1132***	0.1003**	0.0858*	0.0874**
Adj.R-	0.704964	0.773746	0.606014	0.804121	0.748608	0.791113
Adj.R-	0.872878	0.759409	0.898109	0.811228	0.808183	0.844068
Prob (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob(F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

8.15 Autocorrelation for 1, 2, 4, 6, and 12 periods

In this appendix Tables 76, 77, 78 and 79 show the autocorrelation tests for 1, 2, 4, 6, and 12 months. There is a serial correlation for hedge fund strategies and in some cases (e.g. Market Neutral, Relative Value, Multi Strategy) it can be up to 12 months during "good" times. Serial correlation is a common problem when dealing with time-series data hence with hedge funds too (shared by many other authors as well). The estimated regression coefficients are still unbiased and consistent but may be inefficient. This means that the standard errors of the estimates of the regression parameters can be underestimated. However, in the analysis I consider significant and strongly significant results at the $P < 0.05$ and $P < 0.01$, levels. Finally, I found that the hedge fund data are stationary.

Table 76. Hedge Fund Smoothness at Strategy Level – Growth Period

This table shows the results of the regression-based parametric model for raw for raw returns, the Sharpe ratio, and the Information ratio during growth periods. A positive and significant slope coefficient indicates performance persistence. This suggests that a hedge fund (or group) that did well in specific period did well in the sub-sequent period and vice-versa. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

	Time Horizon (month)- Raw Returns					*Time Horizon (month)- Sharpe Ratio*					*Time Horizon (month) - Information Ratio*				
Strategy	1	2	4	6	12	1	2	4	6	12	1	2	4	6	12
Short Bias	0.036	0.016	-0.059	-0.015	-0.032	0.030	-0.061	-0.018	0.113	-0.032	0.091	0.120**	-0.069*	-0.053	0.019
	(0.585)	(0.255)	(-0.963)	(-0.244)	(-0.536)	(-0.476)	(-0.958)	(-0.274)	(-1.765)	(-0.529)	(1.751)	(3.672)	(-2.065)	(-1.583)	(0.968)
Long Only	0.269**	0.187**	0.079	0.174**	0.046	0.243**	0.266**	0.056	0.153**	0.045	-0.066	0.019	0.015	0.032	0.169**
	(4.541)	(3.115)	(1.327)	(2.948)	(0.847)	(3.973)	(4.366)	(0.882)	(2.456)	(0.722)	(-1.051)	(0.305)	(0.262)	(0.570)	(3.001)
Sector	0.214**	0.173**	0.140*	0.239**	0.032	0.148*	0.202**	0.140*	0.129*	0.103	0.031	0.001	0.038	0.043	0.102
	(3.518)	(2.842)	(2.280)	(3.973)	(0.536)	(2.407)	(3.318)	(2.289)	(2.095)	(1.699)	(0.501)	(0.012)	(0.605)	(0.699)	(1.637)
Long Short	0.267**	0.220**	0.123*	0.224**	0.075	0.225**	0.214**	0.096	0.144*	0.044	-0.054	0.051	0.067	-0.031	0.113
	(4.490)	(3.682)	(2.014)	(3.763)	(1.274)	(3.724)	(3.529)	(0.125)	(2.324)	(0.699)	(-0.865)	(0.807)	(1.077)	(-0.508)	(1.850)
Event Driven	0.529**	0.393**	0.323**	0.322**	0.187**	0.541**	0.426**	0.341**	0.324**	0.245**	-0.136*	0.054	-0.029	-0.077	0.051
	(10.095)	(7.018)	(5.714)	(5.666)	(3.436)	(10.341)	(7.520)	(5.828)	(5.425)	(3.972)	(-2.198)	(0.826)	(-0.455)	(-1.232)	(0.859)
Multi-Strategy	0.505**	0.472**	0.428**	0.414**	0.248**	0.464**	0.648**	0.489**	0.306**	0.126**	-0.215**	-0.197**	-0.095	0.018	0.014
	(9.641)	(9.050)	(8.049)	(7.562)	(4.441)	(5.800)	(8.704)	(5.759)	(3.519)	(3.022)	(-3.447)	(-3.136)	(-0.306)	(0.211)	(1.143)
Other	0.516**	0.499**	0.478**	0.501**	0.417**	0.113**	0.058	0.090*	0.067*	0.113**	0.034	0.045	-0.084	0.038	0.036
	(9.758)	(9.485)	(8.967)	(9.585)	(7.711)	(3.158)	(1.577)	(2.485)	(2.266)	(4.308)	(0.474)	(0.611)	(-1.172)	(0.547)	(0.521)
Global Macro	0.249**	0.224**	0.197**	0.159*	0.078	0.022	0.148*	-0.023	0.051	-0.034	0.106	0.071	-0.009	0.218**	-0.011
	(4.129)	(3.734)	(3.195)	(2.550)	(1.253)	(0.335)	(2.230)	(-0.349)	(0.812)	(-0.540)	(1.602)	(1.068)	(-0.134)	(3.434)	(-0.165)
Relative Value	0.663**	0.569**	0.497**	0.487**	0.312**	0.650**	0.573**	0.476**	0.472**	0.357**	-0.161**	0.049	-0.014	-0.050	0.017
	(15.126)	(12.213)	(9.922)	(9.899)	(6.471)	(14.272)	(11.643)	(8.919)	(8.930)	(6.560)	(-2.613)	(0.779)	(-0.218)	(-0.800)	(0.264)

Table 76. Hedge Fund Smoothness at Strategy Level – Growth Period (continued)

Market	0.413**	0.405**	0.418**	0.408**	0.383**	0.308**	0.265**	0.2012**	0.182**	0.239**	-0.024	0.044	0.014	0.020	0.032
	(7.141)	(7.026)	(7.240)	(7.036)	(6.504)	(5.057)	(4.309)	(3.259)	(2.902)	(3.983)	(-0.388)	(0.711)	(0.235)	(0.346	(0.553)
CTA	0.051	-0.022	0.013	0.177**	0.041	0.030	-0.061	-0.018	0.113	-0.032	-0.017	-0.054	-0.020	0.089	-0.004
	(0.818)	(-0.352)	(0.212)	(2.829)	(0.671)	(0.476)	(-0.958)	(-0.274)	(1.765)	(-0.529)	(-0.273)	(-0.843)	(-0.315)	(1.451	(-0.073)

Table 77. Hedge Fund Smoothness at Strategy Level - Recessions

This table shows the results of the regression-based parametric model for raw for raw returns, the Sharpe ratio, and the Information ratio during recessions. A positive and significant slope coefficient indicates performance persistence. This suggests that a hedge fund (or group) that did well in specific period did well in the sub-sequent period and vice-versa. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

	Time Horizon (month)- Raw Returns					*Time Horizon (month)- Sharpe Ratio*					*Time Horizon (month) - Information Ratio*				
Strategy	1	2	4	6	12	1	2	4	6	12	1	2	4	6	12
Short Bias	0.184	0.134	0.125	0.112	0.123	0.145	-0.014	-0.064	-0.256	-17.285**	0.150	-0.011	-0.085	-0.247	-9.641
	(1.094)	(0.772)	(0.851)	(0.819)	(0.676)	(0.819)	(-0.070)	(-0.314)	(-1.289)	(-3.606)	(0.852)	(-0.056)	(-0.416)	(-1.233)	(-1.540)
Long Only	0.551**	0.161	0.036	-0.452*	-0.158	0.335	0.147	-0.034	-0.243	-0.058	0.437	0.121	0.084	-0.054	0.336
	(3.741)	(0.906)	(0.188)	(-2.556)	(-0.497)	(1.926)	(0.783)	(-0.168)	(-1.205)	(-0.243)	(2.688)	(0.767)	(0.612)	(-0.240)	(1.872)
Sector	0.538**	0.190	-0.062	-0.274	-0.248	0.604**	0.360*	-0.091	-0.443**	-0.038	0.141	-0.306	0.152	-0.112	0.603**
	(3.601)	(1.066)	(-0.343)	(-1.644)	(-1.025)	(4.159)	(2.067)	(-0.514)	(-3.009)	(-0.187)	(0.799)	(-1.789)	(0.807)	(-0.421)	(2.911)
Long Short	0.523**	0.204	-0.066	-0.396	-0.180	0.464**	0.260	-0.189	-0.317	-0.016	0.194	-0.287	0.177	-0.081	0.519*
	(3.333)	(1.076)	(-0.340)	(-2.193)	(-0.668)	(2.858)	(1.419)	(-1.045)	(-1.827)	(-0.076)	(1.129)	(-1.772)	(0.993)	(-0.378)	(2.398)
Event Driven	0.623**	0.309	-0.002	-0.494**	0.081	0.366*	0.252	-0.111	-0.216	0.013	0.252	-0.222	-0.049	0.236	-0.077
	(4.478)	(1.743)	(-0.008)	(-2.857)	(0.226)	(2.162)	(1.427)	(-0.581)	(-1.245)	(0.066)	(1.476)	(-1.528)	(-0.315)	(1.474)	(-0.296)
Multi-Strategy	0.528**	0.191	0.087	-0.337	0.173	-0.028	-0.124	0.074	-0.046	0.217	0.206**	0.046	-0.022	0.041*	0.232
	(3.291)	(0.964)	(0.445)	(-1.951)	(0.681)	(-0.447)	(-2.078)	(1.263)	(-0.786)	(1.153)	(2.784)	(0.560)	(-1.153)	(2.305)	(0.999)
Other	0.390*	0.170	0.213	-0.008	0.271	0.266	-0.151	0.059	-0.019	0.106	0.325	-0.216	0.167	0.092	0.114
	(2.506)	(0.922)	(1.124)	(-0.039)	(1.072)	(1.423)	(-0.727)	(0.304)	(-0.099)	(0.637)	(1.676)	(-1.134)	(0.748)	(0.382)	(0.520)
Global Macro	0.253	0.156	0.217	0.339*	0.170	0.094	0.004	0.386*	0.214	0.148	0.324	-0.158	0.136	-0.016	0.556
	(1.381)	(0.734)	(1.239)	(2.081)	(0.815)	(0.488)	(0.018)	(2.312)	(1.219)	(0.917)	(1.732)	(-0.823)	(0.635)	(-0.051)	(1.722)
Relative Value	0.719**	0.240	-0.171	-0.504*	-0.170	0.736**	0.272	-0.247	-0.408	-0.046	0.206	-0.283	0.060	0.069	0.200
	(5.305)	(1.229)	(-0.870)	(-2.650)	(-0.365)	(5.102)	(1.367)	(-1.300)	(-1.984)	(-0.165)	(1.210)	(-1.837)	(0.390)	(0.409)	(0.993)

Table 77. Hedge Fund Smoothness at Strategy Level - Recessions (continued)

Market	-0.026	0.051	0.119	0.125	0.199	-0.193	0.004	0.035	0.170	0.221	0.546**	0.101	-0.171	-0.449	0.123
	(-0.159)	(0.296)	(0.730)	(0.745)	(1.267)	(-1.330)	(0.025)	(0.206)	(1.039)	(1.270)	(3.823)	(0.592)	(-0.929)	(-2.502)	(0.468)
CTA	0.184	0.134	0.125	0.112	0.123	0.151	0.135	0.071	-0.033	0.181	0.354*	0.020	-0.154	-0.019	0.066
	(-1.094)	(-0.772)	(-0.851)	(0.8188)	(0.6755)	(1.064)	(0.964)	(0.587)	(-0.299)	(1.214)	(2.324)	(0.124)	(-0.986)	(-0.111)	(0.253)

Table 78. Hedge Fund Smoothness at Strategy Level – Up Regimes

This table shows the results of the regression-based parametric model for raw returns, the Sharpe ratio, and the Information ratio during up regimes. A positive and significant slope coefficient indicates performance persistence. This suggests that a hedge fund (or group) that did well in specific period did well in the sub-sequent period and vice-versa. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

	Time Horizon (month)- Raw Returns					*Time Horizon (month)- Sharpe Ratio*					*Time Horizon (month) - Information Ratio*				
Strategy	1	2	4	6	12	1	2	4	6	12	1	2	4	6	12
Short Bias	0.046	-0.008	-0.132	-0.094	-0.021	0.418**	0.029	-0.058	-0.198**	0.002	0.383**	0.032	-0.068	-0.186**	0.017
	(0.729)	(-0.123)	(-2.124)	(-1.589)	(-0.342)	(-7.292)	(0.793)	(-1.575)	(-5.652)	(0.054)	(6.586)	(0.865)	(-1.822)	(-5.210)	(0.454)
Long Only	0.290**	0.193**	0.033	0.050	0.066	0.241**	0.275**	0.041	0.140*	0.053	0.042	0.039	-0.011	0.024	0.174**
	(4.936)	(3.209)	(0.566)	(0.882)	(1.143)	(3.936)	(4.499)	(0.643)	(2.242)	(0.834)	(0.667)	(0.648)	(-0.195)	(0.415)	(3.125)
Sector	0.260**	0.247	0.109	0.183**	0.087	0.180**	0.247**	0.124	0.090	0.125*	-0.001	-0.048	0.026	0.042	0.101
	(4.283)	(3.994)	(1.710)	(3.053)	(1.385)	(2.904)	(4.033)	(1.961)	(1.443)	(2.041)	(-0.013)	(-0.801)	(0.428)	(0.681)	(1.647)
Long Short	0.297**	0.262**	0.087	0.163**	0.100	0.234**	0.241**	0.067	0.120	0.054	-0.075	-0.018	0.023	-0.048	0.130*
	(4.978)	(4.278)	(1.389)	(2.709)	(1.560)	(3.853)	(3.914)	(1.067)	(1.918)	(0.848)	(-1.227)	(-0.299)	(0.379)	(-0.793)	(2.150)
Event Driven	0.547**	0.405**	0.278**	0.169**	0.195**	0.541**	0.437**	0.329**	0.294**	0.241**	-0.178**	0.037	-0.100	-0.053	0.075
	(10.466)	(7.078)	(4.727)	(2.887)	(3.407)	(10.238)	(7.702)	(5.509)	(4.861)	(3.896)	(-2.910)	(0.582)	(-1.568)	(-0.876)	(1.246)
Multi-Strategy	0.528**	0.493**	0.443**	0.344**	0.282**	0.404**	0.398**	0.245**	0.173**	0.136**	-0.218**	-0.018	-0.203	0.036**	0.014
	(9.993)	(9.228)	(8.011)	(6.058)	(4.874)	(6.976)	(6.581)	(5.509)	(4.052)	(3.223)	(-3.564)	(-0.084)	(-0.963)	(2.959)	(1.195)
Other	0.524**	0.512**	0.465**	0.479**	0.508**	0.115**	0.059	0.087*	0.066*	0.116**	0.014	-0.024	-0.138	0.028	0.030
	(10.064)	(9.725)	(8.626)	(8.844)	(8.994)	(3.163)	(1.599)	(2.365)	(2.213)	(4.399)	(0.198)	(-0.328)	(-1.959)	(0.414)	(0.438)
Global Macro	0.243**	0.222**	0.196**	0.161*	0.092	0.022	0.148*	-0.019	0.049	-0.032	0.095	0.038	-0.026	0.219**	-0.006
	(3.974)	(3.627)	(3.196)	(2.584)	(1.394)	(0.334)	(2.272)	(-0.283)	(0.769)	(-0.502)	(1.442)	(0.584)	(-0.401)	(3.416)	(-0.089)
Relative	0.707**	0.601**	0.430**	0.280**	0.317**	0.663**	0.556**	0.416**	0.384**	0.353**	-0.184**	0.010	-0.052	-0.042	0.032
	(16.241)	(12.294)	(7.928)	(5.177)	(6.004)	(14.401)	(11.019)	(7.513)	(6.797)	(6.243)	(-3.025)	(0.161)	(-0.815)	(-0.677)	(0.520)

Table 78. Hedge Fund Smoothness at Strategy Level - Up Regimes (continued)

Market	0.339**	0.380**	0.380**	0.379**	0.372**	0.245**	0.253**	0.179**	0.193**	0.239**	0.007	0.046	-0.056	-0.042	0.037
	(5.749)	(6.597)	(6.440)	(6.463)	(6.031)	(4.021)	(4.173)	(2.916)	(3.124)	(3.938)	(0.107)	(0.762)	(-0.948)	(-0.721)	(0.654)
CTA	0.021	-0.035	0.001	0.1649*	0.039	-0.009	-0.049	-0.034	0.076	-0.028	-0.043	-0.063	-0.130*	0.038	0.001
	(0.339)	(-0.555)	(0.009)	(2.696)	(0.631)	(-0.149)	(-0.770)	(-0.541)	(1.247)	(-0.472)	(-0.704)	(-1.022)	(-2.177)	(0.660)	(0.010)

Table 79. Hedge Fund Smoothness at Strategy Level – Down Regimes

This table shows the results of the regression-based parametric model for raw for raw returns, the Sharpe ratio, and the Information ratio during down regimes. A positive and significant slope coefficient indicates performance persistence. This suggests that a hedge fund (or group) that did well in specific period did well in the sub-sequent period and vice-versa. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. For space reasons, I present only the t-statistics in parentheses.

	Time Horizon (month)- Raw Returns					*Time Horizon (month)- Sharpe Ratio*					*Time Horizon (month) - Information Ratio*				
Strategy	1	2	4	6	12	1	2	4	6	12	1	2	4	6	12
Short Bias	0.475*	0.126	0.258	0.196	-0.160	0.010	1.649	-8.441*	3.520	0.033	0.013	2.224	-9.920*	10.790	0.041
	(3.316)	(0.782)	(1.611)	(1.047)	(-1.107)	(0.060)	(0.380)	(-2.302)	(6.467)	(0.182)	(0.076)	(0.446)	(-2.722)	(2.011)	(0.193)
Long Only	0.528*	0.140	0.234	-0.147	-0.221	0.374*	0.023	0.172	-0.114	-0.182	0.171	0.093	0.410*	0.089	0.245
	(3.536)	(0.790)	(1.167)	(-0.577)	(-0.996)	(2.198)	(0.128)	(0.883)	(-0.523)	(-0.863)	(0.854)	(0.473)	(2.279)	(0.435)	(1.223)
Sector	0.347*	-0.108	0.085	-0.130	-0.339	0.326*	-0.075	0.066	-0.170	-0.358*	0.546*	0.138	0.396	-0.058	0.740**
	(2.203)	(-0.684)	(0.540)	(-0.696)	(-2.246)	(2.158)	(-0.482)	(0.459)	(-1.167)	(-2.163)	(2.664)	(0.560)	(1.605)	(-0.244)	(3.084)
Long Short	0.394*	-0.017	0.141	-0.167	-0.147	0.418*	0.009	0.068	-0.151	-0.146	0.290	0.033	0.422*	0.034	0.340
	(2.503)	(-0.103)	(0.822)	(-0.824)	(-0.996)	(2.636)	(0.053)	(0.414)	(-0.888)	(-0.832)	(1.584)	(0.165)	(2.251)	(0.159)	(1.486)
Event Driven	0.577*	0.244	0.137	-0.119	-0.019	0.328*	0.069	0.001	-0.019	-0.022	0.270	-0.123	0.160	0.091	-0.092
	(4.202)	(1.477)	(0.748)	(-0.435)	(-0.066)	(2.086)	(0.408)	(0.003)	(-0.109)	(-0.112)	(1.593)	(-0.747)	(0.990)	(0.501)	(-0.469)
Multi-Strategy	0.398*	0.039	0.016	-0.187	-0.102	0.025	0.152	0.351	-0.810	-0.066	0.283	-0.199**	-0.009	0.119	0.131
	(2.595)	(0.222)	(0.100)	(-1.022)	(-0.508)	(0.149)	(0.946)	(1.013)	(-1.869)	(-0.353)	(1.710)	(-9.128)	(-0.219)	(0.683)	(0.574)
Other	0.286	0.031	0.277	0.193	-0.078	0.103	-0.234	0.276	0.053	-0.066	0.321	0.163	0.401	0.129	0.150
	(1.666)	(0.177)	(1.458)	(1.054)	(-0.564)	(0.584)	(-1.370)	(1.835)	(0.357)	(-0.499)	(1.704)	(0.790)	(1.910)	(0.573)	(0.628)
Global Macro	0.344*	0.192	0.243	0.436*	0.018	0.078	0.007	0.067	0.294*	0.014	0.490*	0.214	0.542*	0.001	0.311
	(2.181)	(1.096)	(1.254)	(2.586)	(0.183)	(0.447)	(0.039)	(0.440)	(2.243)	(0.126)	(2.636)	(0.895)	(2.279)	(0.002)	(1.119)
Relative Value	0.597*	0.097	-0.115	-0.034	-0.0186	0.654**	0.291	-0.079	0.304	-0.073	0.278	-0.003	0.233	-0.003	0.040
	(4.352)	(0.552)	(-0.610)	(-0.115)	(-0.065)	(4.646)	(1.434)	(-0.368)	(1.413)	(-0.357)	(1.559)	(-0.017)	(1.448)	(-0.018)	(0.175)

Table 79. Hedge Fund Smoothness at Strategy Level – Down Regimes (continued)

Market Neutral	0.385*	0.125	0.321*	0.270	0.275*	0.261	-0.012	0.305	-0.016	0.218	0.513**	0.103	0.250	-0.218	0.056
	(2.363	(0.672)	(2.126)	(1.667)	(2.377)	(1.595)	(-0.064)	(1.536)	(-0.077)	(1.472)	(3.268)	(0.568)	(1.115)	(-0.890)	(0.199)
CTA	0.454	0.222	0.243	0.201	0.149	0.478**	0.010	0.195	0.207	0.198	0.509**	0.058	0.290	0.223	0.010
	(3.095	(1.413)	(1.594)	(1.225)	(0.862)	(3.432)	(0.071)	(1.346)	(1.265)	(1.126)	3.134	0.336	1.562	1.049	0.045

8.16 Spread between top P1 and bottom P10 performers

In this appendix Tables 80, 81, 82 and 83 show the spreads between top P1 and bottom P10 performers across all hedge fund strategies during “good” and “bad” market conditions. “Bad” market conditions have a negative impact on hedge fund performance persistence and the spreads between top and bottom performers are low. In all market conditions, on average, directional strategies present higher spreads between top P1 and bottom P10 fund performers, compared to semi or non-directional strategies.

Table 80. Persistence within Strategies - Spreads / Growth Period

This table shows results of spreads between top P1 and bottom P10 performers for each hedge fund strategy, on a quarterly basis during growth periods. Using the regression based parametric model, a positive coefficient denotes persistence in the spread between top and bottom performers. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. The up-left side contains more directional strategies whereas the down-right side contains more non-directional strategies.

Strategy	Monthly Avg Return	Stand. Deviation	Coefficient	t-stat	Strategy	Monthly Avg Return	Stand. Deviation	Coefficient	t-stat	Strategy	Monthly Avg Return	Stand. Deviation	Coefficient	t-stat	Strategy	Monthly Avg Return	Stand. Deviation	Coefficient	t-stat
Quarterly																			
Short Bias Spread P1-P10	8.19%	6.096	0.7946**	10.720	Long Only Spread P1-P10	7.35%	3.646	0.915**	20.186	Sector Spread P1-P10	10.49%	5.424	0.913**	20.246	Long Short Spread P1-P10	8.71%	3.970	0.936**	23.996
Even Driven Spread P1-P10	5.93%	2.001	0.941**	25.857	Multi Strategy Spread	6.37%	3.058	0.922**	21.539	Others Spread P1-P10	7.05%	2.650	0.910**	16.895	Global Market Spread P1-P10	7.68%	3.019	0.934**	18.841
Relative Value Spread P1-P10	5.23%	2.456	0.932**	23.086	Market Neutral Spread P1-P10	4.83%	2.458	0.944**	24.100	CTA Spread P1-P10	11.28%	3.225	0.933**	23.159					
Semi Annual																			
Short Bias Spread P1-P10	6.89%	4.756	0.813**	8.184	Long Only Spread P1-P10	6.19%	3.163	0.874**	11.240	Sector Spread P1-P10	8.80%	4.470	0.896**	12.612	Long Short Spread P1-P10	7.13%	3.158	0.909**	14.035
Even Driven Spread P1-P10	4.94%	1.947	0.910**	14.168	Multi Strategy Spread	5.23%	2.397	0.881**	11.632	Others Spread P1-P10	6.03%	1.973	0.942**	15.149	Global Market Spread P1-P10	6.06%	2.443	0.889**	10.467
Relative Value Spread P1-P10	4.44%	1.908	0.939**	17.023	Market Neutral Spread P1-P10	3.81%	2.005	0.855**	10.546	CTA Spread P1-P10	8.70%	2.746	0.913**	14.055					
Annual																			
Short Bias Spread P1-P10	6.38%	3.198	0.848**	6.376	Long Only Spread P1-P10	5.40%	2.639	0.862**	7.281	Sector Spread P1-P10	7.14%	2.715	0.925**	9.876	Long Short Spread P1-P10	5.80%	1.828	0.956**	13.673
Even Driven Spread P1-P10	4.26%	1.222	0.974**	17.9	Multi Strategy Spread	4.15%	1.465	0.915**	10.14	Others Spread P1-P10	5.28%	2.094	0.902**	7.486	Global Market Spread P1-P10	5.29%	2.301	0.789**	4.636
Relative Value Spread P1-P10	4.01%	1.332	0.943**	11.41	Market Neutral Spread P1-P10	3.24%	1.367	0.942**	11.25	CTA Spread P1-P10	7.47%	2.643	0.854**	7.175					

Table 81. Persistence within Strategies - Spreads / Recessions

This table shows results of spreads between top P1 and bottom P10 performers for each hedge fund strategy, on a quarterly basis during recessions. Using the regression based parametric model, a positive coefficient denotes persistence in the spread between top and bottom performers. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. The up-left side contains more directional strategies whereas the down-right side contains more non-directional strategies.

Strategy	Monthly Averag	Standard Deviation	Coefficient	t-stat	Strategy	Monthly Averag	Standard Deviati	Coefficient	t-stat	Strategy	Monthly Averag	Standard Deviati	Coefficient	t-stat	Strategy	Monthly Averag	Standard Deviati	Coefficient	t-stat
Quarterly																			
Short Bias Spread P1-P10	12.92%	6.917	0.617*	2.524	Long Only Spread P1-P10	15.29%	6.255	0.856**	3.868	Sector Spread P1-P10	17.29%	7.105	0.910**	4.912	Long Short Spread P1-P10	14.74%	5.251	0.860**	4.534
Even Driven Spread P1-P10	11.00%	6.214	0.822**	3.340	Multi Strategy Spread	9.95%	4.136	0.899**	4.555	Others Spread P1-P10	13.59%	7.413	0.626*	2.737	Global Market Spread P1-P10	13.47%	6.291	0.710*	3.018
Relative Value Spread P1-P10	10.31%	5.451	0.779**	3.342	Market Neutral Spread P1-P10	7.02%	2.637	0.943**	5.453	CTA Spread P1-P10	16.61%	7.846	0.768**	3.432					
Semi Annual																			
Short Bias Spread P1-P10	12.83%	6.347	0.643	1.577	Long Only Spread P1-P10	10.16%	6.176	1.147*	3.412	Sector Spread P1-P10	15.14%	4.343	0.970**	5.075	Long Short Spread P1-P10	12.48%	4.324	0.919*	3.886
Even Driven Spread P1-P10	9.35%	6.037	1.171*	3.927	Multi Strategy Spread	8.59%	4.263	0.892*	2.819	Others Spread P1-P10	10.32%	4.415	0.954	2.747	Global Market Spread P1-P10	11.94%	5.332	0.761	1.925
Relative Value Spread P1-P10	8.57%	5.670	0.848	2.282	Market Neutral Spread P1-P10	5.89%	2.644	1.038*	4.373	CTA Spread P1-P10	14.81%	4.878	0.750*	3.144					
Annual																			
Short Bias Spread P1-P10	14.89%	5.762	1.434	3.355	Long Only Spread P1-P10	9.48%	5.328	1.314	1.202	Sector Spread P1-P10	12.94%	4.403	1.271	2.499	Long Short Spread P1-P10	10.18%	4.027	1.371	2.448
Even Driven Spread P1-P10	7.87%	5.892	1.916	1.359	Multi Strategy Spread	8.22%	4.274	1.653	2.642	Others Spread P1-P10	8.65%	3.375	1.292	2.060	Global Market Spread P1-P10	9.35%	3.562	1.402	3.028
Relative Value Spread P1-P10	9.30%	6.196	2.005	2.494	Market Neutral Spread P1-P10	6.00%	1.121	0.958	2.849	CTA Spread P1-P10	10.58%	2.099	1.048	2.998					

Table 82. Persistence within Strategies - Spreads / Up Regimes

This table shows results of spreads between top P1 and bottom P10 performers for each hedge fund strategy, on a quarterly basis during up regimes. Using the regression based parametric model, a positive coefficient denotes persistence in the spread between top and bottom performers. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. The up-left side contains more directional strategies whereas the down-right side contains more non-directional strategies.

Strategy	Monthl y Averag	Standard Deviation	Coefficien t	t-stat	Strateg y	Monthl y Averag	Standar d Deviati	Coeffici ent	t-stat	Strateg y	Monthl y Averag	Standar d Deviati	Coeffici ent	t-stat	Strateg y	Monthl y Averag	Standar d Deviati	Coeffici ent	t-stat
Quarterly																			
Short Bias Spread P1-P10	7.39%	3.395	0.878**	15.028	Long Only Spread P1-P10	7.37%	3.324	0.933**	22.160	Sector Spread P1-P10	10.26%	4.200	0.935**	23.33	Long Short Spread P1-P10	8.73%	3.056	0.947**	26.79
Even Driven Spread P1-P10	6.25%	2.476	0.919**	21.634	Multi Strateg y Spread	6.36%	2.737	0.909**	19.394	Others Spread P1-P10	7.42%	3.410	0.847**	12.270	Global Market Spread P1-P10	8.27%	3.731	0.898**	16.36
Relative Value Spread P1-P10	5.29%	2.377	0.938**	24.352	Market Neutral Spread P1-P10	4.79%	2.155	0.900**	18.354	CTA Spread P1-P10	10.98%	3.037	0.931**	23.25					
Semi Annual																			
Short Bias Spread P1-P10	5.92%	2.907	0.885**	10.632	Long Only Spread P1-P10	5.96%	2.506	0.919**	13.343	Sector Spread P1-P10	8.32%	3.571	0.857**	10.167	Long Short Spread P1-P10	6.79%	2.379	0.929**	15.359
Even Driven Spread P1-P10	5.11%	1.898	0.936**	16.308	Multi Strateg y Spread	4.86%	2.221	0.866**	10.249	Others Spread P1-P10	6.60%	3.124	0.793**	7.173	Global Market Spread P1-P10	6.09%	2.175	0.942**	14.485
Relative Value Spread P1-P10	4.47%	1.937	0.920**	14.562	Market Neutral Spread P1-P10	3.90%	1.525	0.913**	13.363	CTA Spread P1-P10	8.47%	2.010	0.969**	21.719					
Annual																			
Short Bias Spread P1-P10	5.67%	2.691	0.833**	6.254	Long Only Spread P1-P10	5.16%	2.220	0.915**	8.794	Sector Spread P1-P10	7.46%	2.890	0.922**	9.666	Long Short Spread P1-P10	6.03%	1.905	0.904**	11.379
Even Driven Spread P1-P10	4.34%	1.683	0.882**	8.532	Multi Strateg y Spread	4.50%	1.858	0.871**	7.589	Others Spread P1-P10	5.83%	3.235	0.800**	4.854	Global Market Spread P1-P10	5.14%	1.613	0.961**	10.761
Relative Value Spread P1-P10	4.12%	1.251	0.930**	12.63	Market Neutral Spread P1-P10	3.26%	1.342	0.962**	13.34	CTA Spread P1-P10	7.17%	1.441	0.943**	14.71					

Table 83. Persistence within Strategies - Spreads / Down Regimes

This table shows results of spreads between top P1 and bottom P10 performers for each hedge fund strategy, on a quarterly basis during down regimes. Using the regression based parametric model, a positive coefficient denotes persistence in the spread between top and bottom performers. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01. The up-left side contains more directional strategies whereas the down-right side contains more non-directional strategies.

Strategy	Monthly Average	Standard Deviation	Coefficient	t-stat	Strategy	Monthly Average	Standard Deviation	Coefficient	t-stat	Strategy	Monthly Average	Standard Deviation	Coefficient	t-stat	Strategy	Monthly Average	Standard Deviation	Coefficient	t-stat
Quarterly																			
Short Bias Spread P1-P10	12.58%	4.364	0.837**	5.098	Long Only Spread P1-P10	13.45%	4.756	0.846**	5.181	Sector Spread P1-P10	16.59%	6.764	0.877**	5.231	Long Short Spread P1-P10	14.11%	4.686	0.876**	6.457
Even Driven Spread P1-P10	9.53%	5.278	0.774**	3.986	Multi Strategy Spread	9.31%	3.899	0.867**	5.344	Others Spread P1-P10	10.49%	5.487	0.857**	4.283	Global Market Spread P1-P10	13.04%	5.918	0.786**	3.980
Relative Value Spread P1-P10	9.42%	5.517	0.767**	3.578	Market Neutral Spread P1-P10	7.40%	3.187	0.840**	7.935	CTA Spread P1-P10	14.14%	7.282	0.746**	3.577					
Semi Annual																			
Short Bias Spread P1-P10	11.05%	5.841	1.056*	3.316	Long Only Spread P1-P10	10.67%	4.722	0.895*	3.418	Sector Spread P1-P10	15.30%	6.937	0.834*	3.456	Long Short Spread P1-P10	12.38%	5.532	0.846*	3.593
Even Driven Spread P1-P10	8.26%	4.881	0.959	2.553	Multi Strategy Spread P1-P10	9.10%	4.068	1.032*	3.370	Others Spread P1-P10	8.16%	4.265	1.303**	4.845	Global Market Spread P1-P10	11.90%	4.066	1.031**	5.414
Relative Value Spread P1-P10	8.73%	5.364	0.924	2.318	Market Neutral Spread P1-P10	6.88%	3.580	0.629*	3.477	CTA Spread P1-P10	11.74%	5.478	0.869*	3.262					
Annual																			
Short Bias Spread P1-P10	8.59%	3.314	1.336	2.344	Long Only Spread P1-P10	8.18%	3.010	1.360	2.819	Sector Spread P1-P10	11.95%	4.044	1.030	1.618	Long Short Spread P1-P10	9.57%	3.068	1.083	1.846
Even Driven Spread P1-P10	6.34%	3.315	1.535	1.893	Multi Strategy Spread	8.25%	1.737	0.883	2.548	Others Spread P1-P10	6.75%	3.259	1.281	1.445	Global Market Spread P1-P10	11.05%	3.596	0.861	1.463
Relative Value Spread P1-P10	6.28%	3.452	1.601	1.907	Market Neutral Spread P1-P10	5.06%	1.216	0.815	2.425	CTA Spread P1-P10	7.89%	2.569	1.249	1.830					

8.17 Out-of-sample tests – Trading strategies

In this appendix I show the results of the out-of-sample tests for growth and recessions for all hedge fund strategies and for the optimum theoretical trading strategies. During “good” market conditions the returns for trading strategies have mostly the same sign and are significant. During "bad" times the returns for the trading strategies have mostly the same sign although due to limited data availability I did not examine validity beyond one year. The insignificance can be ascribed to just not having enough data. However it can be tested in the future years when more data will be available.

Table 84. Persistence within All Strategies - Spreads / Growths

This table shows the spreads between top P1 and bottom P10 performers for all hedge fund strategies, on a quarterly, semi-annual and annual basis for the first and second half period during growths. HRE: high return exploitation, LRE: low return exploitation. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed t-statistic test.

Momentum Trading Styles			Contrarian Trading Styles		
	Average raw return			Average return	
	First half	Second half		First half	Second half
Quarterly	0.43	0.98**	2 Year	0.07	0.02
Semi annual	0.93**	0.91*	3 Years	-0.35	-0.04
Annual	0.27	0.77**			
Momentrarian Trading Styles (HRE)			Momentrarian Trading Styles (LRE)		
	Average return			Average return	
	First half	Second half		First half	Second half
1st order	0.07	0.35	1st order	0.31	0.39
2nd order	0.26	0.49*	2nd order	-0.32	0.18

Table 85. Persistence within Optimum Strategies - Spreads / Growths

This table shows the spreads (average raw returns) between top P1 and bottom P10 performers for optimum strategies, on a quarterly, semi-annual and annual basis for the first and second half period during growths. HRE: high return exploitation, LRE: low return exploitation. * denotes significance at P < 0.05 and ** denotes significance at P < 0.01 using a two-tailed t-statistic test.

1a. Momentum Trading Styles (same hedge fund strategy)			1b. Momentum Trading Styles (mixed hedge fund strategies)		
	Strategy OT		Strategies LO and SB		
	First half	Second half		First half	Second half
Quarterly	1.28**	1.45**	Quarterly	1.32	2.08**
	Strategy OT			Strategies OT and SB	
	First half	Second half		First half	Second half
Semi Annual	2.18**	1.76**	Semi Annual	2.22**	2.06**
	Strategy OT			Strategies SE and CT	
	First half	Second half		First half	Second half
Annual	0.85	1.65**	Annual	4.00**	2.80**
2a. Contrarian Trading Styles (same hedge fund strategy)			2b. Contrarian Trading Styles (mixed hedge fund strategies)		
	Strategy SB			Strategies LO and CT	
	First half	Second half		First half	Second half
2 Years	-0.28	1.56*	2 Years	3.45**	1.99*
	Strategy SE			Strategies ED and CT	
	First half	Second half		First half	Second half
3 Years	0.82	0.10	3 Years	1.95**	1.25*
3a. Momentrarian Trading Styles (same hedge fund strategy - HRE)			3b. Momentrarian Trading Styles (mixed hedge fund strategies - HRE)		
	Strategy OT			Strategies SE and CT	
	First half	Second half		First half	Second half
1st order	0.09	1.21	1st order	3.66**	2.62**
	Strategy SE			Strategies SE and CT	
	First half	Second half		First half	Second half
2nd order	1.74	1.00	2nd order	2.68*	1.96*
4a. Momentrarian Trading Styles (same hedge fund strategy - LRE)			4b. Momentrarian Trading Styles (mixed hedge fund strategies - LRE)		
	Strategy OT			Strategies SE and CT	
	First half	Second half		First half	Second half
1st order	0.35	1.09	1st order	3.75**	1.97**
	Strategy CT			Strategies ED and CT	
	First half	Second half		First half	Second half
2nd order	0.69	0.07	2nd order	3.13**	2.25**

Table 86. Persistence within All Strategies - Spreads / Recessions

This table shows the spreads between top P1 and bottom P10 performers for all hedge fund strategies, on a quarterly, semi-annual and annual basis for the first and second half period during recessions. HRE: high return exploitation, LRE: low return exploitation. "-"no computation due to limited data availability (I have not tested for significance due to the low number of observations).

Momentum Trading Styles			Contrarian Trading Styles		
	Average raw return			Average return	
	First half	Second half		First half	Second half
Quarterly	-1.03	2.03	2 Year	-	-
Semi annual	-1.22	-1.28	3 Years	-	-
Annual	-	-			
Momentrarian Trading Styles (HRE)			**Momentrarian Trading Styles (LRE)**		
	Average return			Average return	
	First half	Second half		First half	Second half
1st order	-	-	1st order	-	-
2nd order	-	-	2nd order	-	-

Table 87. Persistence within Optimum Strategies - Spreads / Recessions

This table shows the spreads (average raw returns) between top P1 and bottom P10 performers for optimum strategies, on a quarterly, semi-annual and annual basis for the first and second half period during recessions. HRE: high return exploitation, LRE: low return exploitation. "-"no computation due to limited data availability (I have not tested for significance due to the low number of observations).

1a. Momentum Trading Styles (same hedge fund strategy)			1b. Momentum Trading Styles (mixed hedge fund strategies)		
	Strategy SB			Strategies SB and ED	
	First half	Second half		First half	Second half
Quarterly	0.89	4.03	Quarterly	1.39	5.93
	Strategy RV			Strategies SB and RV	
Semi Annual	First half	Second half		First half	Second half
	-0.21	2.13	Semi Annual	-2.42	7.24
	Strategy RV			Strategies GM and RV	
Annual	First half	Second half		First half	Second half
	-	-	Annual	-	-
2a. Contrarian Trading Styles (same hedge fund strategy)			**2b. Contrarian Trading Styles (mixed hedge fund strategies)**		
	Strategy RV			Strategies SB and RV	
	First half	Second half		First half	Second half
2 Years	-	-	2 Years	-	-
3a. Momentrarian Trading Styles (same hedge fund strategy - HRE)			**3b. Momentrarian Trading Styles (mixed hedge fund strategies - HRE)**		
	Strategy RV			Strategies GM and RV	
	First half	Second half		First half	Second half
1st order	-	-	1st order	-	-
4a. Momentrarian Trading Styles (same hedge fund strategy - LRE)			**4b. Momentrarian Trading Styles (mixed hedge fund strategies - LRE)**		
	Strategy RV			Strategies SB and RV	
	First half	Second half		First half	Second half
1st order	-	-	1st order	-	-

9 Abbreviations

ABS	Asset-Based Style
ANOVA	Analysis of Variance
APT	Arbitrage Pricing Theory
AUM	Assets Under Management
BAFA	British Accounting and Finance
CAPM	Capital Asset pricing Model
CEGBI	Centre for Evolution and Global Business and Institutions
CFA	Common Factor Analysis
CISDM	Centre for International and Securities Markets
CME	Chicago Mercantile Exchange
COAG	Commodity Agricultural Index
COEN	Commodity Energy Index
COIM	Commodity Industrial Metals Index
COPM	Commodity Precious Metals Index
CPR	Cross Product Ratio
CRSP	Centre from Research in Security Prices
CS	Chi-Test
CSFB/Tremont	Credit Suisse First Boston
CSR	Cross Sectional Regression
CSWL	Centre for Evolution and Global Business and Institutions
CTA/CT	Commodity Trading Advisors
DEF	Default Premium
DS	Divergence Score
EACM	Evaluation Associates Capital Market
ECRI	Economic Cycle Research Institute
ED	Event Driven Strategy

ETF	Exchange Trading Fund
EXCH	Exchange
FoFs	Fund of Funds
GAV	Gross Asset Value
GEMI	Global Market Index (excluding U.S.)
GM	Global Macro Strategy
GOEF	Global Equity Ownership Feed of Thomson Financial
HFN	Evestment Com
HFR	Hedge Fund Research
HML	High Minus Low
KS	Kolmogorov-Smirnov Test
TERM	Term Spread Premium
TRI	Total Return Index
LL	Losers-Losers
LO	Long Only Strategy
LS	Long Short Strategy
LW	Losers-Winners
MAI	Market Index
MAR	Managed Account Reports
MBS	Mortgage-backed securities
MN	market Neutral Strategy
MOM	Momentum
MS	Multi - Strategy
NAV	Net Asset Value
NBER	National Bureau of Economic Research
OT	Others Strategy
PCA	Principal Component Analysis

RIC	Rank Information Coefficient
RLE	Real Estate
RV	Relative Value Strategy
SEC	Security Exchange Commission
SB	Short Bias Strategy
SDI	Strategy Distinctiveness Index
SE	Sector Strategy
SMB	Small Minus Big
SRC	Spearman Rank Coefficient
TAP	Thesis Advisory Panel
TASS	Tremont Advisory Shareholders Services
VIX	Volatility Index
VOV	Volatility of the Aggregate Volatility of Equity Market Returns
WW	Winners-Winners
WL	Winners-Losers

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