

An Analysis of Technical Trading Strategies

By

Kadida Ramadhani Shagilla Mashaushi

Submitted in accordance with the requirements for the degree of

Doctor of Philosophy

The University of Leeds
Leeds University Business School

September, 2006

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others. The copy has been supplied on the understanding that it is copyright material and that no quotation from the thesis may be published without proper acknowledgement

Acknowledgements

I take this opportunity to express my respectful appreciation on the help, guidance and supervision made by my supervisors Professor David Hillier, the Centenary Professor and Ziff Chair in Financial Markets, Leeds University Business School (LUBS), Professor Kevin Keasey, the Director of the International Institute of Banking and Financial Services (IIBFS), Leeds University Business School (LUBS) and Dr. Charlie Cai. I can not find words that can appropriately represent their contribution to my achievement.

A very special mention is in the name of my farther, the late Ramadhani Shagilla Mashaushi. He had all along inspired and encouraged me towards higher levels in my career progression and achievement.

Special thanks also goes to Professor Joshua Doriye, the Principal, Institute of Finance Management (IFM) and Dr. S.R. Mohamed, the Director of Graduate School, Institute of Finance Management (IFM) for their innumerable and immeasurable contributions to my study.

I would also like to mention Michelle Dickson and Natasha Mullea of LUBS Research Office for their support and encouragement. I sincerely underscore Michelle's support and caring assistance.

I am indebted to my wife, Kamaria, for her patience and moral support; my mum, brothers and sisters; my sons Othman, Ishaq and Luqman and to my daughter Malkia-Bilqis – a big thank to you for your patience and understanding.

Many thanks to my fellow students Iain and Suntharee (Mint) for your fruitful discussions and moral support.

Abstract

This dissertation extends the literature on the efficacy of technical analysis in the direction of the ‘risk premium view’ as an explanation for excess trading rule returns. First, we generally rely on the theoretical alternatives to the efficient market hypothesis which encourages possibilities for markets to be inefficient. We then investigate the link between the risk involved in trading rule strategies and the resulting excess returns. The empirical analysis is based mainly on a sample of stocks drawn from the London Stock Exchange, (LSE), portfolios constructed from three US markets; the New York Stock Exchange, (NYSE), the American Stock Exchange, (ASE), and the National Association of Securities Dealers Automated Quotation market, (NASDAQ). Data from ten small emerging markets of Africa is also used in empirical analyses.

Focusing on documented evidence of differences in risk levels among several markets or market segments, the empirical analyses examined whether these risk differentials can explain excess trading rule profits as compensation for bearing risk. The empirical analyses find that, to a large extent, liquidity, book-to-market ratio, and institutional arrangements can explain the excess profits from technical analysis. These empirical analyses are carried out in chapters three, four and six.

As part of the analysis, I conduct empirical tests to assess the appropriateness of some risk estimates for trading rules. Using recently developed techniques, the evidence in chapter five is consistent with the notion that certain risk estimates may not be appropriate for adjusting trading rule returns for risk.

Contents

Acknowledgements	ii
Abstract.....	iii
Contents	iv
List of Tables	viii
Chapter 1 Introduction.....	1
1.1 Importance of the study.....	1
1.2 Objectives of the study: is return predictability consistent with the EMH?.....	4
1.3 Chapters outlines.....	7
Chapter 2 Literature Review	12
2.1 Introduction.....	12
2.2 The Theoretical Background of Research in Predictability of Asset Returns.....	17
2.2.1 Assumptions of the Efficient Market Hypothesis.....	19
2.2.2 Forms of Market Efficiency.....	20
2.2.3 Theories Supporting the EMH: The Rational Expectations Hypothesis.....	21
2.2.4 Models for Testing Predictability of Asset Returns.....	23
2.3 Alternative theories explaining the behaviour of prices: the theoretical Basis of Technical Analysis	28
2.3.1 Overreaction.....	29
2.3.2 Overconfidence and Optimism	30
2.3.3 Herding Models	31
2.3.4 Asymmetrical Information Diffusion Process	31
2.4 Early Empirical Works	32
2.5 Recent Empirical Works.....	36
2.5.1 The Foreign Exchange Markets.....	37
2.5.2 Futures Markets	39
2.5.3 Stock Markets	40
2.5.4 Technical analysis in Emerging Markets.....	43

2.5.5	Studies of Technical Analysis via non-linear models.....	44
2.6	Empirical Explanations of Sources of Trading rule Profits.....	46
2.6.1	Market Microstructure Deficiencies	47
2.6.2	Data Snooping.....	48
2.6.3	Temporary Inefficiencies	50
2.6.4	Transaction Costs and other adjustments.....	51
2.7	Adjustments for Excess Profits for Risk Premium.....	54
2.7.1	Risk Adjustment Measures	54
2.7.2	Risk Factor Adjustments.....	58
2.7.3	Adjusting for Time – Varying Risk Premium.....	59
2.8	Summary and Conclusions	61
Chapter 3	Applying Simple Trading Rules to B-M based Portfolios.....	66
3.1	Introduction.....	66
3.2	Research Objectives and Significance	69
3.3	Literature Review.....	70
3.3.1	Trading rules	73
3.3.2	Test statistics.....	75
3.3.3	Testable Hypotheses and Test Statistics	77
3.4	Data and Methodology.....	78
3.5	Empirical Results.....	79
3.5.1	Summary Statistics	79
3.5.2	Comparative Performance of Book-to-Market based Assets.....	80
3.5.3	Can Risk Premium explain Excess trading rule returns?.....	83
3.5.4	Can risk premium explain superior performance of trading rules profits: Results from the extended Fama – French (1993) model.....	86
3.5.5	Further tests of time – varying risk premium using the bootstrap method.....	88
3.6	Conclusions.....	91
3.7	Appendix 1.....	95
Chapter 4	Technical Analysis: Returns, Risk and Liquidity.....	101
4.1	Introduction.....	101
4.2	Related works	105

4.3	Data and Portfolio Construction and the risk factors.....	108
4.4	Methodology and empirical tests	110
4.4.1	Hypothesis to be tested	111
4.5	Empirical results	113
4.5.1	Summary Statistics	113
4.5.2	Does liquidity really matter?.....	115
4.5.3	Adjusting for stylized risk factors.....	119
4.6	Conclusion	123
4.7	Appendix 2.....	126
Chapter 5	Can Risk Premium Explain Technical Trading Profits?	132
5.1	Introduction.....	132
5.2	Research Objectives and significance.....	135
5.3	Literature Review.....	137
5.4	The conceptual Framework.....	140
5.5	Methodology.....	143
5.6	Empirical Results.....	150
5.6.1	Summary Statistics	150
5.6.2	The rolling Standard deviation Vs the traditional standard deviation.....	150
5.6.3	Does Technical Analysis provide more stable portfolios?	152
5.6.4	Evaluating profitability and market efficiency	154
5.6.5	Risk adjustment using the X_{eff} statistic.....	157
5.7	Conclusions.....	158
5.8	Appendix 3.....	161
Chapter 6	Technical Analysis and Predictability of Asset Returns in African Markets.....	167
6.1	Introduction.....	167
6.2	Research Objectives and Significance	169
6.3	Previous research	171
6.4	The institutional infrastructure of African markets	173
6.5	The methodology	176
6.6	Transactions Costs	181
6.7	Hypotheses tested.....	181

6.8	Results.....	183
6.9	Conclusions.....	188
6.10	Appendix 4.....	191
	Summary of the Institutional and Trading Arrangements of the Sample African Stock Markets	197
Chapter 7	Summary and Conclusions	203
7.1	Summary of findings.....	203
7.2	Scope for future research	209
	BIBLIOGRAPHY	211

List of Tables

Table 3.1: Summary Statistics for daily returns of portfolios formed on the basis of the book-to-market ratios from the NYSE, AMEX and NASDAQ.	95
Table 3.2: B-M trading rule performance by quintiles	96
Table 3.3: Comparative performance of trading rule returns from high B-M portfolios against trading rule returns from low B-M portfolios.....	97
Table 3.4: Trading rule performance in upward trending markets: Comparative analysis of risk adjusted performance of stocks with higher B-M ratios against stocks with low B-M ratios.....	98
Table 3.5: Trading rule performance in downward trending markets: Comparative analysis of risk adjusted performance of stocks with higher B-M ratios against stocks with low B-M ratios.	99
Table 3.6: Evaluating the significance of excess trading rules returns after adjusting for risk using the Bootstrap method.	100
Table 4.1: Summary Statistics For Daily Returns Of The Most Liquid and Least Liquid Decile Stocks Of The Combined FTSE 350 Stocks and FTSE Small Cap Stocks.	126
Table 4.2: Summary Results of the Trading rule strategy for the Ten LiquidityDeciles Full sample (1990-2004)	127
Table 4.3: Results for the Trading rule strategies for the most liquid and Least Liquid Decile stocks	128
Table 4.4: Intercepts (α s) for factor regressions for the London Stock Exchange Stocks.	130
Table 5.1: List of stocks of the 66 FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004 included in the sample.....	161

Table 5.2: Summary statistics for the stocks of the 64 FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.....	162
Table 5.3: Comparative analysis of traditional and the rolling approaches to calculating risk from technical trading rules for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.	163
Table 5.4: Assessment of power of the rolling approach standard deviation in explaining the trading rule profit vs buy and hold returns for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.....	164
Table 5.5: Analysis of the time varying trading rule performance for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.	165
Table 5.6: Results of testing excess profits from trading rules after adjusting for risk estimates for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.	166
Table 6.1: Summary of Statistics of the daily returns of 10 African markets, Jan 1990 – Dec 2004.	191
Table 6.2: Returns from trading rule strategies applied to 10 African markets for the sample period Jan 1990 – Dec 2004.	192
Table 6.3: Returns from trading rule strategies applied to 10 African markets for the sample period Jan 1990 – Dec 2004.	193
Table 6.4: Summary of VMA trading rule statistics using returns and a trading band of 0 standard deviations. January 1990 – Dec2004.....	194
Table 6.5: Summary of VMA trading rule statistics using i returns and a trading band of 1 standard deviation. January 1990 – Dec 2004.	195
Table 6.6: Trading arrangements of African Markets in the Sample.....	197

Table 6.7: Foreign Investment Regulations of the sample African stock Markets.....	199
Table 6.8: Key Performance Statistics of the sample African Stock Markets	200
Table 6.9: Sub Saharan African Markets - Selected statistics (US \$ millions), ranked by year established.....	202

Chapter 1 Introduction

1.1 Importance of the study

A considerable body of research in the predictability of asset returns has occupied the attention of practitioners and academicians for many years now. When the Efficient Market Hypothesis (EMH) was formulated, it was largely due to an overwhelmingly large amount empirical evidence supporting the notion that returns in speculative markets are unpredictable. Regarding technical analysis, however, the early studies of filter rules by Alexander (1964) and Fama and Blume (1966) contained strong conclusions that discounted the status of technical analysis in the mainstream finance research. However, in the 1980s, a remarkable “come back” in studies of predictability motivated researchers to reconsider technical analysis as well. The renewed motivations in predictability studies followed Banz (1981), Reinganum (1983), Keim(1983) and others who noticed that efficient market hypothesis anomalies such as size, turn-of-the-year and book-to-market could not be explained by the Capital Asset Pricing Model (CAPM).

In the recent past, studies of technical analysis have been extended to more forms of markets; more speculative assets, a variety of market sectors and economies of varied historical backgrounds, markets organised with different technology levels, markets operating under varying governments and governance styles; and even markets operating in economies that differ in their cultural backgrounds. Also, markets of various sizes in terms of volume of transactions (reflecting liquidity),

legal environment etc have been empirically examined. The testing procedures used in studies have also been widened, particularly in the recent past, to include more candidate prices (e.g. intra-daily and high frequency tick data) and they have also considered a wider spectrum of trading systems ranging from simple moving averages to sophisticated genetic algorithms and neural networks.

Non-linear regression analysis techniques/estimation like neural networks that study the identification of patterns from past returns in order to predict future returns have also been rigorously examined apparently because of the quantity of trading strategies, based on these, that have become a common tool in the industry. Many other studies [These studies have been generally concerned with tests of the efficient market hypothesis. For example, Lo and MacKinlay (1988), Conrad and Kaul (1988), Lo and MacKinlay (1988), Cutler et al (1991), Lo and MacKinlay (1990), Chopra et al (1992), De Bondt and Thaler (1985), Fama and French (1986) and Porteba and Summers (1988). Others are Jegadeesh (1990), and French and Roll (1986), Lehman (1990)] on the predictability of asset returns, though not precisely technical analysis in nature, provide evidence of the existence of patterns in returns data series that can be exploited by technical trading rules have also been studied.

Empirical evidence from many recent studies has shown that returns are predictable from the current price, past prices and other variables like volume etc. These studies provide a strong challenge to the efficient market hypothesis.

The theoretical basis of technical analysis is not as strong and generally accepted as the efficient market hypothesis. A few previous works have tried to explain why technical analysis can be able to predict asset price movements or to generate abnormal profits. Similar to the way the efficient market hypothesis was

developed, the theory supporting technical analysis is growing behind and following increasing empirical evidence of, firstly, the existence of patterns in return series and, secondly, evidence of excess trading rule returns capitalizing on such regularities. Empirical evidence of predictable price behaviour, which is not explainable via the efficient market hypothesis and asset pricing models include the day of the week effect, year-end effect, size effect and the momentum effect. These theories are increasing in number and their stake in financial academic research is also growing. This growing body of theories trying to explain the predictability of asset returns (for example, 'investor irrationality' and 'the fads hypothesis') are called behavioural theories.

Some of these theoretical works intertwine with market microstructure theories in explaining theoretically how information is impounded in prices in the markets and then provide a framework for the existence of loopholes leading to delays in absorption of information into prices.

While more empirical evidence on predictability of asset returns is now available, debate on the topic does not appear to have yet resolved itself. For example, several studies (also in the recent past) have observed and concluded that the apparent predictability of technical trading rules are merely a result of data snooping [Jensen and Bennington (1970), Sullivan et al (1999), Jagadeesh (2000)] or methodological flaws in empirical analysis. Other studies have concluded that even where there is significant evidence of the presence of return patterns, these do not necessarily give enough profits in the presence of appropriate transaction costs [Fama and Blume (1966), Bessembinder and Chan (1998) and Ready (2002)]. The strongest argument now emerging in defence of market efficiency is that excess profits are in fact a compensation for time-varying risk premium [Kho (1994), Neely

(2001) and Sapp (2004)], and as such their presence does not violate the efficient market hypothesis.

Recent advances in (rational) asset pricing theory seem to have persuaded a majority of researchers that a certain degree of time-varying expected excess returns is necessary to reward investors for bearing certain dynamic risks associated with the business cycle. Loosely, it is claimed that the equity premium rises during an economic slow-down and falls during periods of economic growth, so that expected returns and business conditions move in opposite directions (e.g., Fama and French, 1989; Chen, 1991; Fama, 1991; Ferson and Harvey, 1991). Consequently, stock market predictability on its own would not imply stock market inefficiency (and irrational behaviour).

Thus, the risk view has remained inconclusive because the empirical evidence suggests substantial time variation in risk premiums that cannot (yet) be delivered by standard models of risk.

1.2 Objectives of the study: is return predictability consistent with the EMH?

The overall objective of this dissertation is to examine and further the understanding of whether and to what extent time varying risk premium can be used to rationalize the presence of regularities in stock returns and excess profits based on conditioning of information contained in prices.

The specific objectives can be outlined as follows; first, it is widely accepted that assets in different segments of the market have different levels of risks. For example assets with higher book to market ratios versus assets with lower book-to-market ratios. This relationship between asset return predictability and book-to-

market ratio has been researched and documented during much of the last decade or so. Therefore, focusing on the documented evidence that book-to-market ratios can be used to predict both cross sectional and time series returns, the dissertation examines the possibility that profits from conditioning on information contained in the book-to-market ratio can be construed to be caused by temporary market mispricing captured by the book-to-market ratio. In other words, the dissertation answers the question whether profits from trading rules based on book-to-market ratios are a compensation for bearing time varying risk premium.

Cross-sectional studies have pointed at the difference in risk levels between high book-to-market ratio assets and the low book-to-market ratios assets as the underlying source of predictability. Since studies using technical analysis are able to detect the presence of patterns in return series it is the objective of this dissertation to determine if technical analysis of assets sorted on the basis of their book-to-market ratio can give a different view of the connection between profits generated from conditioning on past information and risk.

The other groups or segments of the market with known differences of risk levels are the assets with lower liquidity levels versus assets with higher liquidity levels. The studies by Kavajecz's (1996), Brown *et al* (1997) and Kavajecz and White (2004) provide the intuition to consider applying technical analysis to aspects of the microstructure issues that highlight risk factors. Brown *et al*'s (1997) study provided a theory and evidence that quote depths predict intra-day stock returns. Specifically, the spread between the size of the quoted bid and the quoted offer predicts the stock return for the remainder of the day. This insightful documentation is used in this dissertation as the basis for examining assets with liquidity

differentials as the explanatory variables of predictability and profits from technical analysis.

The third objective is due to the classification based on the perceived risk differentials between emerging and developed markets. Emerging markets are known to be associated with the persistence of returns, or autocorrelation. Harvey (1995) finds that return autocorrelation in emerging markets is much higher than in developed markets. He also suggests that the level of autocorrelation is directly associated with the size and the degree of concentration of the market. In another study, Harvey (1995) contends that emerging market returns seem to be predictable when using international and local risk factors. Differences in these drivers or factors leading to inefficiency between markets sets expectations for the presence of the differences in the strength of regularities in return series of mature compared to emerging markets. In the same context, this should be reflected in the difference in profitability of trading rule profits before transaction costs are considered. In this objective, therefore, we compare the risk adjusted trading rule returns of emerging markets of Africa and those of mature markets of the US and Japan.

The last objective concerns appropriate risk adjustment techniques for technical trading rule profits. This objective is prompted by the following factors. 1) returns are known to exhibit non-stationarity behaviour, which supports the time-varying risk premium explanation for excess profits from trading rules, 2) evidence from previous research indicates that the risk premium view of excess returns has not been able to provide conclusive argument(s) for or against the efficient market hypothesis. One of the reasons for such mixed results has been varying and possibly inappropriate estimates of relevant risk for technical analysis profits.

In the last objective, therefore, I follow the insightful works of Dacorogna *et al.* (2001) regarding risk estimates for evaluating trading strategies. The conceptualization of technical trading risk in previous studies has considered technical analysis as a more risky strategy compared to the buy and hold strategy. However, the fact that technical analysis allows the trader to switch between the risky and the risk free asset(s) provides the intuition that the resulting portfolio will have more stable returns than the buy and hold strategy. This intuition is followed through by examining the way through which the standard deviation is determined for the purpose of estimating technical analysis risk. By adapting Dacorogna *et al.*'s (2001) X_{eff} statistic, this dissertation tests whether the standard deviation and its associated statistics, for example the Sharpe ratio, provide an appropriate estimate of technical analysis risk

Using the well and long established understanding that large capitalization stocks, for example FTSE 100 constituents, are less risky compared to small capitalization stocks, such as the FTSE small-cap stocks, we compute the magnitude of technical trading related risk in these two market segments. In theory, we should expect to find stocks in the small capitalization segment to exhibit a larger amount of risk than large capitalization stocks, given a similar set of variables.

The general objective of this thesis, therefore, is to examine how much of the difference in risk levels between assets groups in respective market (segment) pairs is reflected in their predictability differentials and profitability from technical trading rules.

1.3 Chapters outlines

Chapter 2 provides a synopsis of various aspects of the theoretical and empirical evidence relating to the performance of technical trading rules, thereby laying the motivation and foundation for the current study. The major issues discussed include a brief review of the history and the theory of the efficient markets hypothesis, a discussion of theories of the behaviour of prices in speculative markets emerging as alternatives to the efficient markets hypothesis, and a brief discussion of technical analysis as a practice and a technique for evaluating the efficiency of markets. The chapter also discusses various methodological issues found in the literature.

In chapter 3, I examine the extent to which the book to market ratio contains information that can be exploited by technical trading rules. The empirical work carried out in this chapter follows the analytical work of Lakonishok *et al.* (1994) who posit an inefficient market where the book-to-market ratio uncovers stocks with prices which are different from their fundamental values. In this model a period of time passes while the market works through the pricing mechanism to remove pricing errors¹. This period of mis-pricing is associated with delays, or lags, that it takes for information to be encapsulated into prices and it differs with the size of the book-to-market ratio. The period of temporal mis-pricing implies the presence of inefficiency in the market, which can be exploited by trading systems that condition on past information.

Chapter 4 is based on the analytic and insightful works of Kavajecz (1999) and Brown *et al* (1997). In the Kavajecz's (1999) model, the specialist presents a

¹ Pricing errors exist while higher excess returns are obtained from stocks with higher book-to-market ratios, Lakonishok *et al.* (1994)

price schedule consisting of bid and ask prices and a bid and ask size. In this model, the specialist reveals through the bid-ask size spread what she believes to be the expected return on the risky asset. Brown *et al* (1997) tested the implication of the specialist's revelation using intraday quote data and observed that Kavajecz does not investigate the possibility that the specialist's quote can be used to predict stock returns, something which is implied in his model

Brown *et al*'s (1997) study provided a theory and evidence that quote depths predict intra-day stock returns. Specifically, the spread between the size of the quoted bid and offer predicts the stock return for the remainder of the day. Although their findings were not strong enough for the use of trading rules to predict price movements, they were nevertheless consistent with the position that the specialist and/or the limit order book contain information concerning future stock prices.

The chapter first provides the rationale for using the bid-ask spread as a variable for predicting the future price movement in technical analysis. It then discusses the data and sample selection procedure, and the basic methodology adopted in the examination of the ability of liquidity measurements to forecast future price movements by using technical trading rules. Results are given followed by a discussion of whether liquidity can explain excess profits from trading rules. Additional tests based on stylised risk factors are also provided in this chapter. The chapter concludes with a discussion of empirical results and a summary of the main findings.

Chapter 5 focuses on the documented deficiencies of the current risk adjustment techniques, for example the standard deviation and the Sharpe ratio. This chapter examines whether the traditional method for calculating the standard

deviation as a measure of risk which has been extensively used in technical analysis studies is appropriate. Given that results from studies based on the time-varying risk premium paradigm are still mixed, this chapter considers one of the documented potential sources of such mixed results, i.e. the inappropriate adjustments of the risk premium.

The chapter, provides a conceptual framework of the study where the traditional technique for calculating the standard deviation is shown to misrepresent the risk arising from trading rule strategies. The chapter also provides the methodology used and then gives results of empirical tests.

Using the results, the chapter discusses the potential bias arising from using the traditionally calculated standard deviation in estimating trading rule risk. The discussed bias focuses on the effect of such estimates on adjustments for excess profits from trading rules and hence conclusions regarding their efficacy. The chapter then offers a summary and conclusions.

The main purpose of chapter 6 is to further understanding on the connection between the risk premium and the profitability of trading rules by comparing excess trading rules returns from markets operating in environments with significant risk differentials. Theoretically, the absence of appropriate and comprehensive institutional setups that support financial markets in most emerging markets suggests that prices will be more predictable. Relying on other studies of predictability of returns in emerging markets, chapter six examines whether the excess returns from emerging markets can be explained as compensation for risk. The choice of small emerging markets of Africa is motivated first by the fact that this block of economies is under-researched, but second the institutional environment in which these markets are operating can be described as attracting inefficiencies.

The chapter, therefore, first gives a brief review of relevant previous work on the efficiency of emerging markets focusing on their differences with developed markets. It then gives a discussion of possible reasons for the existence of differences in markets efficiency between developed and emerging markets. The discussion of results focuses on whether the relative superior performance of trading rules when applied to emerging markets can be construed as a reflection of the additional risks associated with emerging markets. A summary and conclusion are offered at the end of the chapter.

Finally, Chapter 7 presents the conclusions of the study and indicates areas where future research may be fruitful.

Chapter 2 Literature Review

2.1 Introduction

Technical Trading Strategies

A technical trading strategy is composed of a set of trading rules that can be used to generate trading signals. In general, a simple trading system has one or two parameters that are used to vary the timing of trading signals. Trading rules contained in a system are the results of the parameterizations. For example, the Dual Moving Average Crossover system with two parameters (a short moving average and a long moving average) can produce hundreds of trading rules by altering combinations of the two parameters.

Moving average based trading systems are the simplest and most popular trend-following systems among practitioners. The first analysis of moving averages can be found in the 1930s. Moving average systems take different forms according to the method used to average past prices in the moving average calculations. For example, the simple moving average uses equal weighting on each past price considered, while the exponential moving average gives comparatively more weight to recent prices. Their effect is to smooth out price actions, thereby avoiding false signals generated by erratic short-term price movements, and identifying the true underlying trend. In this study, two moving average systems are simulated: the Simple Moving Average with Percentage Price Band and the Dual Moving Average Crossover. The Moving Average with Percentage Price Band system uses a simple moving average with a price band centered around it. A trading signal is triggered

whenever the closing price breaks outside the band, and an exit signal is triggered when the price re - crosses the moving average. The Dual Moving Average Crossover system involves comparison of two moving averages, generating a buy (sell) signal when a short-term moving average rises (falls) above (below) a long-term moving average. This system is a reversing system that is always in the market, either long or short.

Filter systems “filter” out smaller price movements by constructing trailing stops for price movements above or beneath the current trend and generating trading signals only on the larger price changes . The trailing stops have various forms such as some predetermined amount of past extreme prices (Alexander's Filter Rule) or particular weighted averages of past prices (the Parabolic Time/Price system). Alexander's Filter Rule (ALX) system generates a buy (sell) signal when today's closing price rises (falls) by x % above (below) its most recent low (high) . The Parabolic Time/Price (PAR) system uses the trailing stop that works as a function of both the direction of price movement and the time over which the movement takes place. If the price movement does not materialize or goes in the other direction, the stop reverses the current position and a new time period begins. These filter systems are reversing systems that always take positions in the market. This dissertation is concerned with the analysis of moving averages and filters rules only.

Previous Works

Although a large number of studies on the predictability of asset returns have so far been conducted, the number of such studies that have examined Technical Analysis (TA) as a means of predicting future price or returns movements and indeed as a method of testing market efficiency is relatively small. There is only a

fairly small proportion of predictability of assets returns studies and tests of the weak form efficiency that can be classified under technical analysis. Acar and Satchell (1997) observe that in comparison, the study of technical analysis by academics is relatively new. They point at the study by Alexander (1961) as one of the first of such studies. This is not surprising because historically academics have dismissed technical analysis on the grounds that it is not consistent with efficient market theory despite its popularity by practitioners (Kavajecz and Orders, 2004). The early studies of technical analysis, especially those around the formulation of the efficient market hypothesis dismissed technical analysis by empirically demonstrating that the practice does not predict future prices movements [Fama and Blume (1966), Allen and Karjalainen (1999), and Ratner and Leal (1999)].

However, as it is argued in this chapter, the conclusion regarding the role of technical analysis both in practice and more importantly in academic research is far from over. Literature is divided fairly equally on both sides. Some previous work have found evidence that is in line with the practitioners' view that charting can provide information that is beyond what is already contained in prices and as such is able to predict the movements of stocks prices [Neftci and Policano (1984), Brock *et al*(1992), Neely *et al*, (1997) and Lo *et al* (2000)]. Studies conducted across a wide variety of market segments and types, and for different periods of time give results that are not consistent. In most of the developed markets, for example, the US and UK, technical analysis has been found to be mostly unprofitable. This is in contrast to the emerging markets where several research findings report high profitability.

Recently non-linear techniques like neural networks have been used to identify patterns from past returns in order to predict future returns. These systems have been fairly successful and the literature relating to these systems can also be

included as part of technical analysis studies. Many other studies on predictability of asset returns, though not technical analysis in nature, provide evidence of the existence of patterns in returns data series that can be exploited by technical trading rules have also been reviewed [These studies have been generally concerned with tests of the efficient market hypothesis. For example, Lo and MacKinlay (1988), Lo and MacKinlay (1990), Chopra et al (1992), and Porteba and Summers (1988).

Empirical evidence from many recent studies has shown that returns are predictable from the current price, past prices and other variables. These studies present a strong challenge to the efficient market hypothesis (EMH). It is widely accepted that on the theoretical side, the theory of market efficiency as formulated by Fama (1970) has dominated in market efficiency research although the Arbitrage Pricing Theory (APT) presents itself as a competitive theory. There are few previous works that have tried to explain why technical analysis could predict asset price movements or to generate abnormal profits. Some of these theoretical works intertwine with market microstructure theories in explaining theoretically how information is impounded in prices in the markets, and then provide a framework for the existence of loopholes leading to delays in absorption of information into prices.

Moreover the literature informs an increase in the level of the debate on the usefulness of technical analysis. Further, each side seems to have hardened its resolve, with arguments and evidence suggesting existence of significant profits from conditioning on past information from one side, and the other side defending the null of market efficiency. For example, in the recent past several studies have observed and concluded that the apparent predictability of technical trading rules are merely a result of data snooping [Jensen and Bennington (1970), Sullivan et al (1999), Jagadeesh (2000)] or methodological flaws in empirical analysis. Other

studies have concluded that even where there is significant evidence of systematic return patterns, these do not necessarily give enough profits in the presence of appropriate transaction costs [Fama and Blume (1966), Bessembinder and Chan (1998) and Ready (2002)]. In general, there has been a lack of consensus regarding the causes of the apparent regularity in return series. For example, regarding the excess returns from trading rules, Ang and Bekaert (2001) differentiates between three possibilities: it may reflect time-varying risk premiums (which he calls the “risk view”), it may reflect irrational behaviour on the part of market participants (the “behavioural view”) or it may simply not be present in the data — a statistical fluke due to poor statistical inference (the “statistical view”). The strongest argument now emerging in defence of the null of market efficiency has been that excess profits are in fact a compensation for time-varying risk premium [Sweeney (1988), Allen and Karjalainen (1999), Bho Chan (1996)]. This argument coincides with Ang and Bekaert’s (2001) “risk view”.

The remainder of this chapter is organised as follows. Section 2.2 provides some theoretical background for research in predictability of asset prices in speculative markets. Section 2.3 gives a summary of previous empirical works and Section 2.4 discusses the sources of excess profits from technical analysis as discussed in recent works. The section covers both the theoretical justifications for such profits and empirical findings and conclusions around subtle issues that have emerged. The section also reviews the various techniques for adjusting excess profits that have used in previous studies. Section 2.5 offers a conclusion.

2.2 The Theoretical Background of Research in Predictability of Asset Returns

Roberts (1959) working on the basis of the works of Kendall (1953) and Working (1934) provided the intuition for reformulating early empirical results of predictability of assets in speculative markets in terms of a standard economic theory of pricing in competitive markets. Fama (1965, 1970) later on introduced the EMH which assumes a perfect capital market in which all information is freely available to all participants; there are no transaction costs; and all participants are price takers. Under these assumptions, firms make production-investment decisions, and consumers choose securities. Based on this assumption, the EMH can be tested by revealing information to all participants and measuring the changes of security prices.

Empirical studies in efficient markets recognize three levels of market efficiency which are based on the amount of information that is revealed to the market, 'the information set'. It is common to distinguish three information sets of the EMH. In weak-form efficiency, the information set includes only the history of prices or returns; in semi-strong form efficiency, the information set includes all public information and in the strong form, the information set extends to the private information. Given an information set, studies of predictability and market efficiency test whether trading based on the specified information set earns abnormal returns or not. The abnormal returns are the differences between the realized returns and the expected returns using the given information set. The major null assumption in most empirical studies is that, based on information at time t , it is not possible to have

expected profits or returns in excess of equilibrium expected profits or returns at time $t+1$.

Samuelson (1965) and Mandelbrot's (1966) works, both being concerned with expected future prices of securities, are described by Fama (1970) as expected return theories. The expected return model, according to Fama (1970), can be stated as a discrete time mathematical model;

$$E(p_{i,t+1} | \phi_t) = p_{i,t} [1 + E(r_{i,t+1} | \phi_t)] \quad \dots\dots\dots (2.1)$$

$E()$: the expected value operator

$p_{i,t}$: the price of security i at time t

$r_{i,t+1}$: the one-period rate of return for security i , $(p_{i,t+1} - p_{i,t}) / p_{i,t}$

ϕ_t : the set of information that is fully reflected in $p_{i,t}$

The left hand side of (2.1) describes the expected price of a given security tomorrow, given all available information today, ϕ_t . The set of information ϕ_t available today includes what might be called the state of the world, or the current and past values of any relevant variables. Such variables include earnings of firms, gross national product, political climate, tastes of consumers and investors, and all other relevant economical variables. ϕ_t also includes whatever is knowable about the relationships among the variables (Fama, 1970). The expected price of a security tomorrow is then a function of the price of the security today and the expected return for the security. The expected return theory implies that the price tomorrow less the expected price today, conditioned on ϕ_t , is on average zero. This can be expressed as:

$$X_{i,t+1} = P_{i,t+1} - E(p_{i,t+1} | \phi_t) \quad \dots\dots\dots (2.2)$$

and then,

$$E(X_{i,t+1} | \phi_t) = 0 \quad \dots\dots\dots (2.3)$$

An implicit assumption in the definitions is that investors are certain about the best models to use in forecasting future returns. When this is relaxed, i.e. if agents are assumed not to be in knowledge of the true forecasting model, then the use of the mathematical expectation operator in the definitions of market efficiency becomes not very attractive, and it becomes meaningful to define markets as being efficient locally in time with respect to information set ϕ_t (Timmermann and Granger, 2004). This rather new way of thinking is also corroborated by a growing consensus that forecasting models may work for some time and that some time-varying regularity may exist in asset return series.

2.2.1 Assumptions of the Efficient Market Hypothesis

Fama (1970) also provides three market conditions consistent with efficiency. First it must be easy to determine sufficient conditions for capital market efficiency. Second, all available information is costlessly available to all market participants and third, all market participants agree on the implications of current information for the current price distribution of each security. In such a market, the current price of a security fully reflects all available information.

Fama (1970) also suggests three more important assumptions. First, an efficient market requires a large number of competing profit-maximizing participants that analyze and value securities. Second, information regarding securities arrives in the market in a random fashion, and the timing of

announcements is, in general, independent of others. The third assumption is that competing investors must trade and try to adjust security prices rapidly to reflect the effect of new information. Rational investors immediately exploit any arbitrage possibilities. Thus numerous competitors that analyze and adjust stock prices to news will result in random and unpredictable price changes. As a consequence, all information will be reflected in security prices.

Campbell et al (1997) observe that judgements about market efficiency can be implemented in two ways:

- To determine whether superior returns (after adjusting for risk) can be obtained by market professionals through trading on information.
- An alternative way to implement the suggestion is to ask whether hypothetical trading based on an explicitly specified information set would earn superior returns. A taxonomy of information sets which can be used to define information sets for use in implementing this approach is provided in Campbell et al (1997). The taxonomy distinguishes among the weak-form efficiency, the semi-strong efficiency and the strong-form efficiency.

2.2.2 Forms of Market Efficiency

The Weak-Form Efficiency: The information set includes only the history of prices or returns themselves. The weak-form holds that any information gained from examining the security's *past trading history* is immediately reflected in the price. Of course, the past trading history is public information, which implies that exceptions and counter-examples to the weak-form also apply to the strong and semi-strong forms. Other information such as rates of return, trading volume data,

block trades and odd-lot transactions can also be regarded to be reflected in current prices under weak form efficiency. Any trading based on this kind of information is not expected to give expected abnormal returns. Technical analysts or “technicians” try to analyze past price movements to forecast future price movements. If the weak form EMH is true, this kind of forecasting is of no value.

The Semi-Strong – Form Efficiency: The information set includes all information known to all market participants (*publicly available* information). In the semi-strong form of the EMH, all public information is considered to have been reflected in price immediately as it became known

The Strong-Form Efficiency: The information set includes all information not known to all market participant (*private* information). The strong form states that all information that is knowable is immediately factored into the market’s price for a security. If this is true, then stock analysts are definitely wasting their time, even if they have access to private information.

In the context of the hypothetical trading described above, abnormal returns are computed as the difference between the return on the security and its expected return, and forecasts of the abnormal returns are constructed using the chosen information set. If the abnormal security return is unforecastable, and in this sense “random,” then the hypothesis of market efficiency is not rejected (Campbell et al., 1997).

2.2.3 Theories Supporting the EMH: The Rational Expectations Hypothesis

The assumption that investors are rational and that their behaviour is homogeneous underpins the traditional theory of asset pricing. Our review of literature informs that these assumptions are theoretically responsible for the original view of the Efficient Market Hypothesis (EMH), that asset prices are unpredictable².

According to this theory the essence of non-dependency in asset return series lies in the notion of iterated expectations of rational investors. It is argued that (Samuelson, 1965) any attempt to forecast a favourable future performance leads instead to favourable current performance as market participants all try to get in the action before any price jump. More generally, this implies that the information that could be used to predict stock performance is already reflected in stock prices. As soon as there is any information indicating that a stock is under-priced and therefore offers a profit opportunity investors flock to buy the stock and therefore bid up its price to a fair level, where only ordinary rates of return can be expected. This argument requires individuals to be rational and not to have different comparative advantages in the acquisition of information.

However if prices are bid immediately to fair levels, given all available information, it must be that they increase or decrease only in response to new information. New information, by definition, must be unpredictable; even where this is possible, then that prediction would be part of today's information. Thus asset prices that move in response to new (unpredictable) information also must move unpredictably. This is the essence of the argument that stock prices should follow a random walk, that is, price changes should be random and unpredictable.

² The present view is that asset prices can be predictable but still does not necessarily mean markets are not efficient, Timmermann and Granger (2004)

Samuelson's (1965) hypothesis predicts that the expected rate of return on an asset equals zero:

$$E[p_{t+1} - p_t | \phi_t] / p_t = 0 \dots\dots\dots (2.4)$$

It is also understood that most assets are assumed to yield a non-zero expected return, thus equation (2.4) can be replaced with an assumption that:

$$E[p_{t+1} | \phi_t] = (1 + \mu)p_t \dots\dots\dots (2.5)$$

where μ is a constant. When equation (2.5) is rearranged Bailey (2002) obtain:

$$\mu = \frac{E[p_{t+1} | \phi_t] - p_t}{p_t} \dots\dots\dots (2.6)$$

so that μ can be interpreted as the expected rate of return from holding the asset, conditional on information set ϕ_t . In equation (2.6) it is assumed that the asset's pay-off at date t+1 is equal to p_{t+1} , that is, any dividend or coupons are absorbed in the price. This interpretation of μ as the expected rate of return can be seen clearly by writing the rate of return, r_{t+1} as:

$$r_{t+1} = \frac{p_{t+1} - p_t}{p_t} \dots\dots\dots (2.7)$$

2.2.4 Models for Testing Predictability of Asset Returns

The Martingale and the Random Walk Theory

In view of the work of Samuelson (1965) as cited in LeRoy (1989), perhaps the first useful model of asset prices is the martingale model. In its simplest form the model can be written:

$$E[p_{t+1} | \phi_t] = p_t \dots\dots\dots (2.8)$$

where p_t denotes the price of an asset at date t and ϕ_t is a set of information available at date t . Theoretically ϕ_t is assumed to contain all relevant information (e.g. the prices of other assets, or company's earnings data). The martingale model assumes that all relevant past information is already encapsulated in ϕ_t . According to Bailey (2002) the basic assumptions of the model are;

Investors believe that holding the asset is just like playing a fair game, i.e.,

$$E[p_{t+1} - p_t | \phi_t] = 0 \dots\dots\dots (2.9)$$

and investors have access to the information contained in ϕ_t .

Equation (2.9) asserts that asset prices evolve according to a random or stochastic process which is undefined except that the expectation of the next period's price is conditional on information available now.

An important implication of the martingale model is that non-overlapping price changes are uncorrelated at all leads and lags (Lo 1997), which further implies the ineffectiveness of all linear forecasting rules for future price changes which are based on the price history. A serious shortfall of the model in modern financial economics is that it does not take account of risk in any way. Luca and Brorsen (1989) emphasize this point when they argue that if an asset's price change is positive, it may be necessary to attract investors to hold this asset and bear its associated risk. Indeed, if an investor is risk-averse, he would gladly pay to avoid holding an asset with the martingale property. Thus, they conclude that despite the intuitive appeal that the fair game interpretation might have, it has been shown that

the martingale property is neither a necessary nor a sufficient condition for rationally determined asset prices.

The Random Walk Models – A closer look

In the martingale model only mild restrictions are placed on the random process governing asset prices changes explained above. Roughly the rate of return at one point in time provides no information about the rate of return at any later date, or that the rate of return is uncorrelated with any function of the return at any later point in time. Two additional restrictions are added in order to improve EMH hypothesis testing. These are mentioned by Fama (1965) as:

Successive price changes in an individual security are independently distributed, i.e. ε_{t+k} are statistically independent of one another for all $k \neq 0$ and

The price changes conform to a probability distribution. That is ε_{t+k} are identically distributed for all $k \neq 0$

The above additional restrictions account for the difference between the random walk theory and the more general fair game models. The fair game models do not, in opposition to the random walk, assume independent, identically distributed prices. These models refer only to the expected returns, while the random walk model refers to all moments of the distribution. The random walk model may thus be viewed as a special case of the fair game model as it does not contradict the implications made in the fair game model. As pointed earlier, additional restrictions are added on the underlying probability distribution in order to obtain testable hypotheses. The result is a set of random walk models discussed as follows.

Let X_t , $t = 0, 1, 2, \dots$, denote a sequence of prices of a financial asset. then the random walk hypothesis for the assertion that the log-price process $x_t = \log X_t$ satisfies a model of the form

$$X_t = \mu + X_{t-1} + \varepsilon_t \quad \dots\dots\dots (2.14)$$

Where μ is understood to be constant and where the terms ε_t , $t = 0, 1, 2, \dots$, are understood to represent a white noise process that can be specified in several different ways.

Campbell et al. (1997) distinguish between three versions of the random walk theory; the independent and identically distributed returns version (RW1), the independent returns version (RW2), and the uncorrelated returns version (RW3).

The Random Walk 1 (RW1)

The RW1 is written as ,

$$X_t = \mu + X_{t-1} + \varepsilon_t \quad \varepsilon \sim \text{iid} (0, \sigma^2) \quad \dots\dots\dots (2.15)$$

Where μ is the expected price change or drift, and $\varepsilon \sim \text{iid} (0, \sigma^2)$ denotes that ε_t is independently and identically distributed with mean 0 and variance σ^2 .

Campbell et al. (1997) observe that RW1 is so restrictive that it fails to capture some basic features of the price process. For example the return process $x_t - x_{t-1}$ are empirically found to be leptokurtic, and second, the volatility, $\text{Var}(\varepsilon_t)$, in the return is often observed to change significantly over time.

The Random Walk 2 (RW2)

Therefore, Campbell et al's (1997) RW2 relaxes the assumption of RW1 regarding the distribution of returns to include processes with independent but not identically distributed (inid) increments.

The RW2 is written as;

$$X_t = \mu + X_{t-1} + \varepsilon_t, \quad \varepsilon \sim \text{inid}(0, \sigma^2) \dots\dots\dots (2.16)$$

That is ε_t is independent, $E(\varepsilon_t) = 0$, $E(\varepsilon_t^2) = \sigma_t^2 < \infty$,

They observe that this version allows for unconditional heteroskedasticity in the ε_t 's, a feature which is useful given the time variation in volatility of many financial asset returns series. Lo (1997) describes this version as the one that allows historical performance to influence investment policies, but rules out the efficacy of non-linear forecasting techniques. For example charting or technical analysis will not work if the independent return random walk hypothesis is true.

The Random Walk 3 (RW3)

Version three, the RW3, relaxes the independence assumption of RW2 to include processes with dependent but uncorrelated increments.

RW3 is written as;

$$X_t = \mu + X_{t-1} + \varepsilon_t, \quad \text{Cov}[\varepsilon_t, \varepsilon_{t-k}] = 0 \text{ for all } k \neq 0, \dots\dots (2.17)$$

but where $\text{Cov}[\varepsilon_t^2, \varepsilon_{t-k}^2] = 0$ for some $k \neq 0$.

The second condition in RW3, $\text{Cov}[\varepsilon_t^2, \varepsilon_{t-k}^2] = 0$ for some $k \neq 0$, implies that ε_t , is possibly dependent with ε_{t-k} , $E(\varepsilon_t) = 0$, $E(\varepsilon_t^2) = \sigma_t^2 < \infty$, and $E(\varepsilon_t, \varepsilon_{t-k}) = 0$ for all $k = 1, 2, \dots$

The increments are uncorrelated but the squared increments are correlated hence it is a process that is not independent as such. This version rules out the efficacy of linear forecasting techniques such as regression analysis (Lo, 1997)

In order to realize the dependency feature in RW3, Lo and MacKinlay (1988) proposed to limit the generality of RW3 by allowing for only certain types of heteroskedasticity in the noise process. This, they observe, can be achieved through a mixing process. They use the heteroskedasticity-consistent methods of White (1980) and White and Domowitz (1984) to achieve this. The mixing process is described to be useful in expressing the type of heterogeneity and the amount of dependency in the noise process.

Campbell et al (1997) then demonstrate that all the above three versions imply that the random walk model is non-stationary and that its conditional mean and variance are both linear. While the random walk model presented above has been shown to be able to capture some useful features of asset return dynamics, Campbell et al. (1997, p.481) argued that “it is both logically inconsistent and statistically inefficient to use volatility measures that are based on the assumption of constant volatility over some period when the resulting series moves through time.”

2.3 Alternative theories explaining the behaviour of prices: the theoretical Basis of Technical Analysis

In the wake of growing evidence of systematic patterns in returns series, new paradigms able to depict a broader picture of the behaviour of prices in speculative markets and based on the assumption of psychological biases in the way individuals respond to new information have been proposed. Some of the proposed paradigms involve behavioural aspects of market participants and are generally referred as behavioural theories.

2.3.1 Overreaction

Overreaction is concerned with the degree of reaction of investors following the arrival of information. Day and Wang (2002) maintain that if stock prices systematically overshoot, then their reversal should be predictable from past return data alone. They suggest two specific hypotheses in this aspect: 1) Extreme movements in stock prices will be followed by subsequent movements in the opposite direction. 2) The more extreme initial price movement, the greater will be the subsequent adjustment. According to the overreaction and the long-horizon reversal hypothesis, investors tend to overreact to new information and, thus, past losers will yield higher return than the past winners. The tests of Day and Wang (2002) support this contrarian strategy and report abnormal returns to investors when buying past losers and holding these securities for about three years.

Day and Wang's (2002) findings fit well with the long horizon reversal effect and support the contrarian strategy. They describe this effect with the overreaction hypothesis. This hypothesis predicts that when stocks that go through extreme return experiences, subsequent price reversals will be more or less predictable.

According to DeLong et al (1989) these overreaction effects are asymmetrical; i.e. it is much larger for losers than winners, which means that investors will earn from buying losers than from short-selling winners.

DeLong et al (1989) describe overreaction as a phenomenon whereby investors are subject to waves of optimism and pessimism and therefore create a kind of “momentum” that causes prices to temporarily swing away from their fundamental values.

2.3.2 Overconfidence and Optimism

Overconfidence occurs when people believe that their knowledge is more accurate than it really is. It implies that investors estimate too high a probability for an event when they think will occur. Daniel et al (1998) argue that investors are overconfident, which leads investors to overestimate their knowledge, underestimate risk and exaggerate their ability to control events. Hirshleifer (2001) explains why investors do not learn from their overconfidence. One reason is probably that they attribute good outcomes to their own abilities and bad outcomes to the ‘uncontrollable’ environment. This may cause an illusion of control over surroundings. Self-attribution causes individuals to be overconfident rather than converging to an accurate self-assessment. In other words self-attribution causes individuals to underweight public relative to private information. The self-deception theory suggests that a tendency to adjust attitudes to match past actions is a mechanism designed to persuade the individual that he or she is a skilled decision maker.

Daniel et al (1998) present a theory where the confidence of investors grow when public information is in agreement with their own information, but does not

fall accordingly when public information contradicts this information. The price-moves resulting from own information are on average partially reversed. This indicates that price movements in reaction to the arrival of public information are positively correlated with later price changes. This view can be an explanation for the short run momentum effect presented in Jagadeesh and Titman (1993; 2001).

2.3.3 Herding Models

Herding models are emerging as part of the behavioural area, which tries to explain the behaviour of asset prices. Studies of herding behaviour or 'following the trend' frequently note that the phenomenon could be responsible for events like the stock market crash of 1987 (see Shiller ,1990) and in the foreign exchange market (Frankel and Froot, 1986). Froot *et al.* (1992) showed that the herding behaviour of traders can result in information inefficiency. In the context of technical analysis, Froot *et al.* (1992, pp 1480) argue that, 'the very fact that a large number of traders use chartist models may be enough to generate positive profit for those traders who already know how to chart. Even stronger, when such methods are popular, it is optimal for speculators to choose to chart'

2.3.4 Asymmetrical Information Diffusion Process

According to Hong and Stein's (1999) model investors are categorized as informed and non-informed. The informed investors trade only on the basis of new information about cashflows while the non-informed investors trade on the basis of recent past price information and are the ones who are responsible for the observed

momentum effect. As information is arriving, the information-gap between the two groups narrows. This results into the long-term mean-reversion effect. The theory suggests that information diffusion process is slower for small firms, where company data is not subjected to a depth of analysis that is accorded to larger firms.

2.4 Early Empirical Works

Empirical works on the behaviour of asset prices in speculative markets had been going on as early as 1900 although it wasn't until the 1960s that these works were synthesised to formulate the efficient market hypothesis following overwhelming evidence asserting that asset prices in speculative markets do move randomly. Most early works examined the serial dependency of these prices or the possibility of beating the market. So, most of the early documentation is in the form of the 'Random Walk Model'. For example, Bachelier (1900) who was the first to introduce the concept, assumed that the behaviour of prices should be a 'fair game'. He derived the Brownian motion process for bond prices. Of course, in Bachelier's time, the EMH had not yet been formulated, thus the 'fair game' model was later found unable to provide rigorous testable hypotheses of the efficient market hypothesis as it lacks elements of risk.

Early tests of predictability were based on an examination of serial dependency

Examining the time series of asset prices for possible serial dependency dominated early studies. The pre-EMH studies did not test market efficiency. They only tested for the presence of patterns in the series, i.e. predictability. Kendall (1953) examined the proposition that stock prices reflect the prospects of the firm, where recurrent patterns of peaks and troughs in economic performance ought to show up in those prices. Kendall found no predictable patterns except that stock prices seemed to evolve randomly. Working (1934), Granger and Morgenstern (1963) and also Samuelson (1965) are among the early studies which tested for the presence of serial correlation in stock prices. These studies used various statistical methods, for example the spectral analysis used by Granger and Morgenstern (1963). This work found that stock movements resemble the accumulation of pure random changes. Generally, early statistical studies found no serial correlation in price movements, and thus provided evidence of the random walk hypothesis.

The use of purely statistical methods to test the efficacy of technical analysis was criticised by Fama and Blume (1966). They observed that simple linear relationships that underlay serial correlation models can not capture the complicated patterns that technical analysts perceive in market prices. Fama (1970) also pointed out that the absence or presence of correlation effects in stock prices does not automatically imply presence or absence of profit opportunities for trading systems. The statistical techniques were also criticised for their inability to incorporate subtle market elements for example transaction cost and risk in their analysis. Therefore a more direct testing of the trading rules was recommended in favour of statistical tests as a more effective method for testing market efficiency. (Fama , 1970)

Early Studies Based On Trading Systems

For the purpose of this review, I define early technical studies as those studies on technical analysis that were carried out before and up to 1980. This classification is intended to mark the beginning of the shift towards renewed interest in research in technical analysis after a period of stagnation throughout the 1970s. Although technical analysis as a practice dates far back in history (before the Dow theory), the majority of the early studies were carried out in the 1960s. The studies tested the profitability of trading rules directly, for example filter rules (Alexander, 1961, 1964; Fama and Blume, 1966); Relative strength (Levy, 1967; Jensen and Benington, 1970); Channels (Donchian, 1960) and Momentum Oscillators (Smidt, 1965).

The stock market was the focus of early studies. The Futures, Foreign Exchange and other types of markets were not accorded the same level of attention as was accorded to the stock markets. Some early studies incorporated transaction costs in calculating excess profits from trading rules (Fama and Blume, 1966). But only a few studies considered risk (Jensen and Benington, 1970), or performed statistical tests of the significance of trading profits [James, (1968); and Peterson, (1982)].

In summary, early empirical studies examined the profitability of technical trading rules in various markets. The results varied greatly from market to market. For 30 DJIA individual stock markets, Fama and Blume (1966) found that filter rules could not outperform the simple buy-and-hold strategy after transaction costs. Overall, in the early studies, very limited evidence of the profitability of technical trading rules was found in stock markets (e.g., Fama and Blume 1966; Van Horne and Parker 1967) Thus, stock markets appeared to be generally efficient as studies

generally indicated that trading systems were unprofitable [see for example, Van Horne and Parker (1967); James (1968); Jensen and Benington (1970)].

On the other hand, early studies indicated that trading rules were relatively more successful on the foreign exchange and futures markets than on the stock markets. Technical analysis in these markets found fairly large net profit margins. For example, Leuthold (1972) found filter rules able to make net profits of 115.8% when applied to live cattle futures contracts for the sample period 1965 -1970. Other early studies indicating success of trading rules in these markets included: Smidt, 1965; Stevenson and Bear, 1970; and Cornel and Dietrich, 1978. The conclusions from these studies generally implied that the stock markets were more efficient than the foreign exchange and futures markets.

However, some issues should be considered as necessary qualifications to the conclusions from early studies. Lukac and Brorsen (1990) argue that the way the t-tests were implemented in the early studies could have attracted bias. They argue that the studies by James (1968) and Peterson (1982) which conducted significance testing through the t-tests assumed trading rule returns are normally distributed. This assumption invalidates the t-tests since the distribution of the returns under the null hypothesis of an efficient market is not known. (Taylor, 1985). Thus, it can generally be argued that most early studies did not conduct tests of significance on trading rule returns properly.

The other qualification regards the failure to incorporate risk into testing procedures. The early studies did not make explicit allowance for the difference of returns and consequential excess returns due to different degrees of risk. Under the risk-return paradigm, excess returns over the buy and hold strategy does not necessarily imply a rejection of the null of market efficiency, since the excess profits

may be compensation for bearing the unobserved extra risks. It was only Jensen and Benington (1970) who raised concern about this issue. Most early studies ignored it completely.

2.5 Recent Empirical Works

This section presents a review of recent empirical works in technical analysis. The papers discussed in here are grouped on the basis of key market sectors, i.e. the stock market, the foreign exchange market and the futures markets. This classification allows for a convenient comparison with early studies just discussed above. As pointed earlier, this review considers recent studies in technical analysis to begin after 1980. This is intended to emphasise the historical development in 1) the clarification and purifications of testing procedures; and 2) the shift in the theoretical perspectives about market efficiency.

On the historical developments in empirical testing procedures, the studies of the 1980s onwards have generally improved on the deficiencies of the early studies in terms of incorporating risk, transaction costs, out of sample tests and accounting for data snooping. However, in almost each of these issues, there still exist substantial differences in either the definition or the method of estimating the relevant value for trading cost, risk or other parameters or variables for evaluating technical trading profits or both.³

Regarding the shift in the theoretical perspective about the efficiency of financial markets, empirical studies of the 1980s onwards have steadily accumulated

³ Details of empirical findings from recent studies related to these issues are discussed in subsections 2.6 and 2.7

evidences against the null of market efficiency. Given the complexity involved in testing market efficiency (for example, the joint hypothesis problem, difficulty of estimating transaction costs and risks), these evidences have only managed to reinvigorate research in this area. Examples in this area include the documentation of the size effect. Using the CAPM, size, and an additional explanatory variable, Banz (1981) found that there is a negative statistical association between the size of a firm and its returns. French (1980) and Roll (1983) were the first to document what are now called the calendar effects. French found that returns on Mondays on the S&P500 were relatively small over the period 1953 – 1977. Roll (1983) also found a tendency for stock returns to rebound in January following a year end depression. In another study Summers (1986) found significant evidence positive serial correlation for the weekly holdings-period returns of the equal weighted and value weighted NYSE portfolio over 1962 -1985 period using the variance ratio method. This evidence prompted the emergence of theoretical alternatives to the efficient market theory. These theories include the overreaction/under-reaction hypothesis (DeBondt and Thaler, 1985), the herding hypothesis (Froot *et al*, 1992), and the asymmetric information diffusion process⁴ (Hong and Stein, 1999).

The following subsections discuss the recent previous works grouped by markets involved in the studies.

2.5.1 The Foreign Exchange Markets

⁴ These are discussed in detail in sections 2.4.3 above

In comparison with the early periods, the foreign exchange markets have received more attention than the stock markets during the recent period. Most studies in the foreign exchange markets indicated that technical trading rules could yield annual net returns in the range of 3%-11% for major currency futures markets from the late 1970s to the early 1990s. During the same period the trading rules could also yield profits for some currency spot markets. Neely (1997) tested filter rules and moving average rules on four major exchange rates over the 1974-1997 period and obtained positive net returns in 38 out of the 40 cases after adjusting for transaction costs. Also, following Allen and Karjalainen (1999), Neely, Weller, and Dittmar (1997) investigated six foreign exchange rates (Mark, Yen, Pound, Swiss franc, mark/yen, and pound/Swiss franc) over the 1974-1995 period. Results indicated that average annual net returns from each portfolio of 100 optimal trading rules for each exchange rate ranged 1.0%-6.0%. Trading rules for all currencies earned statistically significant positive net returns that exceeded the buy-and-hold returns. In addition, when returns were measured using a median portfolio rule in which a long position was taken if more than 50 rules signalled long and a short position otherwise, net returns in the dollar/mark, dollar/yen, and mark/yen were substantially increased. Similar results were obtained for the Sharpe ratio criterion.

On the other hand, LeBaron (1999), Neely (2002), and Saacke (2002) reported the profitability of moving average rules in currency markets. For example, LeBaron (1999) found that for the mark and yen, a 150-day moving average rule generated Sharpe ratios of 0.60-0.98 after a transaction cost of 0.1% per round-trip over the 1979-1992 period. These Sharpe ratios were much greater than those (0.3-0.4) for buy-and-hold strategies on aggregate US stock portfolios. However, Kho (1966) and Sapp (2004) showed that trading rule profits in currency markets could

be explained by time-varying risk premia using some version of the conditional CAPM. In addition, there has been serious disagreement about the source of technical trading profits in the foreign exchange market. LeBaron (1999) and Sapp (2004) reported that technical trading returns were greatly reduced after active intervention periods of the Federal Reserve were eliminated, while Neely (2002) and Saacke (2002) showed that trading returns were uncorrelated with foreign exchange interventions of central banks.

Another study by Qi and Wu (2002) also found technical trading capable of generating economically significant excess returns after accounting for transaction costs. They found mean excess returns of 7.2%-12.2% against the buy-and-hold strategy for major currencies except for the Canadian dollar (3.63%) over the period 1973-1998. In another study, Chang and Osler (1999) showed that the head-and-shoulders pattern generated statistically significant returns of about 13% and 19% per year for the mark and yen, respectively, for 1973-1994. These returns appeared to be substantially higher than either buy-and-hold returns or average stock yields on the S&P 500 index, and were still retained after taking account of transaction costs, interest differential, and risk.

2.5.2 Futures Markets

Technical analysis has also attracted research in futures markets. Two studies, Lukac, Brorsen, and Irwin (1988) and Lukac and Brorsen (1990) analysed the profitability of trading systems on the commodities futures market. The later

study being an extension of the former in terms of the number of trading systems testes and test periods involved. Lukac and Brorsen (1990) investigated 30 futures markets with 23 technical trading systems over the 1975-1986 period. The results indicated that 7 out of 23 trading systems generated positive monthly net returns at a 10 percent significance level after transaction costs were factored in. In the individual futures markets, exchange rate futures earned highest returns, while livestock futures had the lowest returns. For soybean-related futures markets, Irwin et al. (1997) reported that channel rules generated statistically significant mean returns ranging 5.1%-26.6% over the 1984-1988 period and beat the ARIMA models in every market they tested.

When Roberts (2003) compared the buy-and-hold return (-\$3.30) with genetic trading rules returns in a wheat futures market, he found a statistically significant mean net return (a daily mean profit of \$1.07 per contract). This was for the period from 1978-1998. For corn and soybeans futures markets, however, genetic trading rules produced both negative mean returns and negative ratios of profit to maximum drawdown. Similarly, Wang (2000) and Neely (2003) reported that genetically optimized trading rules failed to outperform the buy-and-hold strategy in both S&P 500 spot and futures markets. For example, Neely (2003) showed that genetic trading rules generated negative mean excess returns over the buy-and-hold strategy during the entire out-of-sample periods, 1936-1995. Thus generally, technical trading rules formulated by genetic programming appeared to be unprofitable in futures markets, particularly in recent periods.

2.5.3 Stock Markets

Ready (2002) compared the performance of technical trading rules developed by genetic programming to that of moving average rules examined by Brock *et al.* (1992) for dividend-adjusted DJIA data. Brock, Lakonishok, and LeBaron's best trading rule (1/150 moving average without a band) for the 1963-1986 period generated substantially higher excess returns than the average of trading rules formed by genetic programming after transaction costs. For the 1957-1962 period, however, the moving average rule underperformed every one of the genetic trading rules. Thus, it seemed unlikely that Brock *et al.*'s (1992) moving average rules would have been chosen by a hypothetical trader at the end of 1962. This led Ready (2002; p43) to conclude that "...the apparent success (after transaction costs) of the Brock *et al.* (1992) moving average rules is a spurious result of data snooping". He further found that genetic trading rules performed poorly for each out-of-sample period, i.e., 1963-1986 and 1987-2000. Many other studies, for example Allen and Karjalainen (1999), Ready (2002), and Neely (2003) all documented that, over a long time period, genetic trading rules underperformed buy-and-hold strategies for the S&P 500 index or the DJIA index

Brock *et al.* (1992) tested two simple technical trading systems, a moving average-oscillator and a trading range breakout (resistance and support levels), on the Dow Jones Industrial Average (DJIA) from 1897 through 1986. In moving average rules, buy and sell signals are generated by two moving averages: a short-period average and a long-period average.

Bessembinder and Chan (1998) evaluated the same 26 technical trading rules as in Brock *et al.* (1992) on dividend-adjusted DJIA data over the period 1926-1991. As Fama and Blume (1966) pointed out, incorporating dividend payments into data tends to reduce the profitability of short sales and thus may decrease the profitability

of technical trading rules. Bessembinder and Chan also argued that " Brock *et al.* (1992) do not report any statistical tests that pertain to the full set of rules. Focusing on those rules that are ex post most (or least) successful would also amount to a form of data snooping bias" (p. 8). This led them to evaluate the profitability and statistical significance of returns on portfolios of the trading rules as well as returns on individual trading rules. For the full sample period, the average buy-sell differential across all 26 trading rules was 4.4% per year (an average break-even one-way transaction cost^[18] of 0.39%) with a bootstrap p-value of zero. Nonsynchronous trading with a one-day lag reduced the differential to 3.2% (break-even one-way transaction costs of 0.29%) with a significant bootstrap p-value of 0.002. However, the average break-even one-way transaction cost has declined over time, and, for the most recent subsample period (1976-1991) it was 0.22%, which was compared to estimated one-way transaction costs of 0.24%-0.26%. Hence, Bessembinder and Chan concluded that, although the technical trading rules used by Brock, Lakonishok, and LeBaron revealed some forecasting ability, it was unlikely that traders could have used the trading rules to improve returns net of transaction costs.

The results of the bootstrap studies that replicated Brock *et al.* (1992) varied enormously across markets and sample periods tested. In general, for (spot or futures) stock indices in emerging markets, technical trading rules were profitable even after transaction costs (Bessembinder and Chan 1995; Raj and Thurston 1996; Ito 1999; Ratner and Leal 1999; Coutts and Cheung 2000; Gunasekarage and Power 2001), while technical trading profits on stock indices in developed markets were negligible after transaction costs or have decreased over time (Hudson, Dempsey, and Keasey 1996; Mills 1997; Bessembinder and Chan 1998; Ito 1999; Day and

Wang 2002). For example, Ratner and Leal (1999) documented that Brock, Lakonishok, and LeBaron's moving average rules generated statistically significant net returns in four equity markets (Mexico, Taiwan, Thailand, and the Philippines) over the 1982-1995 period. For the FT30 index in the London Stock Exchange, Mills (1997) showed that mean daily returns produced from moving average rules were much higher (0.081% and 0.097%) than buy-and-hold returns for the 1935-1954 and 1955-1974 periods, respectively, although the returns were insignificantly different from a buy-and-hold return for the 1975-1994 period.

Most studies that replicated the original study have similar problems to those in Brock *et al.* (1992). Namely, trading rule optimization, out-of-sample verification, and data snooping problems were not seriously considered, although several recent studies incorporated parameter optimization and transaction costs into their testing procedures.

Taylor (2000) investigated a wide variety of US and UK stock indices and individual stock prices, finding an average breakeven one-way transaction cost of 0.35% across all data series. In particular, for the DJIA index, an optimal trading rule (a 5/200 moving average rule) estimated over the 1897-1968 period produced a breakeven one-way transaction cost of 1.07% during the 1968-1988 period.

2.5.4 Technical analysis in Emerging Markets

Studies analysing international financial markets have paid more attention to developed than to emerging markets. Moreover, the trading rule literature in the foreign exchange market studies only three, five or at most seven developed country

currencies. This lack of research in emerging markets has been associated with the difficulty of obtaining good data.

Ratner and Leal (1999) test variable length moving average trading rules in ten emerging equity markets, finding profitable technical trading strategies in three of them. For the remaining seven, even though there is no strong evidence of profitability, 82 percent of their combinations tested can correctly predict the direction of the change in the return series. Matheussen and Satchell (1998) examine the possibility of using rules in trading stocks in emerging markets based on mean-variance analysis. They introduce high transaction costs because this is a characteristic of emerging markets. Using mean-variance optimization as a trading rule for investors, they find significant risk-adjusted profits even though high transaction costs are used.

2.5.5 Studies of Technical Analysis via non-linear models

Neural Networks

Nonlinear studies attempted to directly measure the profitability of a trading rule derived from a nonlinear model, such as the feed-forward networks or the nearest neighbours regressions, or evaluate the nonlinear predictability of asset returns by incorporating past trading signals from simple technical trading rules (e.g., moving average rules) or lagged returns into a nonlinear model.

Gençay (1998) tested the profitability of simple technical trading rules based on a feedforward network using DJIA data for 1963-1988. Across 6 subsample periods, the technical trading rules generated annual net returns of 7%-35% after transaction costs and easily dominated a buy-and-hold strategy. The results for the Sharpe ratio were similar. Hence, the technical trading rule outperformed the buy-

and-hold strategy after transaction costs and risk were taken into account. In addition, correct sign predictions for the recommended positions ranged 57% to 61%.

In general, technical trading rules based on nonlinear models appeared to have either profitability or predictability in both stock and foreign exchange markets. However, nonlinear studies have a similar problem to that of genetic programming studies. That is, as suggested by Timmermann and Granger (2004), it may be improper to apply the nonlinear approach that was not available until recent years to reveal the profitability of technical trading rules. Furthermore, these studies typically ignored statistical tests for trading profits, and might be subject to data snooping problems because they incorporated trading signals from only one or two popular technical trading rules into the models.

Genetic programming

Allen and Karjalainen (1999) applied the genetic programming approach to the daily S&P 500 index from 1928-1995 to test the profitability of technical trading rules. To determine whether the performance of trading rules can be explained by a given model for the data-generating process, Brock *et al.*'s (1992) bootstrap procedures were used with three null models (a random walk, ARMA, and ARMA-GARCH (1,1)). The best-performing ARMA model could explain only about 11% of the net returns to the dollar/mark rate yielded by 10 representative trading rules.

The genetic programming approach may avoid data snooping problems caused by ex post selection of technical trading rules in the sense that the rules are

chosen by using price data available before the beginning of the test period and thus all results are out-of-sample. However, the results of genetic programming studies may be confronted with a similar problem. That is, "...it would be inappropriate to use a computer intensive genetic algorithm to uncover evidence of predictability before the algorithm or computer was available" (Cooper and Gulen 2003, p. 9). In addition, it is questionable whether trading rules formed by genetic programming have been used by real traders. A genetically trained trading rule is a "fit solution" rather than a "best solution" because it depends on the evolution of initially chosen random rules. Thus, numerous "fit" trading rules may be identified on the same in-sample data. For this reason, most researchers using the genetic programming technique have evaluated the "average" performance of 10 to 100 genetic trading rules.

More importantly, trading rules formulated by a genetic program generally have a more complex structure than that of typical technical trading rules used by technical analysts. This implies that the rules identified by genetic programming may not approximate real technical trading rules applied in practice. Hence, studies applying genetic programming to sample periods ahead of its discovery violate the first two conditions suggested by Timmermann and Granger (2004), which indicate that forecasting experiments need to specify (1) the set of forecasting models available at any given point in time, including estimation methods; (2) the search technology used to select the best (or a combination of best) forecasting model(s).

2.6 Empirical Explanations of Sources of Trading rule Profits

2.6.1 Market Microstructure Deficiencies

Previous studies have shown that returns can be associated with microstructure aspects of the markets. For example Amihud and Mandelson (1989) distinguish between the intrinsic value of an asset and its observed price. They attribute the difference of these two variables to two market microstructure factors; the trading noise and the price adjustment factor, where the first factor relates to the transitory price fluctuations generated by trading process frictions, while the second factor concerns the speed of adjusting to new information.

Other microstructure studies have shown that price depths which are used by the specialist to mitigate adverse selection problems that arise due to the presence of informed traders end up being monotonic transformations of the specialist's expected return on the risky asset and as a consequence reveal a portion of the specialist's private information. Uninformed but rational traders may be able to take advantage of this information. For example Brown *et al* (1997) proposed and showed exactly how the specialist's price schedule would react to changes in the specialist's prior. Their proposition was a follow up to an earlier work by Kavajecz's (1996) who developed a market microstructure model for cross-sectional variation in intraday expected stock returns. In Kavajecz's (1996) model, the specialist presents a price schedule consisting of bid and ask prices and a bid and ask size. In this model, the specialist reveals through the bid-ask size spread what she believes to be the expected return on the risky asset.

Brown *et al* (1997) tested the implication of Kavajecz's (1996) analytical work using 1993-1994 intraday quote data from the NYSE Trade and Quote (TAQ) database. They observed that Kavajecz does not investigate the possibility that the

specialist's quote can be used to predict stock returns, something which is implied in his model. Brown *et al* (1997) therefore first examined whether the ability to act on this revealed information is offset (if only partially) by movements in the remaining choice variables (namely, the bid-ask spread). They then confirmed their theoretical findings that the relative sizes of the bid and ask quotes given by NYSE specialists provide information about future price movements.

More recently Kavajecz and White (2004) also consider the role of micro-structural issues in technical analysis. They assessed the relation between liquidity provision and technical trading rules. Their tests involved examining whether technical analysis captures changes in the state of the limit order book. They were able to demonstrate that support and resistance levels coincide with depth on the limit order book. They also found that moving averages reveal information about the relative position of depth on the book.

2.6.2 Data Snooping

According to White (2000), "Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection" (p. 1097). He argued that when such data re-use occurs, any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results. Lo and MacKinlay (1990: p. 432) also argued that "the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge".

In empirical studies of prediction, when there is little theoretical guidance regarding the proper selection of choice variables such as explanatory variables, assets, in-sample estimation periods, and others, researchers may select the choice

variables "in either (1) an ad-hoc fashion, (2) to make the out-of-sample forecast work, or (3) by conditioning on the collective knowledge built up to that point (which may emanate from (1) and/or (2)), or some combination of the three" (Cooper and Gulen, 2003, p. 3). Such data snooping practices inevitably overstate significance levels (e.g., t-statistic or) of conventional hypothesis tests (Lovell 1983; Denton 1985; Lo and MacKinlay 1990; Sullivan, Timmermann, and White 1999; Cooper and Gulen 2003).

White (2000) developed a statistical procedure that, unlike the genetic programming approach, can assess the effects of data snooping in the traditional framework of pre-determined trading rules. The procedure, which is called the Bootstrap Reality Check methodology, tests a null hypothesis that the best trading rule performs no better than a benchmark strategy. In this approach, the best rule is searched by applying a performance measure to the full set of trading rules, and a desired p-value can be obtained from comparing the performance of the best trading rule to approximations to the asymptotic distribution of the performance measure. Thus, White's approach takes account of dependencies across trading rules tested.

Sullivan, Timmermann, and White (1999) applied White's Bootstrap Reality Check methodology to 100 years of the Dow Jones Industrial Average (DJIA), from 1897 through 1996. The results for the mean return criterion indicated that during the 1897-1996 period the best rule was a 5-day moving average that produced an annual mean return of 17.2% with a Bootstrap Reality Check p-value of zero, which ensures that the return was not the result of data snooping. At first glance, thus, the rule seemed to produce a statistically significant return. The p-value adjusted for data snooping was 0.90, suggesting that the return was a result of data snooping. But they construed that the poor out-of-sample performance relative to the significant in-

sample performance of technical trading rules might be related to the recent improvement of the market efficiency due to the cheaper computing power, lower transaction costs, and increased liquidity in the stock market.

Qi and Wu (2002) also applied White's Bootstrap Reality Check methodology to seven foreign exchange rates during the 1973-1998 period. They created the full set of rules with four trading systems (filters, moving averages, support and resistance, and channel breakouts) among five technical trading systems employed in Sullivan, Timmermann, and White (1999). Results indicated that the best trading rules, which were mostly moving average rules and channel breakout rules, produced positive mean excess returns over the buy-and-hold benchmark across all currencies and had significant data snooping adjusted p-values. In addition, the excess returns could not be explained by systematic risk. Similar results were found for the Sharp ratio criterion, and the overall results appeared robust to incorporation of transaction costs into the general trading model. Hence, Qi and Wu concluded that certain technical trading rules were genuinely profitable in foreign exchange markets during the sample period.

2.6.3 Temporary Inefficiencies

Returns from technical trading appear to decline over time, especially in recent periods. For example, Neely and Weller (1999, 2001) found the profitability of genetic trading rules in a number of foreign exchange markets to gradually decline over time. Neely and Weller's (2001) finding indicated that technical trading profits for four major currencies were 1.7%-8.3% per year over the 1981-1992 period, but near zero or negative except for the yen over the 1993-1998 period. By testing intraday data in 1996, Neely and Weller (2003) also found that genetic trading rules realized break-even transaction costs of less than 0.02% for most major currencies.

Another study by Olson (2004) also reported that risk-adjusted profits of moving average crossover rules for an 18-currency portfolio declined from over 3% between the late 1970s and early 1980s to about zero percent in the late 1990s. Kidd and Brorsen (2004) provide some evidence that the reduction in returns to managed futures funds in the 1990s, which predominantly use technical analysis, may have been caused by structural changes in markets, such as a decrease in price volatility and an increase in large price changes occurring while markets are closed.

In the stock markets, studies by Sullivan, Timmermann, and White (1999, 2003) found technical trading rules to be profitable until the mid-1980s but not thereafter. This phenomenon of diminishing profitability from technical trading rules has been construed as an element of an efficiently functioning market. In another study, Bessembinder and Chan (1998) noted that profits from Brock *et al.* (1992) trading rules for the DJIA index declined substantially over time. In particular, an average break-even one-way transaction cost across the trading rules in a recent period (1976-1991) was 0.22%, which was compared to estimated one-way transaction costs of 0.24%-0.26%.

Timmermann and Granger (2004) called this phenomenon the 'self destruction property' of trading systems. Their argument which is in favour of market efficiency assert that; the publication of models (rules) capable of forecasting future price movements in an efficient market will attract sufficient new capital and remove it in the process.

2.6.4 Transaction Costs and other adjustments

The return statistics reviewed above do not account for transaction costs, and as such costs can play a substantial role in the profitability of a strategy. For a trading strategy Lo and MacKinlay (1997) define the one-way transaction cost measured in percent, with a buy-and-hold as the benchmark strategy as

$$C = \left[1 - \left(\frac{V_T^{BH}}{V_T^{IS}} \right)^{1/N} \right] * 100 \dots\dots\dots(2.18)$$

where N is the total number of one-way transactions. This is a reasonable way to understand the impact of transaction costs on the active strategy since C captures the percentage cost of buying or selling the risky asset such that total return on a strategy equals the total return on a benchmark strategy.

The elements of transaction costs that have been included in previous studies include; brokerage fees (commission), stamp duty, paper work fees and the impact costs. When Fama and Blume (1966) re- examined Alexander's (1961) filter rules they incorporated transaction costs. With transaction costs, none of the filter rules consistently produced large returns. Only filters between 12% and 25% produced positive average net returns. However, these were not substantial when compared to buy-and-hold returns. However, when trading positions were broken down into long and short positions, three small filters (0.5%, 1.0%, and 1.5%) generated greater average returns on long positions than those on the buy-and-hold strategy. For example, the 0.5% filter rule generated an average gross return of 20.9% and an average net return of 12.5% after 0.1% clearing house fee per round-trip transaction. The average net return was about 2.5% points higher than the average return (9.86%) of the buy-and-hold strategy. Fama and Blume, however, claimed that the profitable long transactions would not have been better than a simple buy-and-hold strategy in practice, if the idle time of funds invested, operating expenses of the filter rules, and

brokerage fees of specialists had been considered. Hence, Fama and Blume concluded that for practical purposes the filter technique could not be used to increase the expected profits of investors.

The major components of transaction costs are: (1) brokerage commissions and fees and (2) bid-ask spreads. While commissions and fees are readily available data for bid-ask spreads however, have not been widely available until recent years. To account for the impact of the bid-ask spread on asset returns, various bid-ask spread estimators were introduced by Roll (1984), Thompson and Waller (1987), and Smith and Whaley (1994). However, these estimators may not work particularly well in approximating the actual ex post bid-ask spreads if the assumptions underlying the estimators do not correspond to the actual market microstructure (Locke and Venkatesh 1997).

Although data for calculating actual bid-ask spreads generally is not publicly available, obtaining the relevant dataset seems to be of particular importance for the accurate estimation of bid-ask spreads. It is especially important because such data would reflect market-impact effects, or the effect of trade size on market price. Market-impact arises in the form of price concession for large trades (Fleming, Ostdiek, and Whaley 1996). A larger trade tends to move the bid price downward and move the ask price upward. The magnitude of market-impact depends on the liquidity and depth of a market. The more liquid and deeper a market is, the less the magnitude of the market-impact. In addition to obtaining appropriate data sources regarding bid-ask spreads, either using transaction costs much greater than the actual historical commissions (Schwager 1996) or assuming several possible scenarios for transaction costs may be considered as plausible alternatives. Recent studies in technical analysis have addressed this problem by calculating the break-even

transaction costs. Break-even transaction costs are costs that equate the excess profits from trading rules to the profits from the buy and hold strategy. For example, Sullivan, Timmermann, and White (1999) used a break-even transaction cost of 0.27% per trade and obtained an annual mean return of 17.2% from the best rule for the DJIA index over the 1897-1996 period, with a data-snooping adjusted p-value of zero. Bessembinder and Chan (1998) also employed the break-even cost approach to re-examine profits from Brock *et al.* (1992) trading rules for the DJIA index. They compared an average break-even one-way transaction cost across the trading rules of 0.22% in a recent period (1976-1991) with an estimated one-way transaction costs of 0.24%-0.26%.

2.7 Adjustments for Excess Profits for Risk Premium

The risk consideration in technical analysis studies emerged with growing evidence of the presence of regularity in price movements. Studies which concluded against the null of market efficiency were criticised for ignoring the risk implications of technical trading. In response to these criticisms it has become a standard procedure in technical analysis studies to make adjustments for risks on excess profits from trading rules.

2.7.1 Risk Adjustment Measures

The Sharpe Ratio

The Sharpe ratio (SR) is due to William Sharpe (1966). It is normally annualized for the purpose of evaluating a trading strategy and is defined as

$$SR = \frac{R - R^f}{S}, \dots\dots\dots (2.19)$$

where R and S represent the annualized return and annualized standard deviation of the trading strategy respectively and R^f is the risk free return. The Sharpe ratio is probably the most widely used risk adjustment performance measure. It tries to capture “risk” by comparing a trading strategy’s excess return relative to the total variability of the trading strategy, but despite its popularity the Sharpe ratio has egregious shortcomings. The annualized standard deviation S is subject to criticism and the Sharpe ratio lacks a rigorous economic interpretation. These points and others suggest the need for additional risk adjustment measures (Bodie *et al.* 2002).

Sortino Ratio

The standard deviation takes into account both the positive and negative deviations from the mean, and as a consequence the Sharpe ratio penalizes large negative returns. To address this limitation of the Sharpe ratio, one can consider instead the Sortino ratio which is given by

$$SoR = \frac{R - R^{ref}}{S^-}, \dots\dots\dots (2.20)$$

where R^{ref} is a pre-specified reference rate of return and where S^- is a statistic designed to capture the downside risk. Formally S^- is defined as

$$S^- = \sqrt{K} * \left(\left[\frac{1}{T_{down} - 1} \sum_{t=1}^{T_{down}} \left(R_t - \bar{R}^{-f} \right)^2 * I \left(R_t < \bar{R}^{-f} \right) \right]^{\frac{1}{2}} \right) \dots\dots(2.21)$$

Where the index t denotes weekly or monthly time period and $T_{down} = \sum_{t=1}^T I \left(R_t < \bar{R}^{-f} \right)$. Furthermore, $\bar{R}^{-f} = \frac{1}{T} \sum_{t=1}^T R_t^f$ and the indicator

variable $I\left(R_t < \bar{R}^f\right)$ takes the value one when $R_t < \bar{R}^f$ and is zero otherwise.

The pre-specified reference R^{ref} is typically chosen to accommodate an investor's risk preference.

M² and Diff-M² Measures

Bodie et al. (2002) argue that even though the Sharpe ratio may be a useful measure of performance, in addition to the limitations addressed by the Sortino ratio, the Sharpe ratio also lacks an economic interpretation of the difference in Sharpe ratios between two competing strategies. For example what does it mean if the difference between two competing strategies is 0.50? The M² measure is designed to provide a measure of risk adjusted performance that does have meaningful interpretation.

The M² measure, also known as the Risk Adjusted Performance or RAP measure, was proposed by Modigliani and Modigliani (1997). Formally, if we assume the buy-and-hold strategy as the benchmark strategy, the RAP measure for a trading strategy is defined as

$$M^2 = \frac{S^{BH}}{S^{TS}} R^{TS} + \left(1 - \frac{S^{BH}}{S^{TS}}\right) R^f \dots\dots\dots (2.22)$$

In essence, the RAP measure is calculated by re-scaling the “risk” (standard deviation) of the active strategy to match the risk of the passive strategy. One could think of this procedure as forming a new portfolio that is a mixture of the risky asset and the risk-free asset, such that the volatility in the new portfolio is the same (M²) as the volatility in the benchmark portfolio (here the buy and hold strategy)

Recent studies on technical analysis that have examined the possibility that significant excess profits out of sample could be a compensation for risk premium include; Cheng and Wong (1997), Lee *et al* (2001), Kho (1996), Ito (1999), Levich and Thomas (1993), Pradeep *et al* (1994) and Sweeney (1986).

One of the early studies that incorporated risk was carried by Sweeney (1986). Sweeney (1986) brought more aspects to test by considering risk, transaction costs, post-sample performance, and statistical tests. Based on the assumption that the Capital Asset Pricing Model (CAPM) can explain excess returns to both filter rules and the buy-and-hold strategy and that risk premia are constant over time, Sweeney developed the so-called X-statistic, a risk-adjusted performance measure. The X-statistic is defined as technical trading returns in excess of buy-and-hold returns plus an adjustment factor which takes account of different risk premia of the two trading strategies.

In Sweeney's model, the CAPM explains returns to the buy-and-hold strategy and the filter rules, and implies that expected excess returns to the filter rule over the buy-and-hold strategy should be equal to zero. Thus, the significant returns of the filter rules suggest that the CAPM cannot explain price behaviour in foreign exchange markets. Sweeney concluded that major currency markets indicated serious signs of inefficiency over the first eight years of the generalized managed floating beginning in March 1973. However, he also pointed out that the results could be consistent with the efficient markets hypothesis if risk premia vary over time. In this case, the filter rule on average puts investors into the foreign currency market when the risk premia or the expected returns are larger than average. Then, positive returns on the filter rule may not be true profits but just a reflection of

higher average risk borne. This was an early work where the “risk view” is given as a possible explanation of profits from technical trading rules.

The study by Lukac, Brorsen, and Irwin (1988) also considered risk issues. Based on the efficient markets hypothesis and the disequilibrium pricing model suggested by Beja and Goldman (1980), they proposed three testable hypotheses: the random walk model, the traditional test of efficient markets, and the Jensen test of efficient markets. Each test was performed to check whether the trading systems could produce positive gross returns, returns above transaction costs, and returns above transaction costs plus returns to risk. Over the 1975-1984 period, twelve technical trading systems were simulated on price series from 12 futures markets across commodities, metals and financials.

Dacorogna *et al.* (2001) introduced two measures of performance, the effective return with constant risk aversion X_{eff} and the effective return with relative risk aversion, R_{eff} . They demonstrated the superiority of the X_{eff} and R_{eff} over the Sharpe ratio as measures of investment performance. They demonstrated that these two measures of adjusting investment performance for risk are more robust in capturing the dynamics of active asset management and can accommodate both the variable investor appetite for risk and can also differentiate between periods of profit clustering and periods of drawdown. These two measures do not suffer from Gaussian assumptions on the distribution of returns.

2.7.2 Risk Factor Adjustments

Following the mounting evidence that some factors like the book-to-market, size and momentum can predict price movements, research in technical analysis started using factor models in search for sources of trading rules profits. The basic

idea in these models is to regress the excess returns from trading rules against the factors and then examine the value of the Jensen's α . If the factor(s) and the model are correctly specified, and if the factors explain the excess profits, then the value of Jensen's α should not be significantly different from zero. The factor models found in literature include;

$$1) \text{ CAPM : } R_t - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \varepsilon$$

2) The Fama –French three factor model:

$$R_t - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \beta_{hm} R_{hml} + \beta_{smb} R_{smb} + \varepsilon$$

3) The four factor Model:

$$R_t - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \beta_{hm} R_{hml} + \beta_{smb} R_{smb} + \beta_{liq} R_{liq} + \varepsilon$$

Studies that have used factor models include that of Sweeney (1986)

2.7.3 Adjusting for Time – Varying Risk Premium

In addition to the factor models approach discussed above, models capable of capturing heteroskedasticity in return series have also become popular for adjusting excess profits from trading rules since Brock *et al.* (1992). While Brock *et al.* (1992) were mainly interested in examining the stochastic properties of returns from trading rules; some subsequent studies [see for example Bessembinder and Chan (1998)] have used their ideas and approach to test for the presence of the time-varying risk premium as a source of excess profits from trading rules.

The basic technique has been to examine if the returns from technical analysis follows the model employed, say for example, the GARCH-M model. Such tests determine whether the data generation process is responsible for the trading rule profits. This is achieved by fitting the series of returns from trading rules using one of the popular models (random walk, AR, ARCH etc.), and using the

specification to reconstruct new random price series using a bootstrap procedure. It has also become customary for these tests to create their own-critical values for evaluating the significance of profits obtained from trading rules. This is achieved by applying the trading rules to the simulated price series a number of bootstrap iterations (usually between 500 and 2000 iterations). The p-values obtained are used to decide whether the underlying process responsible for generating the original data belongs to the model. In the above process, the test for time-variability of the risk premium is rather implied than direct. Thus, if it is found that the original data generation process belongs to the model tested, and because (say) the model is known to be capable of capturing, non-stationary statistics, then the excess profits may be explained as compensation for the ‘time-varying risk premium’

According to Brock, Lakonishok, and LeBaron, there are several advantages of using the bootstrap methodology. First, the bootstrap procedure makes it possible to perform a joint test of significance for different trading rules by constructing bootstrap distributions. Second, the traditional t-test assumes normal, stationary, and time-independent distributions of data series. However, it is well known that the return distributions of financial assets are generally leptokurtic, auto correlated, conditionally heteroskedastic, and time varying. Since the bootstrap procedure can accommodate these characteristics of the data using distributions generated from a simulated null model, it can provide more powerful inference than the t-test. Third, the bootstrap method also allows estimation of confidence intervals for the standard deviations of technical trading returns. Thus, the riskiness of trading rules can be examined more rigorously.

The basic approach in a bootstrap procedure is to compare returns conditional on buy (or sell) signals from the original series to conditional returns

from simulated comparison series generated by widely used models for stock prices. The popular models used by Brock, Lakonishok, and LeBaron were a random walk with drift, an autoregressive process of order one (AR (1)), a generalized autoregressive conditional heteroskedasticity in-mean model (GARCH-M), and an exponential GARCH (EGARCH). The random walk model with drift was simulated by taking returns (logarithmic price changes) from the original series and then randomly resampling them with replacement.

In other models (AR (1), GARCH-M, EGARCH), parameters and residuals were estimated using OLS or maximum likelihood, and then the residuals were randomly resampled with replacement. The resampled residuals coupled with the estimated parameters were then used to generate a simulated return series. By constraining the starting price level of the simulated return series to be exactly as its value in the original series, the simulated return series could be transformed into price levels. In this manner, 500 bootstrap samples were generated for each null model, and each technical trading rule was applied to each of the 500 bootstrap samples. From these calculations, the empirical distribution for trading returns under each null model was estimated. The null hypothesis is rejected at the set percent level if trading returns from the original series were greater than the percent cut-off level of the simulated trading returns under the null model.

2.8 Summary and Conclusions

In general, studies testing the efficacy of technical analysis can be traced back to the 1960s. Most of the 1970s recorded a low research output on technical

analysis before it regained momentum in the 1980s. In a total of about 140 studies conducted since 1960, only 14 were carried out during the 1960s (1960 – 1969), and another 14 during the 1970s (1970-1979). Studies in each of these periods represent about 10% of the total studies in technical analysis conducted in the last four decades or so. During the 1980s there was a notable increase of about 43% where in about 23 studies were conducted. The publications of anomalies by Banz (1980) and Reingunum (1981) and the availability of powerful computing resources appear to have encouraged more research during this decade. During the 1990s technical analysis research rose by 83% where about 43 research works were published. And for only the first five years of the 2000s (2000 – 2005), there has been about 45 works carried out, an increase of over 100% over research output during a similar period last decade (1990 – 1995) and accounting for about 32% of the total research output in technical analysis during the last four decades.

Parallel to the above increase in research output is a steady though mild shift towards accepting technical analysis as a useful practice. More studies in the recent past have found technical analysis to be profitable relative to early studies of the 1960s and 1970s. Although the stock markets have been tested more frequently than the other markets, technical analysis has been found to be more profitable in the foreign exchange markets. About 63% of studies conducted in the foreign exchange markets between 1988 and 2004 found trading rules to be profitable compared to 54% in the stock markets during the same period. Overall, about 59% of studies concluded that technical analysis can be profitable, 21% concluded that they are not profitable while about 20% gave mixed results.

However, these results are only very indicative given the fact that such results are influenced by a number of factors such as trading systems used, the

sample period, treatment of transaction costs and risk and other elements of testing procedures. These factors have made each side of the controversy to harden its resolve rather than converging to a common conclusion.

The profitability of technical analysis is reported to have been more pronounced during the second part of the 1980s and in the first half of the 1990s. Less and less profitability is reported for sample periods involving the very recent past (the later half of the 1990s to the present). This phenomenon has been attributed to improved market efficiency, the self – destructive nature of trading rules, data snooping, or a combination of these).

Despite the decline in profitability, some recent studies have been trying to find explanations for these rather anomalous profits from trading rules. Such studies have been conducted on both the theoretical and empirical fronts. Theoretical studies have suggested alternative theories to the EMH for example the behavioural theories. On the empirical side, several explanations have been advanced. For example data snooping, risk premium, inappropriate transaction costs, temporary market inefficiency and market microstructure deficiencies. The most notable and strongly emerging explanations have been data snooping and risk premium (the risk view).

Research trying to explain technical analysis through the risk view can be divided between those which are based on the constant risk premium paradigm and those based on the time-varying risk premium paradigm. The results from the constant risk premium based studies indicate that risk premium can not explain technical analysis profits. On the other hand only a few studies (for example Taylor (1992), Cheng and Wong (1997), Lee *et al* (2001), Kho (1996), Ito (1999), Levich and Thomas (1993), Pradeep *et al* (1994), Sweeney (1986), Neely (2001), Okunev

and White (2003) and Sapp (2004)) have actually tested whether trading rules can be explained by the time varying risk premium and results are still very mixed. For example Sweeney (1986), Taylor (1992) and Okunev and White (2003) conclude that time varying risk premium can not explain profits. While Kho (1996), Sapp (2004) and Neely (2001) on the other hand, conclude that the time varying risk premium is able to explain profits. The reasons for these mixed results could be: differences in data frequencies, pricing model specifications, technical trading systems, market proxies, inappropriate treatment of risk premium and other aspects of testing procedures.

The following important questions that arise from the foregoing review form the basis for empirical studies carried out and documented in this dissertation;

1. Focusing on the documented evidence that book-to-market ratios can be used to predict both cross sectional and time series returns, the dissertation poses a question whether profits from conditioning on information contained in the book-to-market ratio can be construed to be caused by temporary market mis-pricing captured by the book-to-market ratio. In other words, the dissertation answers the question whether profits from trading rules based on the book-to-market ratios is a compensation for bearing time varying risk premium.
2. Can market microstructure deficiencies explain excess returns from trading rules? Specifically, the dissertation tries to answer the question whether liquidity risk can explain profits from trading rules.
3. Given that emerging markets have been found to exhibit higher returns relative to mature and developed markets, and that they have

also been found to be more risky than developed markets, can risk evidence be used to explain excess returns from trading rules?

4. The mixed results from studies based on the time – varying risk premium paradigm suggest that more understanding can be obtained by purifying and innovating more appropriate risk estimates and adjustment procedures. Focusing on the documented deficiencies of the current risk adjustment techniques, for example the Sharpe ratio, this dissertation answers the question whether the traditional method for calculating the standard deviation as a measure of risk which has been extensively used in technical analysis studies is appropriate.

In the next chapter, the first of the empirical studies is provided. The chapter examines the role of Book to Market equity in the creation of trading profits from technical trading rules.

Chapter 3 Applying Simple Trading Rules to B-M based Portfolios

3.1 Introduction

Parallel with the debate on the sources of trading rule profits, there is ongoing debate on the reasons for the pattern whereby stocks with high book-to-market value ratios outperform stocks with low book-to-market value ratios. Several views have been suggested in connection with this, for example survivorship bias (Kothari *et al.* 1995), risk-return trade-off [Fama and French (1993, 1995, 1996)] and mispricing of securities (Lakonishok *et al.* (1994). In their analytical work, Lakonishok *et al.* (1994) consider the superior performance of value stocks against glamour stocks to be caused by pricing mistakes (i.e. market inefficiency). Their work allows one to perceive the market as consisting of continuous segments which differ in terms of efficiency. At one end of the efficiency spectrum there is a segment that can be considered as having stocks with prices below their fundamental values (high book-to-market ratios) while at the other end there is a segment with lowest book-to-market ratios, comprising overpriced stocks. This view can be considered to contradict the risk-return view shared by, among others, Fama and French (1993, 1995, 1996).

Lakonishok *et al.* (1994) show that high book-to-market stocks tend to do better in economic downturns, which is the opposite of what would be expected if their extra returns represented a risk premium. Lakonishok *et al.*'s (1994) view is related to the risk-view of excess returns from trading rules strategies. In this regard,

while the ‘risk view’ of the sources of trading rules seems to be dominating the debate, the majority of the previous studies have failed to notice that the risk-time-return relationship does not hold.

The conclusion that excess trading rules profits are a compensation for time-varying risk premium in several previous studies is contradictory because it is known that periods of general market uptrend (Bull markets) give more buy signals which have higher returns than periods of down trending markets, which are basically periods with relatively more sell signals. In fact most periods following sell signals have negative returns (a phenomenon which has also been difficult to explain). The time varying risk premium would require that periods of higher volatility be matched with periods of higher returns and vice-versa. However, on the contrary, periods following sell signals (bear markets) have been found to exhibit higher volatility than periods following buy signals (bull markets) Brock *et al.* (1992). In this sense the time-varying risk explanation seems implausible.

The objective of this chapter is to use book-to-market based portfolios to examine the above relationship following Lakonishok *et al.* (1994) who show that high book-to-market stocks tend to do better in economic downturns. The intuition here is that periods of economic downturns are generally risky and they conform to the Sell periods in longer term technical strategies. For the purpose of tracing the risk – return – time relationship we investigate whether the performance of trading rules applied to book-to-market based portfolios will give poor (good) returns on periods following Buy (Sell) signals relative to periods following Sell (Buy) signals for the different levels of book-to-market ratios. In this sense we test the general hypothesis that excess returns are a compensation for time varying risk premium.

This chapter investigates the effect of risk on the performance of technical trading rules in the context of investment strategies in the stock markets. The sample is made up of value weighted portfolios constructed from three US markets, the American Stock Exchange (AMEX), the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotation (NASDAQ). Portfolios sorted on the basis of their book-to-market equity are used to improve the robustness of the results because they are already in some form of risk order.

The chapter finds that portfolios at both the two ends of the spectrum (high and low book to market ratios) perform better than the middle part in terms of t-statistics, Sharpe ratio, and annual profits. However, on the argument that time-varying risk premium is the source of excess profits from trading rules based on book-to-market ratios, the study fails to reject this hypothesis.

The rest of this chapter is organised as follows; The next section, 3.2, briefly reviews relevant related literature. In section 3.3 the significance and objectives of this study is provided. This is followed by a description of the data and methodology used in section 3.4. Section 3.5 presents the results and a discussion of their interpretation while section 3.6 offers a conclusion.

3.2 Research Objectives and Significance

The overall objective in this chapter is to examine the connection between the book-to-market ratio of a stock and excess trading rule returns. Focusing on the documented evidence that book-to-market ratios can be used to predict both cross sectional and time series returns, the chapter addresses the question whether profits from conditioning on information contained in the book-to-market ratio can be construed to be caused by temporary market mis-pricing captured by the book-to-market ratio. In other words, the chapter answers the question whether profits from trading rules based on the book-to-market ratios is a compensation for bearing time varying risk premium.

The first specific objective is therefore to examine the relative performance of simple trading rules between assets with high book-to-market ratios and those with low book-to-market ratios. This objective is prompted by documentations from previous studies that the general performance of value stocks is better than that of glamour (also called growth) stocks. At the same time, value stocks have been associated with small capitalization assets where trading rules have been found to perform better than they do for value stocks. If stocks with high book-to-market ratios outperform low book-to-market stocks, the study will discuss the potential implications of higher risks associated with trading rules as has been the case with size stocks.

The second objective is to examine the periodic performance of trading rule profits. The study seeks to ascertain whether trading rule returns increase, decrease or have no relationship with changing economic conditions or other forms of risk

along the time line. This is in fact an evaluation of the presence of a time varying risk premium in profits based on conditioning on past returns.

The third objective is to examine whether profits from conditioning on past returns can be explained by the stylised risk factors. I test the extent to which returns from simple trading rules are explained by risk factors for example the book-to-market ratio, the momentum factor, the liquidity risk factor, the size factor and the market risk factor.

The last objective of this study is to look for evidence of temporal market inefficiencies. I investigate the possibility that the performance of trading rules on US equities may have declined during the recent past.

3.3 Literature Review

It is now widely accepted that the ratio of book-to-market value of equity has significant explanatory power for the cross-section stock returns (see, for example, Raph and Trecartin (2001) Chan, Hamao, & Lakonishok (1991), Davis (1994), Fama & French (1992), Lakonishok, Shleifer, & Vishny (1994), Rosenberg, Reid, & Lanstein (1985)).

Fama and French (1992) found significant size and book-to-market effects in explaining stock returns behaviour. Since then, these two firm characteristics have been researched extensively for their explanatory powers on stock returns and in their relationship with stock return predictability.

Daniel and Titman (1997) show that it is the book-to-market ratio itself that seems to drive expected returns rather than a common sensitivity to an underlying

risk factor, as assumed by Fama and French. Brennan et al. (1998) also show that the book-to-market and size characteristics result in higher average returns after controlling for book-to-market and size factors, but their 1966–1995 sample period is not much larger than that of Daniel and Titman.

According to Lakonishok *et al.* (1994), when the book-to-market ratio is used in studies of market efficiency, it is so used on the basis of two theoretically different models of stock prices⁵. One model posits an inefficient market where the book-to-market ratio uncovers stocks with prices which are different from their fundamental values. In this model higher excess returns are obtained from stocks with higher book-to-market ratios while the market works through the pricing mechanism to remove the mis-pricing. This period of temporal mis-pricing implies the presence of inefficiency in the market. The converse is true for assets with low book-to-market ratios. That, while the market is correcting the over-priced low book-to-market assets, this period will exhibit low returns for the respective asset (Lakonishok *et al.*, 1994).

The academic debate on the profitability of technical analysis has shifted from simply proving whether or not there exist patterns in stock returns to empirical analyses of the various components and theory based explanations. Most of such studies, (carried out across different markets, assets and times) have employed either the three factor model, or the five factor model according to their specific objectives. In connection with studies of weak form efficiency, particularly via technical analysis, a few previous studies have attempted to use the book-to-market ratio as a

⁵ The other model posits an efficient market, in which prices are set as the present value of expected future dividends, book-to-market forecasts returns because it is a proxy for the unobserved discount rate (Fama & French, 1992) in Lakonishok *et al.*, (1994)

suitable basis for classifying stocks in order to investigate their potential for trading rules profits.

Lakonishok *et al.* (1994) posit an inefficient market where the book-to-market ratio uncovers stocks with prices which are different from their fundamental values. In this model a period of time passes while the market works through the pricing mechanism to remove pricing errors⁶. In their study, Lakonishok *et al.* (1994) examined the cross-sectional variations in the book-to-market ratio as a source of superior profits for contrarian value strategies. In their analysis they argue that value strategies might produce higher returns because they are contrarian to 'naïve' strategies followed by other investors.

The opportunities for contrarian strategies to make abnormal returns exist because naïve strategies extrapolate their reactions too far hence assuming a trend into stock prices. These could be in the form of an overreaction to past performance so that glamour stocks become overpriced. They could also underreact to bad news and hence oversell stocks associated with such bad news making them underpriced. Contrarian strategies exploit this mispricing by maintaining a portfolio that puts less weight to overpriced stocks and more weight to underpriced ones.

In their conclusion, Lakonishok *et al.* (1994) noted that their results are not only capable of explaining the differential stock returns between value and glamour stocks cross-sectional wise, but they can also explain such differences in a time series setting. In other words the naïve investors can be considered to create a systematic pattern of expectational errors that is captured by the book-to-market

ratio for the duration of the mispricing. This period of mis-pricing is associated with a delay (lag) that it takes for information to be encapsulated into prices and it differs with the size of the book-to-market ratio. The period of intertemporal mispricing implies the presence of an inefficiency in the market which can be exploited by trading systems that condition on past information.

The empirical questions addressed in this chapter are based on this theoretical framework. The following empirical questions follow from this literature review:

1. Can assets with higher book-to-market ratios do better than stocks with low book-to-market ratios in terms of trading rule profits?
2. When high returns are generated from technical trading rules, is it appropriate to associate such profits with a time varying-risk premium? In other words do the high book-to-market stocks generally do better (in terms of trading rule returns) during economic downturns (which are the periods following sell signals coupled with high volatility)?
3. Do stocks with higher book-to-market ratios do better in bear markets (during economic downturns) than in other periods because bear markets have higher volatility?

3.3.1 Trading rules

Trading rule models are used to test whether patterns in return series can be profitable. This methodology is based on the assumption that technical trading rules

6 Pricing errors exist while higher excess returns are obtained from stocks with higher book-to-market ratios, Lakonishok et al. (1994)

take advantage of positive serial correlation in return series where the autocorrelation bias in the time series are assumed to continue in the same direction.

Given the large number of trading rules available, it has always been difficult to decide on the number and type of trading rules to use in a study of this type. The choice of trading rules is a subject related to data snooping and spurious results. To avoid these problems we choose, 1) trading rules that are most widely used in the industry and 2) those that are simple to implement. These are the same rules which were used by Brock et al (1992), Levich and Thomas (1993) and in several other studies. This study employs the Variable Moving Average (VMA) rules. The VMA rules analyzed are as follows: 1-50-0, 1-100-1 5-150-1, 1-200-1, 2-200-1, where the 1, 2 and 5 represent the number of days in the short moving average, and the 50, 150 and 200 represent the number of days in the long moving average. A buy signal is given when the short moving average exceeds the long moving average. The 1 and 0 are the percentage band filters. 0 for the no filter and 1 stands for the 1% filter. The %-band filter is used to reduce the number of false signals. The band filter is introduced around the slow moving average. If the price of fast moving average crosses the slow moving average with an amount greater than the band, a signal is generated; otherwise the position in the market is maintained.

The two short (S) and long (L) moving averages (MA) are calculated at time t using the most recent price information;

$$SMA_{t,s} = \frac{1}{S} \sum_{j=1}^s P_{t-s+j}, \quad LMA_{t,l} = \frac{1}{L} \sum_{j=1}^L P_{t-l+j} \quad (\text{Sweeney, 1988}) \quad \dots\dots\dots(3.1)$$

Where $R_{i,t}$ is the daily return in period S (1,2 or 5 days) and $R_{i,t-1}$ is the return used to compute the long average over period L (50, 150 or 200 days). This test is

repeated daily with the changing moving averages throughout the sample. The buy position is a long position in the stock and is maintained until the short moving average crosses the long moving average from above. With the sell signal, the investor short sells. A rule is effective if the average buy minus sell (buy - sell) signal is positive, significant, and greater than a buy and hold alternative after trading costs. The study also imposes a ten day holding period on trading rules once a signal is created in order to restrict the trading frequency to a reasonable minimum level and hence avoid transaction costs. According to the time delay filter a signal must hold for d consecutive days before a trade is implemented. If within these d days different signals are given, the position in the market will not be changed. A moving average rule with a fixed holding period holds a position in the market for a fixed number of f days after a signal is generated. This strategy tests if the market behaves different in a time period after the first crossing. All signals that are generated during the fixed holding period are ignored.

3.3.2 Test statistics

The h day holding period return at time t is defined as $R_t^h = \log(P_{t+h}) - \log(P_t)$. They are classified based on price information up to and including day t . This study classifies the trading outcomes each day in our sample as either a buy (b), or sell (s) signal or not to trade. The signals then classifies the total days as buy days or sell days, where the sell days implies short selling. The mean return and variance conditional on a buy (sell) signal over N periods can be written as:

$$\bar{X}_{b(s)} = E(R_t^h | b_t \text{ or } s_t) = \frac{1}{N_{b(s)}} \sum_{t=0}^{N-1} R_{t+1} I_t^{b(s)} \dots\dots\dots (3.2)$$

$$\hat{\sigma}_{(b)s}^2 = E\left[(R_t^h - \bar{X}_{b(s)})^2 | b_t \text{ or } s_t\right] = \frac{1}{N_{b(s)}} \sum_{t=0}^{N-1} (R_{t+1} - \bar{X}_{b(s)})^2 I_t^{b(s)} \dots\dots\dots(3.3)$$

respectively, where $N_{b(s)}$ is the number of total buy (sell) days, R_{t+1} is daily return at time $t+1$, and $I_t^{b(s)}$ is one for a buy (sell) signal observed at time t and zero otherwise.

Calculating the t-statistics

Traditionally, the test statistics have been calculated using the following equations. The t -statistic for returns of the buy (sell) moving average trading rules over the buy-and-hold strategy is

$$t = \frac{\bar{X}_r - \bar{X}}{\hat{\sigma}_r^2 / N_r + \hat{\sigma}^2 / N} \dots\dots\dots (3.4)$$

where \bar{X}_r , $\hat{\sigma}_r^2$, and N_r are the mean return, variance, and number of the buy or sell signals calculated for the entire sample as one solid distribution, and \bar{X} , $\hat{\sigma}^2$, and N are the unconditional mean, variance, and number of returns again for the entire sample period. For the buy-sell or the buy-sell spread, the t -statistic is traditionally calculated as:

$$t = \frac{\bar{X}_b - \bar{X}_s}{\hat{\sigma}_b^2 / N_b + \hat{\sigma}_s^2 / N_s} \dots\dots\dots(3.5)$$

where \bar{X}_b , $\hat{\sigma}_b^2$, and N_b are the mean return, variance, and number of the buy signals, and \bar{X}_s , $\hat{\sigma}_s^2$, and N_s are the mean return, variance, and number of the sell signals.⁷

3.3.3 Testable Hypotheses and Test Statistics

1. Return generated from actively managed portfolios are higher than returns generated from passively held portfolios.

The null, H_0 , $\hat{R}_{tech} = \hat{R}_{bh}$ hypothesis is tested against the alternative hypothesis, H_A , $\hat{R}_{tech} > \hat{R}_{bh}$. Where \hat{R}_{tech} and \hat{R}_{bh} are the returns from the actively managed portfolio and the buy and hold strategy respectively. The buy and hold strategy is used to proxy the benchmark portfolio.

2. Stocks with higher book-to-market ratios do better than stocks with low book-to-market ratios.

The null hypothesis, H_0 , claims that high book-to-market portfolios have the same trading rule returns as low book-to-market portfolios. The alternative hypothesis, H_A , is that abnormal returns from technical trading rules for higher book-to-market portfolios exceed those from low book-to-market portfolios.

⁷ Decision rules and test statistics discussed here are covered in Sweeney (1988)

3. High returns from technical trading rules are associated with time varying-risk premium. Because high book-to-market stocks generally do better during economic downturns (which are the periods following sell signals coupled with high volatility). The null hypothesis, H_0 , claims that abnormal trading rule returns derives from bearing higher risks during economic downturns i.e. periods following sell signals. The alternative hypothesis, H_A , is that abnormal returns from technical trading rules comes from periods following buy signals.
4. Stocks with higher book-to-market ratios do better in bear markets(during economic downturns) than in other periods because bear markets do have higher volatility.

The null hypothesis is, H_0 ; the performance of trading rules is a function of risk. Risk can be associated with general economic condition, where stock prices become more volatile with the uncertainties of a declining market. The alternative hypothesis H_A ; is that performance of stocks with higher book-to-market ratios is independent of economic conditions.

3.4 Data and Methodology

In this study we examine the use of technical analysis on the portfolios constructed from securities listed at the NYSE, AMEX and the NASDAQ. The data

used in this study is obtained from the Kenneth, R. French data library⁸. The sample of daily data runs for the period from 1st Jan 1990 to 31st May 2005. French constructs these portfolios at the end of each June using the June market equity and NYSE breakpoints. The portfolios for July of year t to June of $t+1$ include all NYSE, AMEX, and NASDAQ stocks for which market equity data for June of t could be obtained. Portfolios are constructed on the basis of their book to-market (book-to-market) ratios. The portfolios are formed on book-to-market at the end of each June using NYSE_breakpoints. The Book equity (B) used in June of year t is the book equity for the last fiscal year end in $t-1$. Market equity (M) is price times shares outstanding at the end of December of $t-1$. B is book equity at the last fiscal year end of the prior calendar year divided by M at the end of December of the prior year. Relevant estimates of risk factors are also obtained from the same online database. These are the market risk factor, the size factor (SMB), the book-to-market (B-M) factor and the momentum (MOM) factor.

3.5 Empirical Results

3.5.1 Summary Statistics

Table 3.1 presents a summary of descriptive statistics for the data we have used. It contains two panels A and B, where panel A represents the portfolios with high book-to-market and panel B represents the portfolios with low book-to-market ratios. The high book-to-market portfolios are represented by the highest portfolio decile while the lowest book-to-market decile represents lowest portfolios in panel

⁸ The library is available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

B. Each panel contains summary statistics for the full sample from January 1990 to December 2005 with 3521 observations of daily returns. Also contained in each panel are two sub-samples dividing the sample period. The first sub-sample runs from January 1990 to December 1998 with 2104 observations, while the second sub-sample runs from January 1999 to December 2005 with 1416 observations.

For the full samples, the mean daily returns from the high decile portfolios (0.0346%) are higher than the mean daily return from the low decile portfolio (0.021%). This is consistent with literature which generally expects high book-to-market stocks to perform better than low book-to-market stocks. Both the two types of portfolios exhibit non-normality as the D-statistic is significantly close to zero for both of them at 0.074 and 0.081 for the high book-to-market and low book-to-market portfolios respectively. Non-normality is also exhibited by the high kurtosis and skewness. The kurtosis for the high book-to-market portfolios is 9.96 while that of the low book-to-market portfolios is 54.01.

Both the portfolios experience a slow decay in the information contained in returns. The autocorrelation coefficient for the full sample of the high book-to-market is 0.0079 significant at 5% level and for the low book-to-market portfolios it is -0.0157 also significant at 5% level. Generally the data can be considered to be consistent with and conform to most financial data series distributions.

3.5.2 Comparative Performance of Book-to-Market based Assets

Table 3.2 presents results of comparative performance of portfolios sorted on the basis of their book-to-market ratios and classified in 5 groups i.e. quintiles. It also gives results of the performance of actively managed portfolios against the

passive Buy & Hold strategy. The actively managed hypothetical portfolio is made of the combination of the risky stock being held in alternating long and short positions. The trader moves funds between these two positions on getting a signal. The table contains average results of 5 trading rules tested for each quintile. The third column contains average daily returns across trading rules with their t-statistics in column 4. The annualised average returns and annualised standard deviations are in column 5 and column 6 respectively.

This table gives results of the hypothesis that trading rule returns from actively managed portfolios are higher than returns from the Buy & Hold strategy. The time series of returns from the actively managed portfolios for each rule are strings of returns from short positions and returns from long positions. The average daily returns from the quintile portfolios are 0.095, 0.044 and 0.082, 0.077 and 0.075 for the respective quintiles “low 20” to “high 20”. All the quintiles except one, have returns higher than the benchmark average daily Buy & Hold return which is 0.0482 for the same period. Results for the exceptional quintile which performed poorly against the benchmark Buy & Hold are however not statistically significant. Not surprisingly, the Sharpe ratios from trading rule strategies for all the five portfolios groups exceed that of the benchmark portfolio. The same pattern is repeated for the other book-to-market portfolio classifications. These results are statistically strong evidence of the superiority of the trading rules strategies based on book-to-market ratios.

The results in table 3.2 also indicate a decline in profitability from the highest book-to-market stocks (value stocks) ,26.68%, to the lowest book-to-market stocks (glamour stocks), 23.64%. We interpret these results on the assumption that the high book-to-market portfolios are constituted by value stocks while the low

book-to-market portfolios are constituted by growth stocks⁹. Certain differences in firm characteristics between the growth and value stocks may explain this. While this study is based on the documented existence of systematic extrapolation errors committed by naïve traders, other literature can help to explain the nature of the error. For example, Jagadeesh and Kim. (2003) observe that the recommendations of professional analysts are generally more favourable for growth stocks than for value stocks. Such recommendations can be used by particularly naïve investors in the formation of expectations errors pushing for the underpricing and overpricing of both the value and growth stocks respectively. These differences can be responsible for the monotonic decline in the profitability of trading rules reported in table 3.2 because the higher the size of the book-to-market ratio the larger is the error (and the information lag) which is picked by trading rules to make abnormal profits.

A particular result of interest in table 3.2 is the fact that going by the Sharpe ratio, portfolios with the lowest Book-to-market ratios, i.e. quintile “low 20” and those with the highest book-to-market ratios, i.e. quintile “high 20” perform better than middle quintiles. For example, in table 3.2 the Sharpe ratio for the lowest book-to-market portfolio is 19.89, and the highest book-to-market quintile portfolio is 19.57. The middle quintiles have the following respective Sharpe ratios; “Qnt 2” (9.71), “Qnt 3” (17.4) “Qnt 4” (16.10).

These results indicate that, contrary to what previous studies had suggested, the excess trading rule profits may not be a premium for bearing additional risk. This

⁹ This assumption is important given that the book-to-market ratio can reflect aspects other than the pricing error. For example a low Book-to-market may describe a firm with a lot of intangible assets such as R&D which are written off from the books of accounts, or a firm with attractive growth opportunities that do not enter the accounting books but are captured by the market. (Lakonishok *et al.* (1994))

is because results indicate that even portfolios with low risk levels perform just as good as portfolios with high risk potentials. That middle range containing three quintiles has the lowest trading rule returns. In the next paragraph this phenomenon is examined further. An analysis of the trading rule returns of the highest book-to-market portfolio decile against the trading rule returns of the lowest book-to-market portfolio decile is given.

3.5.3 Can Risk Premium explain Excess trading rule returns?

Table 3.3 contains the results of a test of the hypothesis that trading rule strategies perform better on high book-to-market stocks than on low book-to-market stocks. The table contains panels A and B where panel A gives results for the highest book-to-market portfolio, which is decile 1, while panel B gives results for the lowest book-to-market portfolio which is decile 10. In the first place, although in both the two classes of assets the number of days the stocks were held in long positions exceeds the number days assets were held in short positions¹⁰, high book-to-market stocks attracted more long positions than low book-to-market stocks. It is widely documented in technical analysis literature that buy days (long positions) generate more returns than sell days (short positions). Therefore the relatively longer

¹⁰ For high book-to-market portfolios, trading rules tied the assets in long (short) positions for a average of 2340 (1260)days. In contrast, regarding the low book-to-market portfolios, the rules held the assets for 2059 days and 1541 days in long and short positions respectively.

durations in long positions for high book-to-market stocks may indicate a slower speed for the markets to correct a mis-pricing for these stocks.

Secondly, the returns from both buy days (0.00295 per day) and sell days (0.0420 per day) are higher for the high book-to-market assets compared to the low book-to-market assets with daily average returns for the buy days and sell days of 0.0031 and -0.0613 respectively. In terms of Lakonishok *et al.*'s (1994) inefficient market model, these results give some evidence of inefficiency. Implied in Lakonishok *et al.*'s (1994) inefficient market model is a scenario where the market is unable to make instant corrections of its own mispricing (the mis-pricing is captured by the book-to-market ratio). This period of market correction is longer for the high book-to-market assets and can be attributed to the larger relatively excess profits for these assets.

These results are consistent with previous studies, for example Bokhari *et al.* (2005) who also report of better performance from small assets relative large assets. These results clearly indicate that there is a difference in terms of trading rules performance between the high book-to-market portfolios and the low book-to-market portfolios.

Table 3.3 is also used to discuss results of testing the hypothesis that trading rules do better for stocks with higher book-to-market ratios in bear markets (during economic downturns) than for stocks with low book-to-market ratios during these periods. These results are in respect of the hypothesis that the high performing high book-to-market assets do so at the expense of increased risk to the investor. Given that assets are subjected to higher levels of risk exposure in periods of economic slumps relative to periods of strong overall economic performance, the results of investigations over whether higher book-to-market assets makes most of their profits

from trading rules in periods of high risks is reported in this table and are also consistent with Lakonishok *et al.*'s (1994) inefficient market model.

Panel A of the table contains results of trading rule performance of the highest book-to-market ratio portfolio, while panel B gives results for the least book-to-market ratio portfolio. As explained earlier, on the overall performance of trading rules applied to the high book-to-market portfolios is better than when the same rules are applied to the low book-to-market portfolios. The average number of buy days for the high book-to-market ratio portfolio (2340 days) is larger than the buy days (2059 days) in respect of the low book-to-market portfolio during the same period. In contrast, on average the high book-to-market portfolio are held in short positions for shorter durations (1260 days) compared to the low book-to-market ratio portfolio during the same period (1541). Thus, the two portfolios seem to be sensitive to trading rule signals on opposite directions of the market. The higher returns are, however, generated from the high book-to-market portfolio (about 7% per annum) against returns from low book-to-market portfolios which are about 0.74% per annum.

We also find trading rules holding the high book to market portfolio in long positions for longer periods than they did for the low book-to-market portfolio. In contrast again, the rules tied the low book-to-market portfolios in short positions for longer periods than they did for the high book-to-market portfolio. This finding is consistent with several previous studies where such results are used as evidence supporting the position that days following buy signals do provide more returns than days following sell signals. The sensitivity of the low book-to-market ratios portfolios to trading rules during bear markets, therefore, is contrary to the hypothesis.

3.5.4 Can risk premium explain superior performance of trading rules profits: Results from the extended Fama – French (1993) model

To see whether relative higher returns for the high book-to-market portfolios are a result of taking relatively higher risks compared to the lower book-to-market ratios, results of the test of risk adjustments are given in tables 3.4 and 3.5. Using the extended Fama and French factor model, an analysis of how the risk factors explain the trading rules profits for both the high and low book-to-market ratios in periods of rising and falling markets is given. Table 3.4 contains results for an upward trending market while table 3.5 gives results for a down ward trending market.

In this study downward and upward trending markets are determined by the resistance and support turning points. A support is a price level at which the price of an asset will probably stop falling, while a resistance is a level at which prices will likely stop rising. In typical technical trading strategies these two levels are used to signal the maxima and minimal points and hence give trading signals. For the purpose of this study, however, the monthly maxima and minima of the S&P500 are established ex-post. They are not used as trading signals. They are only used to divide the sample period between up-trending and down-trending markets in order to facilitate testing the difference in risk levels during these two market periods in respect of the high and low book-to-market assets.

In table 3.4 results are given for both the high and low book-to-market portfolios represented by the decile with the highest book-to-market ratio and the decile with the lowest book-to-market ratio respectively. α is the Jensen's statistic measuring the degree of absorption of the trading profits by the model factors. In column 2, ' $R_m - R_f$ ' is the beta of the market. The S&P 500 index is used as a proxy for market return and the 3 months US treasury bill return as the risk free rate of

return. “SMB”, “HML” and “MOM” stands for the betas of the size, book-to-market and momentum factors.

The results indicate that the Jensen’s α s for all the trading rules tested for the high book-to-market portfolios is significantly away from zero. The α lies in the range of 0.008 to 0.014 where smaller values of α (0.010, 0.009, 0.008) were for the shorter moving average rules and the larger value (0.014) was for the two longer moving average rules (1, 200, 1 and 2, 200,1). This implies that the factors absorb more trading rule profits from the shorter moving averages than from the longer moving averages. It therefore suggests that there is more risk-associated profits from shorter moving average trading rules than from longer trading rules profits in up-trending markets. On the factor loadings, the size factor (SMB) has the highest loadings throughout all the 5 trading rules tested followed by the momentum factor. The market factor loadings were all negative.

In comparison, the lower book-to-market assets give larger values of α relative to the higher book-to-market assets across all the rules tested. This implies that the factors can explain less of the trading rule profits from the lower book-to-market assets as they can do in the higher book-to-market segment in the case of an upward trending market. Thus, in relative terms profits from trading rules for the high book-to-market assets in an upward trending market can be considered as compensation for taking higher risks.

Table 3.5 gives results for the down trending markets. Results are similar to those of upward trending markets. The higher book-to-market portfolios give smaller values of the Jensen’s α compared to the lower book-to-market assets. These results corroborate the assertion that trading rule profits from high book-to-market assets can be a reward for bearing higher risks and that they are consistent with

market efficiency. Tables 3.4 and 3.5 also indicate that market risk premium for technical trading returns are negative. These results suggest that the trading rules were resulting in fact following a contrarian strategy because they were moving against the market.

3.5.5 Further tests of time – varying risk premium using the bootstrap method

Models capable of capturing heteroskedasticity in return series have also become popular since Brock *et al.* (1992). While Brock *et al.* (1992) were mainly interested in examining the stochastic properties of returns from trading rules; many subsequent studies have used their ideas and approach to test for the presence of the time-varying risk premium as a source of excess profits from trading rules. The basic technique has been to examine if the returns from technical analysis follows the model postulated, for example, the GARCH-M model. The idea is to find whether the data generation process governed by the model is responsible for generating the trading rule returns series. This is achieved by fitting the series of returns from trading rules using one of the popular models (random walk, AR, ARCH etc.), and using the specification to reconstruct new random price series using a bootstrap procedure.

A strong advantage of using bootstrap tests in financial empirical investigations is their ability to mitigate the non-normality problem that renders t-tests useless. Bootstrap tests are able to create their own-critical values for evaluating the significance of results obtained from trading rules and conducting tests of the null that the data used follows the postulated process. This is achieved by applying the trading rules to the simulated price series a number of bootstrap

iterations (usually between 500 and 2000 iterations). Results of profitability obtained from the iterations are used to create the empirical distributions (t-statistics, means, variances) which can provide a good approximation of the true (population) distribution. The p-values obtained are used to decide whether the underlying process responsible for generating the original data belongs to the model.

The results for the bootstrap tests are given in table 3.6. These results are for additional tests of the performance of trading rules during up trending markets relative to down trending markets for book-to-market portfolios. As with tables 3.4 and 3.5, up-trends and down-trends are determined by the support and resistance levels. So panel A of table 3.6 contains results of up-trending markets while panel B contains results of down-ward trending markets. Panel C gives results of the entire sample period.

The results given in table 3.6 shows the proportion of the results from the bootstrap runs where the performance of the simulated series were better than performance of the original data. These results are the p-values and are interpreted as the extent to which the historical realizations is likely to have been generated from the distribution based on the models postulated. A small or large p-value (less than 5 percent, greater than 95 percent) indicates that the historical performance lies in one of the tails of the distribution and that the assumed data generation process is unlikely to have given rise to this series. By contrast, p-values closer to 0.5 suggest the assumed generating process can not be rejected as a responsible return generating process.

Since our primary concern is to investigate the risk differentials between high book-to-market stocks and low book-to-market stocks we did not include additional instrument variables in the specification. We allowed the conditional mean return to

be influenced only by the past variance and the past shocks and ignored potential influence of variables like day-of-the-week on the estimated parameters. We considered that these additional variables will have equal effects on the estimated parameters of interest for both the high and low book-to-market assets. The bootstrap with replacement was simulated using the GARCH-M model. This model with MA term is:

$$r_t = \alpha + \gamma h_t + \beta r_{t-1} + \varepsilon_t \quad \dots\dots\dots (3.6)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1} \quad \dots\dots\dots (3.7)$$

$$\varepsilon_t = h_t^{1/2} z_t \quad z_t \sim N(0,1) \quad \dots\dots\dots (3.8)$$

where the residual (ε_t) is conditionally normally distributed with zero mean and conditional variance (h_t) and its standardized residuals (z_t) is i.i.d. $N(0,1)$. In this model the conditional return is a function of the conditional variance, h_t , and past disturbance ε_{t-1} . The conditional variance is linear function of the square of the past period's error and of the last period's conditional variance. Hence the expected returns are a function of volatility and past returns, and volatility can change over time. The standard residuals are estimated using actual returns from and for each trading rule tested. The standard residuals are then re-sampled with replacement and used with estimated parameters to generate the GARCH-M series. Since only the standardized residuals are re-sampled with replacement, the heteroskedastic structure captured in the GARCH-M model is maintained in the simulations.

From a quick glance of panel A (up-trending market) of table 3.6 there is a difference between Buy and Sell results. The proportions where the simulated profits exceed those from the actual data are different between the Buy and Sell days in the up-trending market. Results show that Buy days have a relatively smaller proportion

of profits from simulated data that exceed profits from actual data. The p-values range from 0.096 for the 1, 50, 0 rule to 0.138 for the 2, 200, 1 rule with an average p-value of 0.197. For the excess return from Sell days, the p-values are between 0.742 and 0.974 with average of 0.88. These p-values indicate that in the up-trending markets it is not possible to reject the hypothesis that the returns come from a GARCH-M process although this rejection is weak because both the average p-values are near the cut-off points. This is the case for both the Buy and Sell returns.

Panel B presents bootstrap results for the downward trending market. The results are more mixed and no clear difference between simulated results for Buy and Sell days can be seen. However, in comparison, the average p-values for the downward trending markets (0.489) are slightly higher than those of the upward trending markets (0.474). But they are all close to the 50% region. A p-value close to the 50% mark indicates strong failure to reject the postulated data generating process. Therefore it is possible to conclude that there is no difference between the risk ness of trading rule returns during upward trending markets and downward trending markets. These results give evidence in favour of the risk view since failure to reject the GARCH-M as the underlying return generation process implies the presence of a time varying risk premium associated with the excess returns.

3.6 Conclusions

The objective of this chapter is to examine the relative performance of book-to-market based portfolios when trading rules are applied to them. In essence this chapter opens the discussion about the plausibility or implausibility of the view that excess profit from trading rules profits are compensation for bearing time – varying

risk premium and as such are consistent with the market efficiency hypothesis¹¹. Further to this objective, first we determined whether the performance of trading rules on book-to-market portfolios beats the Buy & Hold strategy. We then proceeded to examine the hypothesis that stocks with high book-to-market ratios perform better than those with low book-to-market ratios. The final objective was to determine whether differential trading rule performance in portfolios based on book-to-market ratios can be explained first by the risk factors and secondly by accounting for periods that exhibit different degrees of volatility, i.e. up-trending markets and down-trending markets.

The results strongly suggest that the actively managed portfolios can beat the Buy & Hold strategy when trading rules are based on the book-to-market ratios. The averages of the five trading rules (except one rule) tested give results that reject the null of equality between the trading rule profits and the Buy and Hold strategy. This conclusion also implies that the book-to-market ratio may contain information that can be directly used in trading systems as a conditioning instrument.

On the relative performance of trading rule profits on portfolios based on varying degrees of the book-to-market ratio, the findings indicate that the portfolios at the two extremes, i.e. highest book-to-market ratio portfolios and lowest book-to-market portfolios are significantly more profitable than the middle range. This leads us to conclude that despite the fact that high book-to-market portfolios could be associated with high risk, the trading rule profits from book-to-market based portfolios may not be attributed to this risk. According to these results, it may not be proper to assert that high book to market portfolios beat the buy and hold strategy

¹¹ This discussion is followed through the next chapters.

because of bearing higher risks. The finding that even the low book-to-market portfolios beat the Buy and Hold strategy on profits that are adjusted for risk explains the excess trading rule profits.

A test for the hypothesis that excess trading rule profits from higher book-to-market assets are a compensation for time-varying risk premium was also conducted. This was done by comparing the trading rule returns and risk during periods of rising markets and periods of falling markets for both the high and low book-to-market portfolios. First by using an extended Fama and French factor model, the study finds that in relative terms, excess profits from assets with higher book-to-market ratios are better explained by risk factors than the profits from lower book-to-market assets during rising markets. Results were similar for the down-trending markets where again higher book-to-market portfolios gave smaller values of the Jensen's α than the low book-to-market assets, which implies that the risk factors explain more of the excess profits from the higher book-to-market assets than they do for the latter during these markets as well.

An additional test for the time-varying risk explanation of excess profits from higher book-to-market portfolios was performed using a bootstrap technique. Generally, the results of the bootstrap simulations give evidence in favour of the risk view since the p-values failed to reject the GARCH-M model as the underlying return generation process. Thus, from these two results the study concludes that the excess profits from the higher book-to-market portfolios can be associated with the time-varying risk premium.

In the next chapter we examine the possibility that the stock liquidity contains information that can be conditioned to generate trading profits from technical trading

rules. The chapter also investigates the possibility that liquidity risk is a source of excess profits from trading rules.

3.7 Appendix 1

Table 3.1: Summary Statistics for daily returns of portfolios formed on the basis of the book-to-market ratios from the NYSE, AMEX and NASDAQ.

The statistics given here are for the highest and the lowest deciles only. Returns are calculated as logarithmic returns. D-Statistic is the test for Kolgomorov-Smirnov test of normality. $\rho(i)$ is the estimated autocorrelation at lag i for each period. Numbers with * (**) are significant as the 1%(5%) levels.

Panel A: High B-M Portfolios (Decile 1)				Panel A: Low B-M Portfolios (Decile 10)			
Statistic	Full sample	Sub-Samples		Statistic	Full sample	Sub-Samples	
	Jan,1990- Dec 2005	(Jan 1990- Dec 1998)	(Jan 1999- Dec 2005)		Jan ,1990- Dec 2005	(Jan 1990- Dec 1998)	(Jan 1999- Dec 2005)
Nobs	3521	2105	1416	Nobs	3521	2105	1416
Mean	0.0346	0.0317	0.0378	Mean	0.021	0.0143	0.0289
Std	1.3092	1.2583	1.0086	Std	1.7795	1.5487	1.2682
Skew	-0.67	-0.85	-1.20	Skew	-1.90	-2.77	-1.18
Kurtosis	9.96	28.84	52.28	Kurtosis	54.01	64.22	30.67
D-Stat	0.074*	0.048	0.059	D-Stat	0.081*	0.059	0.055
$\rho(1)$	0.0079**	0.0167**	0.0236	$\rho(1)$	-0.0157**	-0.0062**	0.0769
$\rho(2)$	-0.0373	-0.0631	-0.0274	$\rho(2)$	-0.0280	-0.0230	-0.0181
$\rho(3)$	-0.0375	-0.0497	-0.0206	$\rho(3)$	-0.0278	0.0032	-0.0232

Key: ** Indicates significant at the 5% level

* Indicates significant at the 1% level

Nobs: Number of observations

B-M: Book-to-Market

Table 3.2: B-M trading rule performance by quintiles

Condensed summary of results for trading strategies for the 20% lowest up to the 20 % highest value weighted portfolios from the AMEX, NYSE and the NASDAQ exchanges constructed from stocks sorted on the basis of their B-M ratios. Each trading strategy divides the days into either buy or sell (earning risk-free rate). Return is the mean daily return earned by implementing the trading strategy, and 't' is the standard t-statistic testing for the mean return being significantly different from Buy & Hold strategy. Breakeven cost is the trading cost that makes a trader indifferent between Buy & Hold strategy and technical trading strategy.

Sample from Jan 1 st , 1990 – 31st May, 2005							
Portfolio	Av # of trading /yr	Return	t	Annual return	σ	Sharpe Ratio	Break Even Cost
Low 20	56	0.095	12.85	23.68	0.005	19.89	11.57
Qnt 2	63	0.044	0.353	10.91	0.004	9.71	-1.19
Qnt 3	48	0.082	8.155	20.53	0.004	17.4	8.42
Qnt 4	61	0.077	8.028	19.3	0.005	16.10	7.19
High 20	58	0.075	12.82	23.64	0.004	19.57	11.53
Benchmark buy & hold	N/A	0.0482	N/A	12.1012	0.9262	0.0348	N/A

Table 3.3: Comparative performance of trading rule returns from high B-M portfolios against trading rule returns from low B-M portfolios.

“Rule” is the trading rule applied. “# buy” is the number of days following buy signals, “#sell” is the number of days following sell signals. “#trades/year” is the number of one way transactions generated by the rule. The label “Buy” stands for returns from buy days while “Sell” stands for returns from days following sell signals while bs is the difference between buy and sell returns. The labels “t-buy”, “t-sell” and “t-bs” stands for t-values of the buy returns, sell returns and buy returns minus sell returns respectively, all adjusted for transaction costs at 0.1% per one way transaction.

Panel A: Portfolio of assets with highest B-M ratios, Decile 1

Rule	# Buy	# Sell	# trades /year	Buy	Sell	bs	t-buy	t-sell	t-bs
(1, 50,0)	2046	1554	98	0.0585	0.0264	0.0321	7.90*	7.10*	3.87392
(1, 100,1)	2213	1387	32	0.0477	0.0096	0.0381	5.77*	2.14*	4.050771
(5, 150,1)	2343	1257	21	0.0229	0.0304	-0.0075	2.53*	4.58*	-0.66819
(1, 200,1)	2485	1115	19	0.0103	0.0650	0.0547	0.91	9.33*	-4.11559
(2, 200,1)	2615	985	16	0.0084	0.0788	-0.0704	0.74	11.39*	-5.29583

Panel B: Portfolio of assets with Lowest B-M ratios, Decile 10

Rule	# Buy	# Sell	# trade	Buy	Sell	bs	t-buy	t-sell	t-bs
(1, 50,0)	1984	1716	113	-0.0423	0.0160	-0.0583	-9.56*	5.13*	-10.76
(1, 100,1)	1977	1623	38	0.0141	-0.0225	0.0366	0.94	-2.04*	1.96
(5, 150,1)	2057	1543	24	0.0248	-0.0384	0.0632	2.51*	-4.20*	4.69
(1, 200,1)	2143	1457	19	0.0059	-0.0209	0.0268	0.26	-2.10*	1.08
(2, 200,1)	2168	1432	15	0.0129	-0.241	0.2539	1.19	-2.54*	2.65

Key:

* : Indicates significant at 5 % level

B-M: Book-to-Market

Table 3.4: Trading rule performance in upward trending markets: Comparative analysis of risk adjusted performance of stocks with higher B-M ratios against stocks with low B-M ratios.

The table presents estimates of the Five Factor Model coefficients. Panel A compares high B-M portfolios, while panel B compares low B-M. α is Jensen's alpha, "Rm-Rf" is the market return minus the risk free return, "SMB" is the small minus large factor, "HML" is the "high minus low factor while "MOM" stands for momentum factor. The trading rule return series are determined by the execution of signals. Each day's return is either a buy return if the short moving average crosses the long moving average from below or a sell return if the short moving average crosses the long moving average from above.

The factors are obtained from the following four factor model:

$$R_{Tr} - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \beta_{hml} (R_{hml} - R_{rf}) + \beta_{smb} (R_{smb} - R_{rf}) + \beta_{mom} R_{mom} + \varepsilon$$

Highest B-M Decile stocks

Rule	A	Rm-Rf	SMB	HML	MOM
(1, 50,0)	0.010	-0.058	0.737	0.393	0.672
t-stat	(2.86)	(-0.55)	(4.6)	(2.56)	(5.71)
(1, 100,1)	0.009	-0.052	0.74	0.388	0.701
t-stat	(2.7)	(-0.55)	(4.71)	(2.67)	(6.62)
(5, 150,1)	0.008	-0.068	0.699	0.358	0.709
t-stat	(2.31)	(-0.69)	(4.47)	(2.41)	(6.71)
(1, 200,1)	0.014	-0.052	0.811	0.360	0.507
t-stat	(3.73)	(-0.48)	(5.19)	(2.52)	(4.09)
(2, 200,1)	0.014	-0.069	0.805	0.350	0.506
t-stat	(3.59)	(-0.64)	(5.16)	(2.48)	(4.18)

Lowest B-M Decile stocks

Rule	A	Rm-Rf	SMB	HML	MOM
(1, 50,0)	0.022	-0.063	0.786	0.433	0.369
t-stat	(4.1)	(-0.79)	(6.05)	(1.43)	(4.35)
(1, 100,1)	0.030	-0.021	0.67	0.223	0.052
t-stat	(9.16)	(-0.2)	(4.64)	(1.55)	(0.43)
(5, 150,1)	0.029	-0.014	0.705	0.244	0.075
t-stat	(8.6)	(-0.14)	(4.83)	(1.71)	(0.61)
(1, 200,1)	0.025	-0.073	0.752	0.193	0.126
t-stat	(7.69)	(-0.7)	(5.33)	(1.47)	(1.08)
(2, 200,1)	-0.009	0.281	0.03	0.053	0.034
t-stat	(-0.13)	(1.24)	(0.64)	(0.65)	(0.04)

**Table 3.5: Trading rule performance in downward trending markets:
Comparative analysis of risk adjusted performance of stocks with
higher B-M ratios against stocks with low B-M ratios.**

The table presents estimates of the Five Factor Model coefficients. Panel A compares high B-M ratio portfolios, while panel B contains and compares low B-M ratio portfolios. α is Jensen's alpha, "Rm-Rf" is the market return minus the risk free return, "SMB" is the small minus large factor, "HML" is the "high minus low factor while "MOM" stands for momentum factor.

The factors are obtained from the following four factor model:

$$R_{Tr} - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \beta_{hml} (R_{hml} - R_{rf}) + \beta_{smb} (R_{smb} - R_{rf}) + \beta_{mom} R_{mom} + \varepsilon$$

Highest B-M Decile stocks

Rule	α	Rm-Rf	HML	SMB	MOM
(1, 50,0)	0	-0.273	0.044	0.164	0.267
t-stat	(-0.08)	(-3.42)	(0.48)	(1.73)	(3.92)
(1, 100,1)	-0.001	-0.259	0.025	0.144	0.296
t-stat	(-0.48)	(-3.19)	(0.27)	(1.5)	(4.22)
(5, 150,1)	-0.004	-0.334	0.098	0.181	0.346
t-stat	(-1.55)	(-3.55)	(0.91)	(1.77)	(4.15)
(1, 200,1)	0	-0.26	0.059	0.113	0.137
t-stat	(-0.23)	(-3.18)	(0.68)	(1.22)	(1.94)
(2, 200,1)	-0.001	-0.253	0.052	0.134	0.161
t-stat	(-0.25)	(-3.07)	(0.57)	(1.45)	(2.26)

Lowest B-M Decile stocks

Rule	α	Rm-Rf	HML	SMB	MOM
(1, 50,0)	-0.002	-0.27	0.065	0.162	0.226
t-stat	(-0.96)	(-3.29)	(0.73)	(1.8)	(3.35)
(1, 100,1)	0.002	-0.214	0.05	0.062	0.021
t-stat	(-0.79)	(-2.55)	(0.64)	(0.7)	(0.29)
(5, 150,1)	-0.001	-0.181	0.04	0.067	0.005
t-stat	(-0.23)	(-2.14)	(0.46)	(0.71)	(0.07)
(1, 200,1)	-0.004	-0.195	0.089	0.097	0.065
t-stat	(-1.85)	(-2.43)	(1.06)	(1.12)	(0.98)
(2, 200,1)	0.012	-0.093	0.786	0.343	0.539
t-stat	(3.1)	(-0.89)	(5.05)	(2.43)	(4.45)

Table 3.6: Evaluating the significance of excess trading rules returns after adjusting for risk using the Bootstrap method.

Results of bootstrap runs presented in this table are the proportion of the 2000 bootstrap runs where returns or the standard deviations from the bootstrap runs exceed the returns or standard deviations from the actual return series respectively.

Panel A: Periods of upward trending markets

Rule	Buy	BuyStdev	Sell	SellStdev	Buy-Sell
(1, 50,0)	0.096	0.536	0.974	0.81	0.022
(1, 100,1)	0.098	0.63	0.96	0.628	0.026
(5, 150,1)	0.202	0.69	0.86	0.442	0.102
(1, 200,1)	0.27	0.634	0.864	0.488	0.148
(2, 200,1)	0.318	0.646	0.742	0.442	0.222

Panel B: Periods of Downward trending markets

Rule	Buy	BuyStdev	Sell	SellStdev	Buy-Sell
(1, 50,0)	0.442	0.55	0.568	0.642	0.406
(1, 100,1)	0.39	0.448	0.68	0.78	0.276
(5, 150,1)	0.368	0.44	0.794	0.75	0.2
(1, 200,1)	0.184	0.662	0.846	0.428	0.084
(2, 200,1)	0.258	0.642	0.848	0.396	0.138

Panel C: Entire period

Rule	Buy	BuyStdev	Sell	SellStdev	Buy-Sell
(1, 50,0)	0.324	0.606	0.704	0.424	0.222
(1, 100,1)	0.372	0.486	0.622	0.676	0.32
(5, 150,1)	0.356	0.436	0.636	0.736	0.294
(1, 200,1)	0.39	0.42	0.768	0.708	0.238
(2, 200,1)	0.128	0.576	0.243	0.437	0.513
Average	0.314	0.505	0.595	0.596	0.317

Chapter 4 Technical Analysis: Returns, Risk and Liquidity

4.1 Introduction

Extant literature accepts the presence of regularities and it also accepts that there are some significant excess trading rule returns even after accounting for transaction costs. In view of the risk argument, a number of existing research papers suggests that trading rule excess returns can be related to liquidity. This risk involves the lack of ability to trade large blocks of the stock without significantly affecting the price. For example, previous studies have shown that returns increase with the bid-ask spread, increase with the price impact of trade, and decrease with trading volume. Amihud and Mendelson (1986) sort firms into portfolios according to their bid-ask spread and showed that the risk-adjusted returns of the high-spread portfolio exceed those of the low-spread.

This study follows the works of Kavajecz (1999), Brown *et al.* (1997) and Kavajecz and Orders-White (2004). Brown *et al.* (1997) proposed and showed that the specialist's price schedule is related to past prices. Their proposition was a follow up to an earlier work by Kavajecz's (1999) who developed a market microstructure model for cross-sectional variation in intraday expected stock returns. In Kavajecz's (1999) model, the specialist presents a price schedule consisting of bid and ask prices and a bid and ask size. In this model, the specialist reveals through the bid-ask size spread what she believes to be the expected return on the risky asset.

Brown *et al* (2004) tested the implication of Kavajecz's (1996) analytical work using 1993-1994 intraday quote data from the NYSE Trade and Quote (TAQ) database. They observed that Kavajecz does not investigate the possibility that the specialist's quote can be used to predict stock returns, something which is implied in his model. Brown *et al* (1997) therefore first examined whether the ability to act on this revealed information is offset (if only partially) by movements in the remaining choice variables (namely, the bid-ask spread). They then confirmed their theoretical findings that the relative sizes of the bid and ask quotes given by NYSE specialists provide information about future price movements.

Brown *et al*'s (1997) study provided a theory and evidence that quote depths predict intra-day stock returns. Specifically, the spread between the size of the quoted bid and the quoted offer predicts the stock return for the remainder of the day. Although their findings were not strong enough on the use of trading rules to predict price movements, they were nevertheless consistent with the position that the specialist and/or the limit order book contain information concerning future stock prices.

A more recent study is due to Kavajecz and Orders-White (2004) who also consider the role of micro-structural issues in technical analysis. They assessed the relation between liquidity provision and technical trading rules. Their tests involved examining whether technical analysis captures changes in the state of the limit order book. They were able to demonstrate that support and resistance levels coincide with depth on the limit order book. They also found that moving averages reveal information about the relative position of depth on the book.

Microstructure differences between US and UK markets

What motivates this chapter is that the above analytical works were confined to the US markets. It is interesting to investigate the relationship between liquidity and trading rules for the UK markets where microstructure effects could be different from those of the US. The US and UK markets have certain market microstructure differences that could have liquidity implications. While the underlying assumptions of major exchanges and authorities alike is that immediacy of order execution is an element of efficiency, the manner in which this is regulated and implemented across markets may not be exactly the same, hence contributing to liquidity differentials for securities trading in these markets.

In the US the structure of the equity market is fairly complex compared to that of the UK markets. There are many more trading environments in the US than in the UK providing a larger room for traders to choose their mode of participation than in UK markets. Although there are two main organizations in the US, the NASDAQ and the NYSE through which most of the equity trading is conducted, there are more Alternative Trading Systems (ATS) in the US than in the UK, a situation which can improve the liquidity of US listed stocks relative to stocks listed in UK markets.

The London Stock Exchange on the other hand, operates a hybrid trading system where trading can take place either anonymously through an electronic order book or through a competitive dealer market. There are two main trading systems at the LSE namely the SETS and the SEAQ. SETS which stands for Stock Exchange Trading Systems is an order driven system. It is a continuous trading system where anonymously displayed orders are automatically executed when price

details match each other. Up to five types of orders can be submitted to the SETS providing a variety of options available to participants and hence increasing liquidity of stocks trading in the market.

SEAQ is the other major trading mechanism at the LSE. SEAQ stands for Stock Exchange Automated Quotation system. This system uses market makers who are registered. They can quote bid and offer prices on securities and they can do so on more than one security. This multiple quotation of the same stock by more than one dealer provides competition and helps to drive down costs. Dealers can also quote for the largest stocks which are traded mainly through the order book via SETS.

Therefore, while some previous studies have examined the extent to which technical trading profits are explained by the size effect or other risk factors for example the market risk, book-to-market or the momentum effect, the liquidity factor has not been examined. The majority of previous studies have not examined the extent to which the profits from technical trading rules are explained by the liquidity factor. Specifically, the use of liquidity variables to test the efficacy of technical analysis for the UK markets has not been done

In this chapter using the UK market and its segments, I examine whether the liquidity of an asset contains information that can be conditioned to generate abnormal profits. I investigate whether simple trading rules are capable of providing the investor with higher returns in those market segments where asymmetric information is more pronounced and public information is likely to be less accurate.

I use the bid-ask spread to proxy for differences in information content of the current price. In other words we try to answer the question whether the bid-ask

spread as a proxy for liquidity and hence risk can explain the profitability of technical trading rules, and secondly whether the profitability of trading rules can be different in market segments which differ by their liquidity. I also examine whether the predictive ability of liquidity is explained by various pricing models. Using stocks from the FTSE 350 and 100 randomly selected stocks from the FTSE small capitalization stocks, we find assets with less liquidity to be more predictable than those which are more liquid. Trading rule strategies generate significant profits over the buy and hold strategy before transaction costs for assets which have higher bid-ask spreads. However, when transaction costs are considered all the profits disappear. The conclusion that I reach is that the bid-ask spread contains information that is not in current and past prices. I also conclude that this information can be used to make profits in excess of the buy and hold strategy for the small liquidity stocks.

The remainder of this chapter is organised as follows. Section 4.2 presents a brief summary of some research work that has direct implications for the current empirical exercise. Section 4.3 describes the data and portfolio construction procedure, while section 4.4 presents the methodology and the empirical tests to be performed. Empirical results are discussed in section 4.5. Section 4.6 examines how much of the trading rule profits are explained by the known stylized risk factors. The last section offers concluding remarks.

4.2 Related works

The liquidity of an asset summarises a great deal of the market perception of the accuracy of information and how much this information has already been

embodied into the price. The relation between market efficiency and liquidity has been considered by, among others, Chordia *et al* (2005). In their framework, they postulated market efficiency to be a function of the market's risk bearing capacity which they considered to be restricted by the risk-bearing capacity of market makers. Predictability arises when market makers increase their capacity to bear risk and this is reflected in the bid – ask spread. Thus the market informational inaccuracies or the delay in adjusting prices to new equilibrium levels following new information is partially absorbed by market makers if they have the capacity.

The existing empirical evidence suggests that stock returns can be related to liquidity. Other things being equal, a relatively illiquid security should carry a lower price because the holder should be rewarded for bearing the extra risk. The risk involves the lack of ability to trade large blocks of the stock without significantly affecting the price. Previous studies have shown that returns increase with the bid-ask spread, increase with the price impact of trade, and decrease with trading volume. For example, when Amihud and Mendelson (1986) sort firms into portfolios according to their bid-ask spread, once a year from 1961 to 1980, the risk-adjusted returns of the high-spread portfolio exceed those of the low-spread portfolio by 0.7 percent per month.

Several previous studies have sought explanations for the sources of predictability in stock returns following an increase in the number of studies reporting evidence that support the presence of predictable patterns in stock returns [see for example, Gencay and Stengos (1997, 1998), Fernandez-Rodriguez *et al.*(2000) and Brock *et al* (1992) and LeBaron (1998, 1999). Recent research on sources of technical analysis profits have examined the size factor, as well as the time varying risk premium. For example, Bhokhari *et al* (2005) investigated the

predictive ability of asset returns across segments of stock sizes in the London Stock Exchange and found predictability to be related to the size of capitalization. Neely (2001) applied a genetic programming approach to examine the relationship between risk and the predictability of trading rules. He found little evidence to associate trading rule profits with risk.

Recent research in asset return predictability also links market microstructure theories with market efficiency. For example the behaviour and interaction between the informed and uninformed traders has been examined by among others, Hvidkjaer (2003). Through examining trade imbalances among small and large trades¹² the author provides evidence in support of the heterogeneity explanation used by Hong and Stein (1999) to model investors' trading behaviour. Accordingly, while the imbalance among smaller investors (momentum traders) is explained by initial underreaction followed by delayed overreaction, simple "rationality" seems to drive the action among larger traders (news watchers).

Literature has not yet been able to categorically explain why a firm whose stock is chronically illiquid has higher returns than one whose stock is more liquid. One objective of this chapter is to make a contribution towards understanding the sources of predictable patterns in return series. This study can bring more insight to the risk strand in explaining the predictability of asset returns given that liquidity of an asset has been traditionally related to its risk. As Whitcomb (1988) points out, the "bid-ask spread" in the inventory model of Grossman and Miller (1988) can be interpreted as the premium that market makers demand to bear inventory risk. This

¹² As prices respond predominantly to the trade direction of the active trader (Easley & O'Hara, 1987; Kyle, 1985), trade imbalances refer exclusively to imbalances among this group of traders.

justifies one to consider liquidity as a risk factor in line with the Fama-French three factor model in studying the sources of return predictability. In this regard we follow Eleswarapu and Krishnamurti (2004) to investigate the behaviour of patterns in stock time series in relation to their liquidity.

4.3 Data and Portfolio Construction and the risk factors

This study utilises bid-ask spreads of a sample of stocks listed in the London Stock Exchange in the FTSE 350 and the FTSE small capitalization categories as indicators of liquidity and hence risk. Liquidity is considered because technical trading can be influenced by the availability of buyers or sellers after a signal has been issued by a trading rule. This can be especially serious with thinly traded stocks where previous research has found assets to be predictable due to the size effect but where the bid-ask spreads are known to be usually wider (Schwartz, 1988). The use of the spreads as liquidity indicators in empirical analyses has been justified in literature, Chordia *et al* (2006).

In order to fully capture the liquidity differential and its effect on predictability we randomly mix stocks in the FTSE 350 with 100 randomly selected stocks from the FTSE small capitalization stocks. The 100 stocks from the FTSE small caps are randomly selected each time the portfolios are reconstructed. The inclusion of stocks from the small capitalization segment of the London Stock Exchange is intended to broaden the search for sources of return predictability because many earlier studies on predictability of asset returns have focused their attention on large stocks ignoring the fact that small firms can have different firm characteristics. [See for example, Ito, (1999), Brock *et al*, (1992), and Bessembinder and Chan (1998)]

The portfolios are constructed using stocks that were FTSE 350 constituents and FTSE Small Cap constituents for the period from 1st January 1990 to 31st December 2004. These are a combination of relatively large, actively traded, and closely watched stocks and fairly small thinly traded securities which receive relatively less analyst coverage.

I follow Fama and French (1992) to construct portfolios in such a manner that using a regression technique they can reveal whether stylized risk factors can explain profits from trading rules. From the four hundred and fifty stocks I make six portfolios after each six months period. The first two portfolios are intended to capture risk related to value. This is done by first sorting the 450 stocks in order of their book-to-market ratios then making them in two groups of the first 50%, and last 50%. These portfolios are then used to compute the value premium where the factor HML (High minus Low) is computed as the average return for the 50% of stocks with the highest B/M ratio minus the average return of the 50% of stocks with the lowest B/M ratio. A positive HML indicates that value stocks outperformed growth stocks in that period. A negative HML in a given period indicates the growth stocks outperformed.

Similarly, for the size factor, I follow Fama and French (1992) to make three groups of stocks after sorting them in order of their capitalization size, i.e. the first largest 30%, the middle 40% and the last smallest 30%. SMB, which stands for Small Minus Big, is designed to measure the additional return investors have historically received by investing in stocks of companies with relatively small market capitalization. This additional return is often referred to as the “size premium.” In this chapter, the SMB factor is computed as the average return for the

smallest 30% of stocks minus the average return of the largest 30% of stocks in that period. A positive SMB in a period indicates that small cap stocks outperformed large cap stocks in that period. A negative SMB in a given period indicates the large capitalizations outperformed.

The liquidity factor is computed by constructing portfolios in a similar manner, i.e. by first grouping stocks in order of their bid-ask spread and then dividing them in three groups of the first 30%, middle 40% and the last 30%. The liquidity factor is computed as the average return for the largest 30% of bid-ask stocks minus the average return of the smallest 30% of bid-ask stocks in that period. A positive SMB in a period indicates that less liquid stocks outperformed more liquid stocks in that period. A negative SMB in a given period indicates the more liquid stocks outperformed the less liquid stocks.

4.4 Methodology and empirical tests

As in the previous chapter, trading rule models are used to test whether patterns in return series can be profitable. This methodology is based on the assumption that technical trading rules take advantage of positive serial correlation in return series where the autocorrelation bias in the time series are assumed to continue in the same direction.

Given the large number of trading rules available, it has always been difficult to decide on the number and type of trading rules to use in a study of this type. Choice is a subject related to data snooping and spurious results. To avoid these problems we choose, 1) trading rules that are most widely used in the industry and 2)

those that are simple to implement. These are the same rules which were used by Brock *et al.* (1992), Levich and Thomas (1993) and in several other studies. These are: (1) 1,200,0; (2) 2,200,0; (3)5,200,0; (4) 1,150,0; (5) 2,150,0; (6) 5,150,0; (7) 1,50,0; (8) 2,50,0; (9) 5,50,0; (10) 1,200,1; (11) 2,200,1; (12) 5,200,1; (13) 1,150,1; (14) 2,150,1; (15) 5,150,1; (16) 1,50,1; (17) 2,50,1; (18)5,50,1.

4.4.1 Hypothesis tested

The hypotheses tested derives from the analytical predictions of Avramov and Chordia (2003) and some other previous empirical evidence on pricing models and the regularity of liquidity and the relation between liquidity and expected returns. Consistent with chapter 3, the empirical work does not, however, attempt to conduct any formal hypotheses regarding abnormal returns or the control variables used because these are not the primary focus of the current study.

Previous empirical evidence by, among others, Chordia and Subrahmanyam (2005) appear to suggest that the predictive ability of an asset is likely to be negatively correlated with liquidity. Literature also holds the view that firms with lower liquidity have higher expected returns compared to those with higher liquidity. Consistent with this view, the appropriate null and alternative hypotheses for the relationship between predictability and liquidity are:

Hypothesis 1

The first hypothesis follows the insightful work of Goyenko (2005) who found that the liquidity risk of the stock market dominates the momentum factor in the Carhart's (1997) four-factor model. I also incorporate the ideas of Charoenruek and Conrad (2004), who analyze whether SMB, HML, momentum and liquidity factors

are risk-based, where they conclude that momentum factor is not related to fundamental risk and hence in this chapter the momentum factor has not been incorporated. Based on the conclusions from these previous works the first hypothesis tests whether asset prices in the least liquid stocks segment of the market contain the same amount of information as assets in the most liquid segments of the market.

H_{01} : Excess profits from various liquidity classes are not different

H_{A1} : The lack of the ability of markets to quickly trade large blocks of illiquid stocks when supplied to the market creates predictable patterns in returns above what is found in liquid stocks.

Hypothesis 2

Trading costs in respect of trading rules that requires high trading frequency to make excess profits have been found to take away much of the trading rule returns. This has also been the case with apparent trading rule profits from market segments exhibiting significant patterns in past returns, for example small size stocks (see for example Bokhari *et al.* (2005))

H_{02} : The profits from trading rules are not sufficient enough to cover the trading costs

H_{A2} : Significant trading rules profits can still be obtained from trading rules strategies even after adjusting for trading costs

Hypothesis 3

The third hypothesis asserts that trading rule returns is a compensation for taking additional risk. We carry out an analysis for both the full sample and for two sub-samples.

H_{03} : Any trading rule profits remaining after adjusting for appropriate trading costs is a compensation for holding more risky assets in the form of illiquidity

H_{A3} : Liquidity risk does not account for the excess profits from trading rules

4.5 Empirical results

4.5.1 Summary Statistics

Table 4.1. presents summary statistics for the returns for the full sample and the two sub samples. Panel A presents results for the least liquid decile stocks. The results show that the series are highly skewed and are also leptokurtic with the second sub sample (1998 – 2004) being stronger (31.41) than the full sample (1990 – 2004) with kurtosis of 9.29 and the other sub sample (1990 – 1997) with kurtosis of 7.65. A similar scenario is found for the most liquid stocks portfolio in Panel B. The table also gives results for the test of normality, the Kolmogorov – Smirnov test. Since the Kolmogorov – Smirnov D-statistics are close to zero, it can be said that consistent with findings from other previous studies, these financial data series have statistical distributions which are not normal.

Table 4.1 also gives insights into the rate of decay of information. In Panel A, which contains the least liquid stocks, the autocorrelation coefficients are

generally positive and are more pronounced in the second sub sample (0.15 in average) than in either the full sample (0.10) or the first sub sample (0.09). For the most liquid stocks, however, Panel B indicates that the autocorrelation coefficients are generally smaller compared to their least liquid stock counterparts.

These results are comparable to the results found on US data for the small and large stock autocorrelations. They can also be considered to be consistent with Bokhari *et al* (2005) who tested for the differences of trading rule performance by size based market segments in the London Stock Exchange. They also found differences in the speed at which information is revealed to be different between the FTSE 250 and the FTSE small capitalization stocks.

Since it is now accepted that small size stocks are generally illiquid. This can imply that the time series of large stocks, e.g. the FTSE 100 stocks have similar distribution properties to those of the time series of stocks of the most liquid segment of this market. The same can also be said of the similarity between the small capitalization stocks and least liquid stocks. These results postulate that returns from the least liquid segment of the market can be more predictable than returns from the more liquid segment. This is because previous studies (for example Bhokhari *et al*, 2005) have found that returns from small capitalization stocks can give significant trading rule profits before adjusting for transaction costs. They further noted that:

“The dominant factor that prevents the rules for small capitalization companies being profitable is the size of the bid-offer spreads. The rules could be profitable if the level of predictive ability exhibited on the small size

companies was combined with the bid-offer spreads appropriate for large companies” Bokhari et al (2005:pp 24)

4.5.2 Does liquidity really matter?

Tables 4.2 presents the results of the tests of existence of differences in strength of signals of momentum effects between stocks with different levels of liquidity. This test was executed by applying trading rule strategies to ten different segments of the market represented by the ten portfolios based on liquidity levels. The first column of table 4.2 contains the labels of the ten deciles of portfolios. Column two labelled ‘Annual’ is the annualised averaged return earned by all the 18 trading rules tested on each respective decile. Returns generally decrease as the liquidity is increasing. The least liquid decile has an average return of 16.29% across all 18 trading rules tested, while the most liquid portfolio has an average of -2.33%. This can be taken as evidence that the lack of the ability of market to quickly trade illiquid stocks when supplied to the market creates predictable patterns in returns above what is found in liquid stocks.

The trading rules also perform better than the buy and hold strategy in terms of the Sharpe ratios for the large spread deciles compared to the small spread deciles. The third and fourth columns labelled ‘Buy & Hold’ and ‘Trading Rule’ respectively, are the respective average Sharpe ratios for the buy & hold and trading rule returns. Given that trading rule strategies can suffer heavy trading costs, we also bring this aspect into our discussion. We compute the break-even transaction costs in respect of all trading rules tested. We prefer the use of break-even approach because certain trading costs are difficult to estimate. The break-even cost is the average trading cost that makes the Sharpe ratios from the Buy & hold strategy equal the one

from the trading rule strategy. We follow the break-even transaction cost approach used by Bessembinder and Chan (1998) who adjusted the break-even transaction costs with a risk factor. The aspect of risk was considered by Bessembinder and Chan (1998) to be important given that different trading rules can result in different levels of risk exposure. Ignoring this risk factor implies that the investor is assumed to be risk neutral. The following formula is used to compute the breakeven cost:

$$\frac{R_{Tr} - c}{\sigma_{Tr}} = \frac{R_{bh}}{\sigma_{bh}} \dots\dots\dots(4.1)$$

$$c = R_{Tr} - R_{bh} \frac{\sigma_{Tr}}{\sigma_{bh}} \dots\dots\dots(4.2)$$

where R_{Tr} is the daily average return from a specific trading rule strategy, c is the break-even cost of a particular trading rule strategy and R_{bh} is the daily average return from the buy and hold strategy. σ_{Tr} and σ_{bh} are the standard deviations for the trading rule strategy and a buy and hold strategy respectively. The last column of table 4.2 labelled ‘Break-even Cost’ contains the respective break-even costs.

The break-even cost is 0.43% for the least liquid decile and it is -0.07% for the most liquid stocks. These results of break-even trading costs suggest that technical trading rules can not generate excess profits. According to Bokhari *et al* (2005) the average bid-ask spread at the London Stock Exchange can be estimated at 4.5%, while the other two major explicit trading costs are estimated as 2% on commission for round trip transaction and 1.25 % again per round trip transaction for stamp duty. Given this structure of trading costs it is clear that none of the trading rule strategies’ profit remain after adjusting for transaction costs. In fact this is consistent with Bokhari *et al* (2005) who found that an initial investment in a

hypothetical fund gets exhausted before the end of the investigation period because of transaction costs.

In table 4.3 we take the analysis a step further. We analyse the profitability of specific trading rules relative to the buy and hold strategy only for the least and most liquid stocks. We also present further results of tests of predictability that adjust for the time variability of the returns in the sample period. The first column contains the trading rules. Rules are written as (short, long, band) where short and long is the respective short and long period simple moving averages, and band is the percentage difference required to generate signals. Each trading strategy divides the day into buy, sell or neutral (earning a risk free rate) positions. Return is the mean daily return earned by implementing the strategy and 't' is the t-statistic testing the mean return being significantly different from the buy and hold. σ is the standard deviation of the daily returns strategy. Break-even-cost is the trading costs that make one indifferent between the Sharpe ratios from the Buy and Hold strategy and the simple moving average strategy. Panels A and B present results for the full sample of least liquid and most liquid deciles for the stocks of the FTSE 350 and some stocks from the FTSE small capitalization. Panels C and D present results for the two sub-periods.

There are a total of eighteen (18) rules considered in this study with different combinations of the parameters. These rules divide the days into buy (long), Sell (short) or neutral (earning the risk free rate). The second column denotes the average number of one way trades required to implement the strategy throughout the sample period. Technical trading rules generate on average eight one way trades in a year which indicates that this does not require a lot of trading. The third column return indicates the mean daily return from implementing each rule and t is the standard t-

statistic testing for the mean daily return being significantly different from the buy & hold return. While the previous table gave a more general indication, the results in this table is intended to give more detailed information on whether the mean daily return from the trading rule is better than the buy and hold strategy. A majority of the t-statistics for the least liquid decile stocks are positive and significant compared to the most liquid decile stocks. For the most liquid decile stocks not a single t-statistic is positive and significant which shows that the trading strategy for most liquid stocks do not outperform the buy and hold strategy.

In the last row of panel A we provide results for the benchmark buy and hold. About half the Sharpe ratios for the most illiquid stocks are significantly higher than the benchmark buy and hold strategy. For the more liquid stocks, their Sharpe ratios are not significantly different from those of the buy and hold strategy. The average Sharpe ratio of the most liquid stock portfolio from the trading rule strategy is -0.02 compared to 0.09 for the least liquid stocks. I also report on the possibility that the higher trading rule return from the least liquid stocks are due to higher risk as measured by the variance of the returns. We use the standard deviation of returns from a strategy, σ , to estimate this variability. The standard deviations from the least liquid decile stocks are significantly smaller (0.864%) compared to that of the buy and hold strategy (2.8%). Results are similar for the most liquid decile stocks where the standard deviation for the returns from the trading rules strategies is also smaller (0.44%) than that of the returns from the buy and hold strategy (2.8%). The break-even trading costs for the least liquid stocks are greater than that of the most liquid stocks. The break-even trading cost for the trading rule (1,200,0) for the least liquid stock is 0.27% per trade. This is unfavourable in the light of the trading costs at the London Stock Exchange where the commission fees and stamp duty costs

alone are around 3.25% per round transaction. This reinforces the argument that the trading rule strategies can not make significant profits when transaction costs are considered even where there are significant signs of predictability.

4.5.3 Adjusting for stylized risk factors.

In the previous section returns were adjusted by using the Sharpe ratio and the trading costs. This section follows Neely (1997) and Neely (2001) who uses the Jensen's α (1967) which implements the calculation of risk adjusted returns arising from some risk benchmarks factors. The α measures the return in excess of the risk free rate that is uncorrelated with the risk factors. Neely's studies focused only on the market risk. In this study we consider more risk factors which have been found in other studies to be correlated with return from momentum based strategies, which also condition on information contained in the current and past prices and other variables with fundamental information. I consider the risk factors such as market, size, and book-to-market ratios as sources of ability of simple trading rules capitalizing on the small amounts of autocorrelations to predict price movements of assets in speculative markets and the profits deriving from simple trading rules.

In several previous studies, these factors have not been able to absorb the returns from technical trading rules sufficiently enough to leave the Jensen's α with a loading that could be considered insignificant enough to reject the null of market efficiency. In most studies the value of the Jensen's α has remained significantly larger than zero implying that the risk factors used in the regression analysis could not explain all the profits generated, which suggests that perhaps the model is correctly specified or that the trading rules can not indeed predict stock price

movements or vice versa. While we report results for all the factors used, we put more focus on the loading of the liquidity factor which is the objective of our study.

I use the value of the Jensen's α in respect of the three models below to determine the source of predictability in price movements using a regression method. The models are the CAPM, the Fama and French (1992) three factor model and the four factor model, a variant of Pastor and Stambaugh (2003) five factor model. While the CAPM model considers only the market risk, the Fama and French (1992) three factor model considers three factors; market, size and book-to-market as being able to capture the patterns of returns deriving from conditioning on current and past prices.

The four factor model adds on the liquidity factor as the fourth factor into the regression equation trying to reduce the value of the Jensen's α . The three models are as follows;

$$\text{CAPM : } R_{Tr} - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \varepsilon \dots\dots\dots(4.3)$$

where R_{Tr} is the return from the trading rule strategy, R_{rf} is the risk free return, β_{mkt} is the beta of the market, α is the Jensen measure of unexplained return from trading rule, R_{mkt} is the return from the market portfolio and ε is the error term.

Fama – French three factor model:

$$R_{Tr} - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \beta_{hml} R_{hml} + \beta_{smb} R_{smb} + \varepsilon \dots\dots\dots (4.4)$$

Where, in addition to the variables defined in the CAPM model above, β_{hml} is the beta associated with book-to-market ratio, R_{hml} is the risk factor associated with book-to-market ratio. This is the difference between the asset with the highest book-to-market ratio and the asset with the lowest book-to-market ratio in a

portfolio. β_{smb} is the risk associated with size of the asset while R_{smb} is the risk associated with the size factor.

Four factor Model:

$$R_{Tr} - R_{rf} = \alpha + \beta_{mkt} (R_{mkt} - R_{rf}) + \beta_{hml} (R_{hml} - R_{rf}) + \beta_{smb} (R_{smb} - R_{rf}) + \beta_{liq} (R_{liq} - R_{rf}) + \varepsilon \quad \dots \dots \dots (4.5)$$

Where, in addition to the variables defined in the Fama – French model above, β_{liq} is the risk associated with the liquidity of the asset while R_{liq} is the return for holding an asset which is risky of illiquidity. The liquidity factor returns are calculated following Pastor and Stambaugh (2003). They calculated the liquidity factor by first sorting stocks into portfolios on the basis of their liquidity. The returns are then obtained by subtracting the return for the most liquid stock in each portfolio from the return of the least liquid stock in that portfolio.

In each of the three models above, the left hand side is the monthly average returns from the trading rule strategy minus the risk free return. We use the monthly return series instead of the daily returns. Our interest is to observe the value of α in the three models above. Consistent with previous studies our expectation is that if the value of α is significantly close to zero, then we can conclude that profits from trading rule returns cannot be explained by the respective risk factors in the models. We are interested in examining the size and level of significance of the loadings of the factor coefficients, with specific attention to the liquidity factor. The larger the significance of the liquidity factor in the four factor model will suggest that liquidity can explain the predictability of assets in speculative markets to a large extent.

Table 4.4 gives results of the test regarding how much profits from trading rules can be explained by the stylized risk factors. The larger (and more significant) the size of the intercept in the models used the more implausible is the possibility that the all the factors combined can explain the profits. Panel A contains results for the least liquid decile stocks. For all the rules tested the panel reports significant α for the least liquid stocks. While panel B for the most liquid stocks indicates that, except for one rule, all the α s reported are not significant.

Two things can also be seen from the results. Starting with panel A containing results for the stocks with the higher spreads, the value of the intercept α decreases as more factors are used in the regression. The CAPM model which has only the market risk as the explanatory variable, has the largest value for the intercept α in all the strategies tested. The average value of the intercept for the CAPM model is 0.052 followed by 0.046 for the Fama-French (1992) three factor model and the α for the four factor model which includes liquidity factor is 0.035. The same scenario is repeated for the most liquid stocks.

The second thing is the difference in the model intercept values when the results of the most liquid stocks are compared with the results of the least liquid stocks. The cross-sectional comparison of the stocks of these two market segments indicates that the value of the intercept for the more liquid stocks is less than the intercept for the less liquid stocks in each model and for each respective trading strategy tested. Although this result seems to be inconsistent with our theoretical expectation but the intercept α for the most liquid stocks in panel B are not significant. However, for all the strategies tested the results for the least liquid stocks indicate the intercept α s to be significant. We therefore concentrate our analysis with the least liquid stocks.

Results in table 4.4 also indicate that liquidity risk premium is higher for the least liquid assets than for the more liquid assets. The α for the four factor model is generally smaller for the model than for the other models across all the trading rules tested. This is both for the least and the most liquid stocks. It appears like the inclusion of the liquidity factor in the four factor model can be responsible for the lower α intercepts in that model. This suggests that although the α intercepts are still generally significantly different from zero, the liquidity factor can contribute in explaining the excess trading rule profits.

Results from the four factor model indicates that liquidity can explain the sources of predictability in speculative asset returns. However, although the average value of the intercept is smaller for the four factor model, (which includes the liquidity factor) compared to both the CAPM and the Fama – French model, this value is still significantly different from zero, and therefore we can say that liquidity alongside the other factors cannot completely explain the predictability of movements of assets in speculative markets. The remaining intercept (α) represents the unexplained part of the profits from trading rule strategies. Thus, even after adjusting for various systematic risk factors, the trading rule strategies still earn excess return.

4.6 Conclusion

The purpose of this chapter is to investigate the relationship between firm liquidity and the predictability of returns via technical analysis. Specifically I analysed for the possibility that liquidity data contain useful information beyond what is already contained in prices. I constructed portfolios of stocks using repeatedly drawn samples 350 FTSE 100 stocks and FTSE small capitalization

stocks. The portfolios based on the liquidity of the stocks were reconstructed after every six months.

Three main research hypotheses were tested. The first hypothesis focused on the issue of regularities of stock return series and the second focused on the possibility of consistently obtaining abnormal returns over and above the buy and hold strategy. The third hypothesis contends that there can still remain economic returns when trading on past information even after adjusting for risk factors.

A large majority of previous studies that have found predictable patterns in past prices or returns also tested the economic significance of trading rules. Tests conducted by adjusting excess profits with transaction costs reveal that most excess profits are wiped out when appropriate transaction costs are applied [See for example Fama and Blume (1966), Hudson *et al* (1996) and Knez and Ready(1996)]. This evidence is especially strong when the sample used involves small capitalization stocks with high trading frequencies. In studies where significant excess profits were reported even after adjusting for transaction costs, these excess profits have been explained as compensation for bearing risk premiums. The bid-ask spread we use in this study to proxy risk was suggested by Bokhari *et al* (2005) to be a possible explanation of predictability of the respective asset returns. It was noted that the varying demand characteristics of smaller stocks, which are generally thinly traded can help in explaining the large bid-offer spreads and hence the predictability effect.

This study provides further empirical evidence that returns to technical trading strategies vary across market segments, in particular, decreasing in the bid-offer spread, i.e. predictability is higher for stocks with larger bid-offer spreads and

lower for stocks with smaller spreads. A possible explanation for this effect could be that the higher risk associated with larger spreads is compensated with higher returns. Banz (1981) argued that the lack of information about small firms (normally associated with larger spreads) could cause investors to remove them from their portfolios. Although this argument has been countered by Reinganum and Smith (1983) who argued that the risk due to lack of information is only firm specific and as such can be diversified way in a large portfolio, it can still be argued that market makers would want to set larger spreads when the information about the asset in question is relatively lacking. This can be true especially with smaller firms whose analyst coverage is relatively smaller.

This chapter also investigates if technical trading profits are associated with known measures of risk such as those reflected by Sharpe ratios and those reflected by aggregate risk factor models such as the CAPM, the Fama-French model. The results show that Sharpe ratios and Jensen's α from the technical strategies are sharply decreasing in liquidity. When the strategies are applied to the less liquid stocks, there is positive and significant alpha using any of the factor models. In contrast, the alphas from these strategies when applied to more liquid stocks are not significantly different from zero. The strategies on the less liquid stocks earn excess returns to the extent of 16 % per annum, on average. For more liquid stocks, technical trading strategies do not earn excess returns over a buy & hold strategy.

The next chapter addresses the issue of potential estimate bias that is inherent in methods of adjusting excess trading rule profits for risk.

4.7 Appendix 2

Table 4.1: Summary Statistics For Daily Returns Of The Most Liquid and Least Liquid Decile Stocks Of The Combined FTSE 350 Stocks and FTSE Small Cap Stocks

Returns are computed as log differences of the level of the liquidity decile index. D-Stat is the test statistic for Kolmogorov-Smirnov test of normality. $\rho(i)$ is the estimated autocorrelation at lag i for each period. Numbers with * (**) are significant at the 1% and (5%).

Panel A: Least Liquid Decile Stocks

Statistic	Full Sample 1990-2004	Sub Periods	
		1990-1997	1998-2004
Number of Observations	3391	1935	1456
Mean	0.00044	0.00071	0.00015
Standard Deviation	0.0198	0.00916	0.01755
Kurtosis	9.29445	7.65323	31.4167
Skewness	-0.37	0.07	-0.63
D-Stat	0.069*	0.083*	0.086*
$\rho(1)$	0.12*	0.11*	0.16*
$\rho(2)$	0.09	-0.07**	0.15*
$\rho(3)$	0.08**	0.12*	0.16*

Panel B: Most Liquid Decile Stocks

Statistic	Full Sample 1990-2004	Sub Periods	
		1990-1997	1998-2004
Number of Observations	3391	1935	1456
Mean	0.000314	0.00036	0.00027
Standard Deviation	0.0156	0.00912	0.00637
Kurtosis	27.98	2.86	26.66
Skewness	-2.12	0.23	-1.73
D-Stat	0.07	0.05*	0.067
$\rho(1)$	0.11*	0.22*	0.05*
$\rho(2)$	-0.03*	-0.05*	-0.04*
$\rho(3)$	-0.007	0.03*	-0.03*

Table 4.2: Summary Results of the Trading rule strategy for the Ten Liquidity Deciles Full sample (1990-2004)

Column labelled 'Decile' contains the ten deciles where decile 1 portfolio is the least liquid and decile 10 is the most liquid portfolio. The second column labelled 'Annual' is the average annual return earned by the trading rule strategy. The average Sharpe ratios for the 'buy & hold' strategy and trading rule strategy are reported in the third and fourth columns respectively. Break-even cost is the risk adjusted average trading cost that makes us indifferent between the Sharpe ratios from the buy & Hold strategy and the trading rule strategy.

Decile	Annual(%)	Average Sharpe Ratios		Break-even Cost (Round trip)
		Buy & Hold	Trading Rule	
1	16.29	0.02	0.14*	0.13%
2	12.65	0.01	0.78*	0.27%
3	9.94	0.90	1.50	0.64%
4	10.84	1.20	1.36*	0.32%
5	9.20	0.32	1.20	0.14%
6	4.72	0.38	1.07*	0.67%
7	11.64	0.35	0.85	0.46%
8	7.83	0.35	0.73	0.27%
9	5.49	0.34	-0.50	0.06%
10	-2.33	0.01	-0.02	-0.07%

Note:

* Indicates significance at 5 percent level.

Table 4.3: Results for the Trading rule strategies for the most liquid and Least Liquid Decile stocks

The first column contains the trading rules. Rules are written as (short, long, band) where short and long is the respective short and long period simple moving averages, and band is the percentage difference required to generate signals. Each trading strategy divides the day into buy, sell or neutral (earning a risk free rate) positions. Return is the mean daily return earned by implementing the strategy and 't' is the t-statistic testing the mean return being significantly different from the buy and hold. σ is the standard deviation of the daily returns strategy. Break-even-cost is the trading costs that make one indifferent between the Sharpe ratios from the Buy and Hold strategy and the simple moving average strategy. Panels A and B presents results for the full sample of least liquid and most liquid deciles for the stocks of the FTSE 350 and some stocks from the FTSE small capitalization. * Indicates significance at 5 percent level.

Panel A

Full sample of least liquid decile stocks 1st January 1990 – 31st December 2004

Rule	Avg # of trades /year	Return	t	Annual	σ	Sharpe ratio	Break-even Cost(annual)
1, 200, 0	7	0.00051	2.27*	12.42%	0.00304	0.17*	0.27%
2, 200, 0	6	0.00058	1.8	13.98%	0.00451	0.13*	0.27%
5, 200, 0	4	0.00047	0.95	11.34%	0.00884	0.05	0.13%
1, 150, 0	8	0.0004	3.61*	9.73%	0.00162	0.25*	0.22%
2, 150, 0	6	0.00055	3.20*	13.41%	0.00784	0.07*	0.26%
5, 150, 0	5	0.0006	2.27*	14.42%	0.00785	0.08	0.24%
1, 50, 0	14	0.00038	9.53*	9.33%	0.00717	0.05*	0.38%
2, 50, 0	12	0.00075	8.81*	18.04%	0.00747	0.10	0.77%
5, 50, 0	9	0.00092	7.27*	22.12%	0.00251	0.37	0.71%
1, 200, 1	7	0.00066	2.49*	16.05%	0.00258	0.26	0.43%
2, 200, 1	6	0.00102	2.06*	24.69%	0.00445	0.23	0.54%
5, 200, 1	4	0.00049	1.09	11.75%	0.00785	0.06	0.15%
1, 150, 1	9	0.00083	3.71*	19.92%	0.00352	0.24	0.63%
2, 150, 1	6	0.00079	3.41*	18.96%	0.00768	0.10	0.40%
5, 150, 1	5	0.00069	2.65*	16.55%	0.00758	0.09*	0.29%
1, 50, 1	15	0.00041	9.65*	10.02%	0.00568	0.07	0.42%
2, 50, 1	12	0.00115	8.99*	27.66%	0.00784	0.15*	1.24%
5, 50, 1	9	0.00095	7.66*	22.91%	0.00764	0.12	0.75%
Average	8	0.00067	4.52	16.29%	0.00764	0.09	0.43%
Benchmark buy & Hold		0.00072		17.28%	0.03701	0.02	

Panel BFull sample of most liquid decile stocks 1st January 1990 – 31st December 2004

Rule	Avg # of trades /year	Return	t	Annual	σ	Sharpe ratio	Break-even Cost
1, 200, 0	5	0.00024	0.73	5.76%	0.00068	0.35	0.11%
2, 200, 0	4	0.00031	1.2	7.44%	0.00124	0.25	0.12%
5, 200, 0	3	-0.00143	-2.05*	-34.32%	0.00680	-0.21	-0.46%
1, 150, 0	9	0.00038	0.61	9.12%	0.00092	0.41	0.33%
2, 150, 0	7	0.00026	0.2	6.24%	0.00185	0.14	0.16%
5, 150, 0	5	-0.00051	-0.73	-12.24%	0.00108	-0.47	-0.26%
1, 50, 0	4	0.00031	0.53	7.44%	0.00079	0.39	0.12%
2, 50, 0	7	0.00045	0.81	10.80%	0.01125	0.04	0.20%
5, 50, 0	5	-0.00029	-1.23	-6.96%	0.00362	-0.08	-0.17%
1, 200, 1	4	-0.00033	-0.51	-7.92%	0.00061	-0.54	-0.14%
2, 200, 1	4	-0.00032	-0.94	-7.68%	0.00049	-0.65	-0.13%
5, 200, 1	2	-0.00028	-1.91	-6.72%	0.00112	-0.25	-0.06%
1, 150, 1	5	0.00038	0.71	9.12%	0.00633	0.06	0.14%
2, 150, 1	4	0.00037	0.41	8.88%	0.00205	0.18	0.14%
5, 150, 1	3	-0.00034	-0.35	-8.16%	0.00125	-0.27	-0.11%
1, 50, 1	8	-0.00028	-0.21	-6.72%	0.00075	-0.37	-0.23%
2, 50, 1	4	-0.00016	-0.56	-3.84%	0.00145	-0.11	-0.07%
5, 50, 1	2	-0.00051	-1.54	-12.24%	0.00283	-0.18	-0.11%
Average	4	-0.000097	-0.73	-2.33%	0.00441	-0.02	-0.07%
Benchmark buy & Hold		0.00042		10.32%	0.02801	0.01	

Table 4.4: Intercepts (α) for factor regressions for the London Stock Exchange Stocks

This table contains intercept coefficients obtained by regressing the daily portfolio excess returns to the moving strategy on factor models. In column 5 the “liq coefficient” is the loading for the liquidity factor.

$$\text{CAPM : } R_t - R_{rf} = \alpha + \beta_{\text{mkt}} (R_{\text{mkt}} - R_{rf}) + \varepsilon$$

$$\text{Fama - French three factor model: } R_t - R_{rf} = \alpha + \beta_{\text{mkt}} (R_{\text{mkt}} - R_{rf}) + \beta_{\text{hml}} R_{\text{hml}} + \beta_{\text{smb}} R_{\text{smb}} + \varepsilon$$

$$\text{Four factor Model: } R_t - R_{rf} = \alpha + \beta_{\text{mkt}} (R_{\text{mkt}} - R_{rf}) + \beta_{\text{hml}} R_{\text{hml}} + \beta_{\text{smb}} R_{\text{smb}} + \beta_{\text{liq}} \text{Liq} + \varepsilon$$

Panel A: Least Liquid Stocks

Rule	CAPM	Fama-French	4 Factor Model	
α	α	α	α	Liq coefficient
1, 200, 0	0.024	0.21	0.19	0.069
t-stat	(1.18)	(1.87)	(0.68)	(0.18)
2, 200, 0	0.019	0.015	0.005	0.024
t-stat	(4.59)*	(4.36)*	(2.36)*	(0.31)
5, 200, 0	0.015	0.014	0.010	0.004
t-stat	(3.28)*	(1.21)	(1.33)	(0.09)
1, 150, 0	0.031	0.025	0.012	1.640
t-stat	(4.52)*	(1.27)	(1.25)	(1.4)
2, 150, 0	0.041	0.027	0.024	0.139
t-stat	(2.13)*	(0.90)	(1.02)	(1.29)
5, 150, 0	0.063	0.051	0.044	0.119
t-stat	(1.25)	(4.11)*	(4.21)*	(1.08)
1, 50, 0	0.036	0.030	0.019	0.224
t-stat	(5.18)*	(3.02)*	(2.10)*	(2.38)
2, 50, 0	0.091	0.081	0.041	0.234
t-stat	(1.11)	(2.17)	(2.15)	(2.41)
5, 50, 0	0.031	0.014	0.006	0.214
t-stat	(1.32)	(4.82)*	(1.10)	(2.18)
1, 200, 1	0.072	0.056	0.031	0.025
t-stat	(2.82)	(1.54)	(0.79)	(0.74)
2, 200, 1	0.074	0.045	0.023	0.004
t-stat	(4.31)*	(2.71)	(3.13)*	(2.38)
5, 200, 1	0.090	0.041	0.036	1.722
t-stat	(5.19)*	(5.10)*	(4.32)*	(2.41)
1, 150, 1	0.031	0.028	0.019	0.146
t-stat	(4.21)*	(2.34)	(1.34)	(2.18)
2, 150, 1	0.061	0.041	0.038	0.125
t-stat	(0.01)	(4.10)*	(1.28)	(1.48)
5, 150, 1	0.056	0.041	0.032	0.235
t-stat	(1.29)	(3.47)*	(8.10)*	(2.37)
1, 50, 1	0.081	0.021	0.020	0.246
t-stat	(3.96)*	(5.18)*	(2.10)*	(2.62)
2, 50, 1	0.071	0.041	0.039	0.225
t-stat	(1.09)	(3.58)	(2.08)	(2.26)
Average	0.052	0.046	0.035	

Panel B: Most Liquid Stocks

Rule	CAPM	Fama-French	4-Factor model	
α	α	α	α	Liq coefficien t
1, 200, 0	0.018	0.017	0.012	0.021
t-stat	(4.98)*	(4.87*)	(2.68)*	(0.52)
2, 200, 0	0.017	0.016	0.003	0.019
t-stat	(4.59)*	(4.36)*	(2.36)*	(0.45)
5, 200, 0	0.015	0.011	0.006	0.036
t-stat	(5.78)	(4.51)	(3.73)	(0.49)
1, 150, 0	0.021	0.019	0.009	0.083
t-stat	(5.59)	(5.37)	(4.25)	(1.71)
2, 150, 0	0.028	0.017	0.014	0.087
t-stat	(5.13)	(4.92)	(3.02)	(1.72)
5, 150, 0	0.033	0.034	0.031	0.045
t-stat	(10.25)	(7.56)	(8.02)	(1.1)
1, 50, 0	0.029	0.024	0.010	0.143
t-stat	(9.68)	(6.52)	(8.60)	(2.03)
2, 50, 0	0.032	0.031	0.025	0.138
t-stat	(8.61)	(8.75)	(6.58)	(2.18)
5, 50, 0	0.013	0.013	0.005	0.146
t-stat	(6.32)	(6.18)	(3.40)	(2.25)
1, 200, 1	0.028	0.022	0.011	0.023
t-stat	(5.82)	(5.53)	(2.99)	(0.57)
2, 200, 1	0.025	0.015	0.013	0.021
t-stat	(7.34)	(5.77)	(4.73)	(0.49)
5, 200, 1	0.030	0.030	0.028	0.039
t-stat	(7.09)	(6.82)	(5.39)	(0.53)
1, 150, 1	0.026	0.034	0.021	0.090
t-stat	(6.51)	(6.24)	(3.83)	(1.86)
2, 150, 1	0.029	0.028	0.022	0.095
t-stat	(13.01)	(9.60)	(10.18)	(1.87)
5, 150, 1	0.033	0.027	0.013	0.049
t-stat	(12.29)	(8.28)	(10.92)	(1.20)
1, 50, 1	0.030	0.018	0.015	0.156
t-stat	(10.93)	(11.12)	(8.35)	(2.21)
2, 50, 1	0.035	0.036	0.033	0.150
t-stat	(1.93)	(2.1)	(5.31)	(2.05)
Average	0.026	0.023	0.016	

Chapter 5 Can Risk Premium Explain Technical Trading Profits?

5.1 Introduction

Measuring risk takes a centre stage in the evaluation of the efficiency of financial markets given its central role in investment performance evaluation. Since the evaluation of weak form efficiency via technical analysis is in fact an evaluation of the performance of trading models, the argument of risk concerns becomes even more important.

Neely (2003) observes that because technical trading strategies spend some time out of the market, they should therefore have less volatile returns than the buy and hold rule. Despite this rather compelling argument, most of the literature positions the technical trading strategy as generally riskier than a buy and hold strategy. This view in the literature is supported by the empirical evidence where estimates of risk from the buy and hold strategy have been found to be less than the estimated risk from trading rule strategies. Second, despite the numerous documentations in the literature that discuss the heteroskedastic nature of financial asset distributions, the standard deviation as a measure of risk is still being captured as a stationary statistic throughout the entire investment period.

Campbell *et al.* (1997, p.481) argued that "...it is both logically inconsistent and statistically inefficient to use volatility measures that are based on the assumption of constant volatility over some period when the resulting series moves

through time.” This argument is even more obvious for strategies that are also changing with time, for example technical analysis. The potential for estimation error lies in the manner in which risk for technical trading is perceived in most previous empirical studies. Because the standard deviation is calculated as an average dispersion of all the observations in the sample, the implied perception in its traditional calculation is that it is stationary. This perception allows its calculation to ignore the chronological order of events (reflected in contiguous price movements) which could be important if it is used to estimate the risk of strategies that are time varying. When risk is estimated in this way, technical analysis strategies will be penalised for exposing the investment to riskier positions relative to the buy and hold strategies only at some intervals, and in other intervals the strategy’s risk exposure may be less.

The risk arising from undertaking trading rule strategies can be significant and some may not be easily captured by risk estimates. But where these estimates can, it makes sense if they can be made to take account of the chronological order of price movements (which produce signals) for such and within a period that actually ‘matters’ to the investor¹³. The periods that matters are the short or long periods that traders switch assets between long and short positions by following trading signals. It is within some of these periods that the risk position of a trading rules strategy may differ from that of the buy and hold. Ideally, risk estimates should be able to

13 Some aspects of stock trading make technical trading an obvious risky strategy compared to the buy and hold strategy. The risk of shorting, the risk of liquidity and the ‘bad signal’ risk. These can be described as risks associated with technical trading than buy and holding. The buy and hold rule does not take these risks. These are what should concern the technical trader for the risk of her strategy relative to the buy and hold alternative.

chronologically track down the relative risks for technical trading and buy and hold strategies during these periods. Unfortunately the standard deviation does not consider the chronological order of occurrences of price movements along the time line. The standard deviation is calculated using values of observations regardless of the chronological order in which these values occurred. This can be a source of bias if this statistic and other associated risk estimates like the Sharpe ratio are used in evaluating the efficacy of trading rules strategies.

The work of Dacorogna *et al.* (2001) provides a useful insight regarding the conceptual and theoretical basis of the problem. In their work they consider the limitations of the Sharpe ratio in evaluating investment strategies. For example, they pointed out that the Sharpe ratio does not take account of clustering of profits and losses and its instability as the variance of an investment approaches zero. They therefore proposed performance measures which observe returns over different time intervals. Dacorogna *et al.* (2001) also observe that the Sharpe ratio treats the variability of returns and variability of losses in the same way despite the fact that the variability of profits is not an important issue to the investor.

This chapter extends the literature on the relationship between technical analysis and risk adjustment by investigating whether technical trading rules are useful on a risk-adjustment basis in equity markets by adapting the technique used by Dacorogna *et al.* (2001) to the UK market. I use a multi-horizon framework to capture the chronological order of price movements where time intervals (windows) are conceived to open and close on the occurrence of trading signals and not fixed as in Dacorogna *et al.*'s (2001) case. For each window an average return is obtained to be used as an observation in a set of means.

In this chapter risk estimates are explored in the context of the investment strategies in the stock markets. Sixty four stocks from the London Stock Exchange (LSE) are examined via simple moving average trading rules. The sample runs from 1st Jan, 1990 to 31st December, 2004. For each asset in the sample the study compares the performance of ten trading rules used by Brock *et al.* (1992) and Hudson *et al.* (1996) against the buy and hold benchmark by examining differences in their annualised returns, Standard deviation, break-even transaction costs, and the Sharpe Ratio.

The rules fail to significantly and consistently outperform the buy and hold strategy even after using the rolling standard deviation as a measure of risk. Thus this study extends results in previous studies which found that return predictability and apparent trading rule profits are consistent with market efficiency.

The rest of this chapter is organised as follows. In the next section, section 5.2 we describe the objectives and significance of this study. In section 5.3 we give summary of previous related works in this area, summarizing statistics that have been attempted, their contributions and pitfalls. In section 5.4 we develop the conceptual framework for our study. Section 5.5 provides the methodology including data and testable hypotheses. The results are presented in section 5.6 and section 5.7 concludes.

5.2 Research Objectives and significance

The main objective of this chapter is to ascertain the effect of using an inappropriate estimate of risk on evaluating the efficacy of trading rules. The first specific objective is to investigate whether there is a significant difference in the

traditional estimate of risk for technical trading (the standard deviation and the Sharpe ratio) when this is calculated with due consideration to the chronological order of price movements and when it is simply taken as a measure of dispersion on the entire sample regardless of the chronological order in which prices were moving.

The second objective is to examine whether the standard deviation calculated with a consideration of price movements explains the profits from technical analysis. The chapter compares the profits from simple trading rules after adjusting for risk using a measure of risk that considers order of price movements with the buy and hold strategy.

It also examines the time varying risk aspect of trading rules profitability. Through examining how the rolling technique we use in calculating the standard deviation matches with the returns from technical trading rules, we will determine whether there are more returns during periods of more risk or otherwise.

The fourth objective is an attempt to use an appropriate numeric figure as a quantity of risk from technical trading. While in the literature, most studies adjust for risk by simply examining the risk – return relationship, or a variant of that (for example the Sharpe ratio), in this study we follow the insightful work of Dacorogna *et al.* (2001) who attempted to calculate the amount of risk that is related to technical trading decisions. The X_{eff} statistic is risk adjusted excess profit from trading rules where the adjustment process involves directly deducting a risk quantity from profits after adjusting for appropriate transaction costs.

The fifth objective is to examine the predictability of the stock returns of the FTSE 100 for a period that has never been examined before. Taylor (2000) examined a sample of 10 stocks from the FTSE 100 for the period from 1972 to

1991. In view of the temporary market inefficiency argument, this study determines whether the ‘declining profitability’ phenomenon suggested in the literature applies to the sample. This period was just before the European monetary union and the structural changes of the LSE in 1997. Together with this, we also consider the efficiency of the FTSE 100 during the same period using trading rules analysis.

5.3 Literature Review

The seriousness of appropriately adjusting for risk has been highlighted by, among others, Sharpe, 1966; Jensen, 1968; Kho, 1996; Brown, Goetzmann and Kumar, 1998; Ready, 1998; Allen and Karjalainen, 1999; and Neely, 2001, 2003. Recent studies on technical analysis that have explained significant excess profits out of sample as a compensation for risk include the following: Cheng and Wong (1997), Lee *et al* (2001), Kho (1996), Ito (1999), Levich and Thomas (1993), Pradeep *et al* (1994) and Sweeney (1988).

Previous attempts to use risk as an explanation for excess returns did not quantify the risk estimates. The risk rationality has been subsumed into the general risk–return relation via some popular models. For example CAPM based explanations argue that predictability could be driven by changing market volatility. Harvey (1991) attributed the predictability in stock returns and bonds to predictable shifts and market wide reward for shifts in risks (risk premiums). Sweeney (1988) used the X-Statistic as a risk adjusted measure of performance. He concluded that no significant excess profits remain after adjusting for risk and accounting for transaction costs.

The problem that documented measures of risk used to evaluate the efficacy of technical trading rules do not reflect the real risk concerns of a technical trader were first addressed by Dacoragna, *et al* (2001). The R_{eff} statistic of Dacoragna, *et al* (2001) captures changes in investors utility and appetite for risk across the sample period on the assumption that investor's risk attitude can be altered by certain events. Specifically the R_{eff} recognizes that the consequential impact of trading losses can be higher to a moderate compared to a wealthy investor. Hence, the R_{eff} assigns high risk aversion in the windows with negative returns and a low one in the windows with profits. The X_{eff} on the other hand measures the utility that the trading strategy gives an excess return over a weighted average of return horizons.

Neely, Waller and Dittmar (1997) applied the following four measures to adjust technical profits returns for risk or correlation to market returns: changes in the Sharpe ratio of a portfolio when a traded asset is added, Sweeney's (1988) X statistic and Sweeney and Lees's (1990) X. Both the Sharpe ratio, and Sweeney and Lees's X statistic suffer from way they model volatility of returns. Sweeney and Lees' X statistic is calculated as

$$X^* = \frac{1}{T} \sum_{t=0}^{T-1} \left[z_t \ln \left(\frac{P_{t+1}}{P_t} \right) + (1 - z_t) \ln(1 + i_t) \right] + \frac{n}{2T} \ln \left(\frac{1-c}{1+c} \right) - \left[\frac{P_1}{P_t} \sum_{t=0}^{T-1} \ln \left(\frac{P_{t+1}}{P_t} \right) + \frac{P_2}{T} \sum_{t=0}^{T-1} \ln(1 + i_t) \right] \quad \text{-----} \quad (5.1)$$

Where T is the number of observations, n is the number of one-way trades, c is the proportional transaction cost, p_1 is the proportion of the time spent in the market and p_2 is the proportion of the time spent in T-bills ($p_1 + p_2 = 1$). In this model, Sweeney and Lee (1990) has the third and fourth terms responsible to estimate the expected return to a zero transaction cost strategy that randomly is in the

market on a fraction of p_1 of the days, earning the market premium, and in T-bills otherwise. Under the null of no predictive ability, the risk adjusted return is calculated as actual return less expected return. A positive X statistic is considered as indicative of excess risk adjusted returns. Sweeney and Lees' model suffers from both the issues that this paper is set to address. That is, their model does not consider the time variability of standard deviation, in the context described below which implies that this model assumes that the investor has a constant utility function throughout.

A more rigorous risk adjustment measure, the X_{eff} is proposed by Dacorogna et al (2001)¹⁴. The X_{eff} measures the utility that technical trading can provide to an investor with a constant utility function that can be described as convex (i.e. risk averse) over a weighted average of return horizons. It is expressed as

$$X_{eff} = \frac{252.100}{T} \left(\sum_{t=1}^T r_t - \frac{n}{2} \ln \left(\frac{1+c}{1-c} \right) \right) - \frac{\gamma}{2} \frac{\sum_{i=1}^n \tilde{w}_i \sigma_i^2 (1 \text{ year} / \Delta t_i)}{\sum_{i=1}^n \tilde{w}_i}, \text{-----} \quad (5.2)$$

Where $\frac{252.100}{T} \left(\sum_{t=1}^T r_t - \frac{n}{2} \ln \left(\frac{1+c}{1-c} \right) \right)$ is the annualized excess return to

technical trading expressed in percentage terms and is net of transaction costs; r is the average daily return; σ_i^2 is the variance of non-overlapping returns of length Δt_i days; $(1 \text{ year} / \Delta t_i \text{ days})$ is the number of returns of length Δt_i days in one year; and γ is a risk aversion parameter¹⁵. The sequence of weights $\{\tilde{w}_i\}$ takes on a maximum value at holding period of 90 days;

¹⁴ A complete derivation of the X_{eff} statistic is found in Dacorogna *et al.* (2001)

¹⁵ Dacorogna et al (2001) recommend values of γ between 0.08 and 0.15.

$$\tilde{w}_i = \frac{1}{2 + \left(\ln \left(\frac{\Delta t_i}{90 \text{days}} \right) \right)^2}, \quad \text{-----} \quad (5.3)$$

They set the return horizons Δt_i to be derived by geometric sequence $\{1,2,4,8,16,\text{etc}\}$ with a maximum value which is less than or equal to one quarter the number of days in the sample. In this paper we will use time horizons that are determined by events happening in the market. I consider such a model to be more realistic than the geometric sequence used by Dacorogna *et al.* (2001). Our model will give X_{eff} , the risk adjusted excess technical trading profit, which considers the horizons governed by trading signals.

5.4 The conceptual Framework

The distribution of returns seldom represents appropriately the actual chronological order of price movements. Even in the case where there are large drawdowns¹⁶ these are nevertheless represented by price movements which evolve in time to a minimum low. For example, when the price of an asset hits a three months record low, there are chances that this low prices may be flanked by a two weeks period on each of its sides with observations that are very close to it. Such periods can be associated with positions that traders take in short term investment strategies. It is logical to imagine that the variability of returns within these shorter periods are what actually matter to investors. Therefore obtaining statistical quantities from distributions that ignore these shorter intervals can attract bias. This is especially serious when using quantities to assess the efficacy of weak form

efficiency of the Efficiency Market Hypothesis (EMH) because the risk inferred by the statistics could be biased.

Studies of technical analysis may need a special approach in determining the risk that a technical trader bears relative to a buy and hold investor. This is particularly in the way in which risk that is borne by a technical trader can be conceived. Technical trading is a short term investment strategy where positions can range from one day to usually ten to fifteen days depending on the nature of the specific rule applied. The intervals of time in which a trader takes a position are governed by the generation of alternating buy and sell signals. Thus each period of time between two contiguous buy and sell signals can be considered to have different volatility estimates.

The intuition we have is that each of these fairly short horizons contain its own return variability, a variability that is more associated with the chronological order of price movements within the window itself. We also recognize that a specific window's volatility is impacted by the long term memory process. Thus, memory effects from previous windows can affect the volatility of a particular window besides the price movements within the window itself. Since this conception is similar to Dacorogna *et al.*'s (2001) effective risk this study is the first to test effective risk adjustment on UK data.

In order to capture the chronological order of risk attracting events we use the rolling windows technique to capture periods that represent the order of price movements. We define a window, Δt_i , to be a period of time from a signal is issued

¹⁶ A drawdown can be described as a peak to trough decline during a specific period of severe decline of an investment or fund. It is usually quoted as the percentage between the peak to the trough

by a trading rule up to the next signal, for $i = 1, 2, \dots, n-1$, where n is the total number of trades executed throughout the investment period.

$$X_{eff} = \frac{252.100}{T} \left(\sum_{t=1}^T r_t - \frac{n}{2} \ln \left(\frac{1+c}{1-c} \right) \right) - \frac{\gamma}{2} \frac{\sum_{i=1}^n \tilde{w}_i \sigma_i^2 (1year/\Delta t_i)}{\sum_{i=1}^n \tilde{w}_i} \quad (5.4)$$

We use the same weighting scheme used by Dacorogna *et al.* (2001) except that the length of the window, Δt , in our case are given by length of windows as determined by the occurrence of the buy and sell signals. This means that our windows open and close with technical signals issued by the trading rules. This innovation is intended to make the risk estimate more realistic by effecting the widely recognised fact that equal movements of upward and downward deviations do not inflict the investor with equal risk. We also use a different length of time to proxy the maximum value the sequence of weights can take. While accepting the arguments used by Dacorogna *et al.* (2001) for their choice of 90 days, we consider more appropriate to use the days where the memory effect is still strong. Thus, the weight is calculated as;

$$\tilde{w}_i = \frac{1}{2 + \left(\ln \left(\frac{\Delta t_i}{d} \right) \right)^2} \quad (5.5)$$

where d is the number of days the autocorrelation effect is still significant. The other variables are as defined before.

By executing a 10 days fixed moving average rule, our shortest window has at least 10 observations. This is still too short for high precision standard deviation.

We increase the number of observation points in each window by following Muller (1993) who advises the use of overlapping intervals in computing the standard deviation. Standard deviations from each window are then annualised before calculating the average for the entire sample.

5.5 Methodology

Our sample runs for the period from 1st January 1990 to 31st December 2004. The sample comprises of 64 stocks from the London Stock Exchange where all data is obtained from the Datastream database. We initially started with 100 stocks in our sample. The number of firms in our sample is reduced because not all firms were able to give data for the entire sample period. We needed to include stocks which have continuous price histories from January 1990 to December 2004.

Trading Rules tested

Given the large number of trading rules available, it has always been difficult to decide the number and type of trading rules to use in a study of this type. Choice is a subject related to data snooping and spurious results. To avoid these problems we choose, 1) trading rules that are most widely used in the industry and 2) those that are simple to implement. We test the same rules used in the studies by Brock *et al.* (1992), Hudson *et al.* (1996), Bokhari *et al.* (2005) and in several other studies.

We do not search for the best ex-post MA rule as do most previous studies since this may lead to data snooping biases. Instead, we implement a simple recursive trading strategy to simulate real-time speculation. Specifically, the investor is assumed to trade each day using the MA rule that is considered "best" using data up to the previous day. Following Sullivan *et al.* (1999), we define the best MA rule

as the rule that has the highest cumulative returns over the past ninety days¹⁷. These rolling ninety days means that the evaluation is done every day. We use ten trading rules that were originally used by Brock *et al.* (1992)

The return from the buy and hold strategy (buy first day sell last day) is

$$r_{BH} = \sum_{t=1}^T r_t + \log \frac{1-c}{1+c} \quad \text{-----} \quad (5.6)$$

The h day holding period return at time t is defined as $R_t^h = \log(P_{t+h}) - \log(P_t)$ as in Brock *et al.* (1992). They are classified based on price information up to and including day t , we classify the trading outcomes each day in our sample as either a Buy (b), or a Sell (s) signal. The mean return and variance conditional on a buy (sell) signal over N periods can be written as:

$$\bar{X}_{b(s)} = E(R_t^h | b_t \text{ or } s_t) = \frac{1}{N_{b(s)}} \sum_{t=0}^{N-1} R_{t+1} I_t^{b(s)} \quad \text{-----} \quad (5.7)$$

$$\hat{\sigma}_{(b)s}^2 = E\left[(R_t^h - \bar{X}_{b(s)})^2 | b_t \text{ or } s_t\right] = \frac{1}{N_{b(s)}} \sum_{t=0}^{N-1} (R_{t+1} - \bar{X}_{b(s)})^2 I_t^{b(s)} \quad \text{-----} \quad (5.8)$$

respectively, where $N_{b(s)}$ is the number of total buy (sell) days, R_{t+1} is daily return at time $t+1$, and $I_t^{b(s)}$ is one for a buy (sell) signal observed at time t and zero otherwise.

¹⁷ The ninety days is derived as an average of the long moving averages for all the trading rules available to the trader

When we introduce the rolling-windows approach equation (5.8) is calculated in respect of windows determined by the occurrence of trading signals throughout the sample period. Hence the overall sample standard deviation calculated using the rolling approach is a weighted average of the sub-sample standard deviations

$$\hat{\sigma}_{b(s)} = \frac{\sum_{i=1}^n \tilde{w}_i \sigma_i^2}{\sum_{i=1}^n \tilde{w}_i} \text{-----(5.9)}$$

where the weighting scheme is as explained in equation (5.6) above.

The t-statistics

Traditionally, the test statistics have been calculated using the following equations. The t -statistic for returns of the buy (sell) moving average trading rules over the buy-and-hold strategy is

$$t = \frac{\bar{X}_r - \bar{X}}{(\hat{\sigma}_r^2 / N_r + \hat{\sigma}^2 / N)^{1/2}} \text{-----(5.10)}$$

where \bar{X}_r , $\hat{\sigma}_r^2$, and N_r are the mean return, variance, and number of the buy or sell signals calculated for the entire sample as one solid distribution, and \bar{X} , $\hat{\sigma}^2$, and N are the unconditional mean, variance, and number of returns again for the entire sample period. For the buy–sell or the buy–sell spread, the t -statistic is traditionally calculated as:

$$t = \frac{\bar{X}_b - \bar{X}_s}{(\hat{\sigma}_b^2/N_b + \hat{\sigma}_s^2/N_s)^{1/2}} \text{-----} \quad (5.11)$$

where \bar{X}_b , $\hat{\sigma}_b^2$, and N_b are the mean return, variance, and number of the buy signals, and \bar{X}_s , $\hat{\sigma}_s^2$, and N_s are the mean return, variance, and number of the sell signals (Sweeney, 1988)

Transaction Costs

The transaction costs for companies in the FTSE 100 are estimated to comprise of brokerage fees, stamp duty and the bid-ask spread. We deliberately favour the use of latest data to estimate realistic transaction costs knowing that the costs might have probably declined after the introduction of electronic trading at the London Stock Exchange. For example, the commission has decreased since the introduction of electronic trading at the London Stock Exchange and they can be as low as a £10 fixed fee for deals of any size (Bokhari *et al*, 2005). This cost is estimated at approximately 0.10 percent per trade and 0.2 per round trip transaction (Ellik and Thomas, 2003). Stamp duty is also fixed. It does not vary with company size and is charged at the rate of 0.5% of the purchase price on the purchase of all UK listed stocks. These are estimated at 0.125 percent per transaction. The bid-offer spreads do vary significantly. For companies in the FTSE 100 bid-offer spreads should be fairly low, these are estimate these to be about 0.65% per round trip

transaction¹⁸. We therefore follow Ellik and Thomas (2003) to estimate round trip transaction cost to be approximately 1.05% for companies in the FTSE 100.

Testable Hypotheses and Test Statistics

1. Standard deviations that consider chronological order of price movements are more appropriate for evaluating trading rule profits.

The null hypothesis, H_0 , claims that $\hat{\sigma}_{rol} = \hat{\sigma}_{tr}$. This is tested against the alternative hypothesis, H_A , $\hat{\sigma}_{rol} - \hat{\sigma}_{tr} < 0$, where $\hat{\sigma}_{rol}$ and $\hat{\sigma}_{tr}$ are the standard deviations for trading rule returns determined with the rolling approach and the traditional entire sample approach respectively.

2. I also test the hypothesis that the risk from technical trading is less than the risk from buy and holding. This follows the argument that by being able to switch between stock and the risk free asset, the technical trader provides himself a cushion against instability. The returns from the risk free asset are more stable than returns from the stock or the market in general (index returns). Since stable risk free asset returns do actually moderate and reduce the impact of the volatility of the technical trader's portfolio we test whether the magnitude of risk, estimated as a weighted average of non-overlapping intervals of returns is significant enough to offset the returns from technical

¹⁸ Ellik and Thomas (2003) estimate the bid-offer spread for all companies in the FTSE 350 by considering the distribution of such spreads for companies present in the index as of July 2003.

trading against return from buy and hold strategy. The null hypothesis, H_0 , claims that $\bar{X}_{Tr} - \bar{X}_{bh} = 0$. This is tested against the alternative hypothesis, H_A , of $\bar{X}_{Tr} - \bar{X}_{bh} > 0$, where \bar{X}_{Tr} and \bar{X}_{bh} are the mean return from the buy or sell trading rules and the unconditional (buy-and-hold) mean return respectively adjusted for risk using rolling standard deviations.

3. A significant difference between average returns from buy and average returns from sell is indicative of the information value of trading rules. Taylor (2000) clarifies that when a trading rule is applied to a stochastic process representing prices it will produce two sets of time indices b and s defined by $t \in s$ if period $t+1$ is classified as a sell and $t \in b$ if period $t+1$ is classified as a buy. The hypothesis that there is predictability is based on the requirement that there is a difference between the returns from these two classes of days from trading decisions if the expected return depend on the buy/sell information. We therefore test the hypothesis that there is no difference between these two returns.

The null hypothesis, H_0 , claims that $\bar{X}_{buy} - \bar{X}_{sell} = 0$. This is tested against the alternative hypothesis, H_A , of $\bar{X}_{buy} - \bar{X}_{sell} \neq 0$, where \bar{X}_{buy} and \bar{X}_{sell} are the mean returns from the buy days and mean returns sell days respectively.

4. Given that we have made an innovation to estimate the time-varying risk premium, we are not making the standard assumption about risk as has been made in literature. That,

“... the risk from holding stock is the same on Buy days as on Sell days” Taylor (2000, pp58)

We test the hypothesis that risk of trading rules returns from buy days is not the same as the risk of trading rules returns from sell days. This test is a necessary secondary test for the test of market efficiency via the difference between average returns on buy and sell above.

The null hypothesis, H_0 , $\hat{\sigma}_{buy} > \hat{\sigma}_{sell}$ is tested against the alternative hypothesis, H_A , alternative hypothesis $\hat{\sigma}_{buy} - \hat{\sigma}_{sell}$ can be positive or negative or zero. Where $\hat{\sigma}_{buy}$ and $\hat{\sigma}_{sell}$ are the standard deviations from buy days and sell days respectively. These standard deviations are calculated using non-overlapping rolling windows. To obtain time series for the periods of upward and downward trending markets, I concatenate all days when the strategy is long to make a time series for the upward trending market. We also concatenate the days when the strategy is short (i.e. sell days) to make a time series of downward trending market.

5. Following Dacorogna *et al* (2001) we also use the statistic X_{eff} for the test of market efficiency. A positive X_{eff} indicates that the trading strategy has produced excess returns that exceed both the transaction costs and risk. In our case the risk that is considered by X_{eff} is a time-varying risk premium because the calculation of variability of return considered the heteroskedastic nature of return volatility. The return volatility has incorporated this behaviour in two ways. First the use of non-overlapping rolling windows and second the use of multi-horizons determined by trading rule signals. The null hypothesis is that returns from trading rules that remain after accounting for transaction costs are not significant. H_0 , claims that $X_{eff} = 0$. This is tested against the alternative hypothesis, H_A , of $X_{eff} > 0$.

5.6 Empirical Results

5.6.1 Summary Statistics

In Table 5.2 the summary statistics for the average of the 64 individual stocks from a sample of stocks from the FTSE 100 for the period from January 1990 to December 2004 are presented. The summary contains the distribution characteristics: mean standard deviation, skewness and kurtosis. Return is defined as the natural logarithm of value relatives, which is similar to the arithmetic return for small values. The statistics indicates that there is dependency in the return generating process. The stock prices do not give indication of random walk symptoms.

5.6.2 The rolling Standard deviation Vs the traditional standard deviation

Table 5.3 contains results of the test of the difference between the standard deviation of returns from trading rules calculated using the traditional entire sample approach and the standard deviation determined using a non-overlapping rolling approach. Each of the ten rules was applied to 64 stocks independently thus giving a total of 640 models altogether. The standard deviations given in columns 2 and 3 of the table are the averages for each rule with column 2 containing the traditionally computed estimate while column 3 provide the rolling approach estimate.

All the rules give smaller average deviations from the rolling approach except for one rule. Larger differences in the standard deviations between the two methods come from shorter dual moving averages [for example (1,5,0); (1,15, 0)] than from longer moving averages [for example (1, 150, 0); (1, 150, 0.01) and (1, 200, 0)]. However, only a few models out of a total of 640 models tested produced significant results in terms of difference. In all the 640 models tested, results for 69 models indicated that the standard deviation calculated using the traditional approach is significantly smaller than the standard deviation calculated from the rolling approach, while only 75 models produced results indicating that the rolling approach gives a standard deviation that is significantly smaller than the traditional approach.

This means that only 144 results rejected the null of equality between the two standard deviations against 396 trading models which gave insignificant differences either way. Thus, percentage wise, only 22.5% of results indicate there is significant difference while 77.5% indicate that there is no difference. Of the 22.5% only 11.72% indicate that the standard deviation of returns from trading rules based on the rolling approach is significantly less than standard deviation based on the traditional entire sample approach. The remaining 10.78% holds that the traditional approach gives standard deviation which is significantly less than the rolling approach. These results, however, are not sufficient to reject the null of equality of the two estimates of risk.

Table 5.3 also gives results of tests of the effect of using different methods for estimating relevant risk on risk adjusted profits trading rules. The Sharpe ratio is examined about how it responds to the two version of the standard deviation.

Returns are adjusted for risk using the traditionally computed standard deviation on one hand and the rolling approach on the other. In column 6 of the table are the annualised average returns from each trading rule model applied to the 64 LSE stocks. Columns 7 and 8 contain the Sharpe ratio for the average trading rules profits. All except one Sharpe ratio based on the rolling approach are larger than those based on the traditional approach. This finding suggests that when the significance of the differences in the two approaches to estimating the standard deviation is disregarded, the rolling approach gives better results from trading rule profits because of its lower values.

5.6.3 Does Technical Analysis provide more stable portfolios?

Table 5.4 gives results for the test whether a technically managed portfolio is more profitable than the buy and hold portfolio after risk adjustment because the volatility of returns from the former are calmed by the switching to asset types of lower volatility. The general position of the literature, as mentioned earlier, is that actively managed portfolios are more riskier than passively managed portfolios. We, therefore, compare a passively managed buy and hold portfolio with an actively managed portfolio both adjusted by their respective rolling standard deviations. The test is carried out to determine whether the way risk is estimated can alter the risk adjusted performance of trading rules versus buy and holding.

In table 5.4, the first column labelled “rule” contains the trading rule applied to each of the 64 LSE stocks. As above, a total of 640 (64 rules x models 10 trading rules) were tested. “Rule Return” and “BH Return” are annualised average returns per trading rule from the 64 stocks, and the annualised average return from investing

in the 64 stocks using the buy and hold strategy respectively. “ $TR_{\sigma_{rol}}$ ” and “ BH_{rol} ” are the standard deviation for the trading rule and the buy and hold both calculated using the rolling approach. “Sharpe (BH)” and “Sharpe (TR)” are the Sharpe ratios for the buy and hold returns and the trading rule returns respectively. Both ratios are calculated using respective standard deviations, “ $TR_{\sigma_{rol}}$ ” and “ $BH_{\sigma_{rol}}$ ”, both calculated using the rolling approach. Column 8 contains counts of values of t from the individual 64 stocks to which each rule was applied that rejects the null of no predictability implied by equality of the two risk adjusted performance measures. The last column contains the breakeven transactions costs which is adjusted for risk using the rolling standard deviation.

The average raw returns from the two strategies indicate that on the overall the actively managed stocks perform better than the buy and hold strategy. On all except three trading rules, the average returns from the trading rules exceeds those from the buy and hold strategy. This is consistent with most previous studies including Hudson *et al.* (1996) and Taylor (2000). However we are interested in risk adjusted returns rather than raw returns.

The average risk per trading rule across the 64 stocks indicate that the trading rules have higher risks than the buy and hold strategy. The annualised standard deviations of 8 rules returns are higher than their respective buy and hold standard deviations. This conforms with the risk-return relationship well established in the financial economics literature. It was noted by Hudson *et al.* (1996), that reporting on averages can mitigate the true picture when examining the performance of individual stocks or individual trading rules. Therefore, I examine how each of the

trading rules performed against the buy and hold strategy on a risk adjustment basis, i.e. we consider results for each of the sixty four stocks individually.

I make counts of the number of models (a specific rule on a specific stock) that give results significantly indicating that trading rule profits (adjusted by the rolling standard deviation) exceeds the buy and hold returns, also adjusted by the rolling standard deviation. Column 8 gives 76 counts out of 460 models where trading rules exceed the buy and hold strategy at 5 % level of significant. This is only about 16% of superior performance for trading rules. It is a rather weak outcome for the trading rules even when the standard deviation is calculated using the rolling approach.

I also consider the risk adjusted break-even transaction costs as suggested by Neely (2001). In this case the last two columns of table 5.4 indicate that it takes higher trading costs to break even with the rolling approach than with the traditional standard deviation. This, however, does not mean that the rolling breakeven transaction costs imply that trading rules are profitable. Since the breakeven transaction costs are estimated at 1.05% per round trip transaction these results are in favour of the Buy and Hold on the overall.

5.6.4 Evaluating profitability and market efficiency

Table 5.5 gives results of tests of predictability, which also implies the information value of technical trading rules i.e. market efficiency. The table provides details about differences in performance between buy days and sell days. It contains average results per trading rule for 64 stocks from the FTSE 100 tested over 10 trading rules. The results of this test provide evidence of power of the rolling

approach standard deviation in testing whether conditioning on information contained in past prices by using trading rules is useful. This is done by comparing the returns from the Buy days against the returns from Sell days.

In table 5.5, “rule” is the trading rule applied. “# trades (no. of buy days)” is the number of days in a long position. “Buy-Return” is the average daily return per trading rule across the 64 stocks in the sample obtained from taking long positions throughout the sample period. “Buy-TR_{σrol}” is the standard deviation of returns from long positions. “Sharpe (Buy-TR)” is the Sharpe ratio of returns from long positions adjusted using the standard deviation of returns from long positions. “# trades (no. of Sell days)” is the number of days in short positions. “Sell-Return” is the average daily return per trading rule across the 64 stocks in the sample obtained from taking short positions throughout the sample period. “Short-TR_{σrol}” is the standard deviation of returns from short positions. “Sharpe (Sell-TR)” is the Sharpe ratio of returns from short positions adjusted with the respective standard deviation of returns from short positions. “buy-sell” is the difference between return from Buy and return from Sell days for each strategy. Columns 11 and 12 contain counts of values of t from 64 stocks to which each rule was applied that rejects the null of no difference between the Buy return and Sell returns. The test statistic, t, is calculated using the formula (Taylor, 2000);

$$t = \frac{\bar{r}_b - \bar{r}_s}{\left(\frac{s_b^2}{n_b} + \frac{s_s^2}{n_s} \right)^{0.5}} \quad \text{-----} \quad (5.12)$$

where \bar{r}_b and \bar{r}_s are the average returns from buy and sell days respectively. s_b^2 and s_s^2 are the variances of returns from Buy and Sell days respectively, while n_b and n_s are the number days in long and short positions respectively.

The results indicate that the stocks were in long positions for more days (an average of 1596 days) than they were in short positions (average of 1518 days). The difference in the average returns from Buy days and the average returns from Sell days can give evidence about whether the two returns are not equal (Taylor, 2000). Trading rules is said to be able to uncover evidence of predictability of the price process if expected returns depend on Buy/Sell information. The average Buy returns are positive but some Sell returns are negative and overall the average sell returns (5.75% annually) are less than the Buy returns (25.5% annualized). This unadjusted result implies the presence of information in past prices. These results are consistent with Taylor (2000) who also found the past prices of FTSE 100 stocks to have information before risk adjustments are considered. To evaluate market efficiency, the value of this information has to be analysed in the presence of transaction cost and risk. Taylor (2000) observes that;

“Significant differences between average returns on Buy days and Sell days are only evidence against market efficiency if transaction costs are sufficiently low and special assumptions can be made about risk. A standard assumption made here and in related literature, e.g. Sweeney (1986), is that the risk from holding stock is the same on Buy days as on Sell days. There is no escaping the possibility that there is a time varying risk premium that the trading rules track in such a way that Buy days have a higher average risk premium than Sell days” Taylor (2000: pp. 57-58)

Results on the Buy/Sell risk differences in table 5.5 show that the returns from Buy days are less volatile (average of 1.593 % per day) than the returns from Sell days (average of 1.673 % per day). The Buy/Sell return series that we have created by concatenating all daily Buy day returns into a Buy series, and the same for Sell days, show that out of the 10 trading rules tested the average standard deviation of Buy returns from only 2 trading rules [(1, 150, 0) and (1, 5, 0)] are found larger than those from Sell returns. At the same time the Buy average returns exceed the Sell average return significantly.

Of the 640 models tested, 292 reject the null of no difference between the two, giving evidence that Buy days have larger returns than Sell days. This is against only 40 models which give evidence of returns from Sell days significantly exceeding those from Buy days. This contradicts the implicit assumption of equality of the volatility of the returns from Buy days and those from Sell days in previous studies. These results also give evidence against Taylor's (2000) proposition above that there is a time varying risk premium that the trading rules track in a such a way that Buy days have a higher average risk premium than Sell days.

5.6.5 Risk adjustment using the X_{eff} statistic

Table 5.6 reports excess profits from trading rules after adjusting for risk . "rule" is the trading rule applied. "Rule Return" and "BH Return" are the returns from the trading rule and the Buy and Hold strategy respectively. "Excess Trading rule return" is the average return obtained from dynamic trading throughout the sample period. " X_{eff} " is the Dacarogna *et al.*'s (2001) test statistic for risk adjusted

trading rule returns. It is calculated by considering and quantifying the risk via a constant risk aversion factor [see equation 5.4 above]. A positive X_{eff} implies that there still remains some profits from trading rules even after deducting transaction costs and risk. Column 8 contains counts of values z from 64 stocks to which each rule was applied that rejects the null of no positive X_{eff} statistic. Results show that only one rule (5, 150, 0) give an average positive X_{eff} . But even this positive X_{eff} is not significant at the 5% level. The rest of the returns are negative.

5.7 Conclusions

The purpose of this chapter is to examine whether the computation of the standard deviation and its subsequent use as a risk adjustment factor applied to the excess profits when evaluating technical trading rules significantly affects the results. We use an alternative rolling approach to computing the standard deviation, and then use it to compute the Sharpe ratio, the risk adjusted breakeven transaction costs of profits from conditioning on current and past prices.

Overall, the results indicate that the standard deviation for trading rule returns computed using the rolling approach is lower than when the statistic is calculated using traditional entire sample approach. The rolling approach, therefore, captures the stability in the portfolio returns that is a direct consequence of using a dynamic strategy. When these lower standard deviations are applied to the returns from technical trading rules we are able to conclude that the way the standard deviation is computed can affect the analysis of trading rules performance in terms of the Sharpe ratios.

The second conclusion regards the comparison of trading rules performance and the buy and hold strategy when the rolling standard deviation is applied in adjusting for risk. Despite the above conclusion that the rolling approach standard deviation is less than the traditional entire sample standard deviation, this approach, however, does not give strong indications that trading rules are more profitable than the buy and hold strategy.

Regarding the test statistic X_{eff} , consistent with Neely (2001) we find that the use of X_{eff} does not give sufficient evidence to rationalize apparent profits trading rules. All the results from 10 trading rules averages except one, give a negative X_{eff} .

On the difference between performances of trading rules during Buy days against Sell days, our findings give strong evidence that supporting the idea that more profits can be obtained from conditioning from past prices. The rolling standard deviation was able to capture the order of price movements. However when the overall returns from trading rules is compared with the returns from the Buy and Hold strategy, the Buy and Hold strategy is more superior.

Therefore I cannot conclude categorically that risk from active trading is lower than from a buy and hold strategy. Nevertheless, we are able to conclude that the use of rolling windows in estimating risk results in risk measures that are lower than that estimated from traditional standard deviations. A more general conclusion is that there is not enough evidence to reject the null of the market is efficient for the FTSE 100 segment of the London Stock Exchange.

In this chapter I have attempted to track the chronological movement of prices in order to model appropriately the risk that is relevant for technical trading. We have also quantified the risk using a technique suggested by Dacorogna *et*

al.(2001). While this study has dealt with the aspect of profit or loss clusters, it can still be advanced by considering the fact that volatility of losses gives higher risk to an investor than the volatility of profits.

There is growing body of evidence supporting the notion that emerging markets are more riskier than developed markets. In the next chapter we follow this line of ideas to investigate whether such differences in market riskness can be used to explain trading rule profits. This follows from another line of research which has shown that trading rules returns are higher in emerging markets compared to the developed markets.

5.8 Appendix 3

Table 5.1: List of stocks of the 66 FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004 included in the sample

1	ABBEY NATIONAL	33	JOHNSON MATTHEY
2	ALLIED DOMECQ	34	KINGFISHER
3	AMERSHAM	35	LAND SECURITIES
4	AMVESCAP	36	LEGAL & GENERAL
5	ASSD.BRIT.FOODS	37	MARKS & SPENCER GROUP
6	AVIVA	38	PEARSON
7	BAA	39	PROVIDENT FINL.
8	BAE SYSTEMS	40	PRUDENTIAL
9	BARCLAYS	41	RECKITT BENCKISER
10	BG GROUP	42	REED ELSEVIER
11	BOC GROUP	43	RENTOKIL INITIAL
12	BOOTS GROUP	44	REUTERS GP
13	BP	45	REXAM
14	BRIT.AMERICAN TOBACCO	46	RIO TINTO
15	BRITISH LAND	47	ROLLS-ROYCE GROUP
16	BT GROUP	48	RYL.BK.OF SCTL
17	BUNZL	49	SAFEWAY (UK)DEAD -
18	CABLE & WIRELESS	50	SAGE GROUP
19	CADBURY SCHWEPPE	51	SAINSBURY (J)
20	DAILY MAIL 'A'	52	SCHRODERS
21	DIAGEO	53	SCHRODERS NV
22	DIXONS GP.	54	SCOT.& NEWCASTLE
23	EMAP	55	SHELL TRANSPORT & TRDG.
24	EXEL	56	SMITH & NEPHEW
25	FOREIGN & COLONIAL	57	SMITHS GROUP
26	GKN	58	STD.CHARTERED
27	GLAXOSMITHKLINE	59	TESCO
28	ITV	60	TOMKINS
29	GUS	61	UNILEVER (UK)
30	HANSON	62	VODAFONE GROUP
31	HILTON GROUP	63	WHITBREAD
32	IMP.CHM.INDS.	64	WPP GROUP

Table 5.2: Summary statistics for the stocks of the 64 FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004

Statistic	Mean	S.D.	Kurt	Skew	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$
Average for all stocks	0.07527	0.09512	31.76311	0.29265	0.16953*	0.04145	0.02885*	0.02375	0.01603

Note:

Formulas for skewness and kurtosis are $1/n \sum_{i=1}^n (x_i - \bar{x})^3 / s^3$, and $1/n \sum_{i=1}^n (x_i - \bar{x})^4 / s^4$, respectively. ρ_i is the estimated average for autocorrelation individual stocks at lag i for each individual stock series. Numbers marked with (*) are significant at the 5%.

Table 5.3: Comparative analysis of traditional and the rolling approaches to calculating risk from technical trading rules for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.

“rule” is the trading rule applied, while σ_{tr} and σ_{rol} are the annualized standard deviations of returns from technical trading calculated using the traditional method and rolling approach respectively. Columns 4 and 5 contain counts of values t from 64 stocks to which each rule was applied that rejects the null of no difference between the two standard deviations.

rule	σ_{tr} %	σ_{rol} %	$t > 1.96$	$t < 1.96$	Rule Return %	Sharpe (σ_{tr})	Sharpe (σ_{rol})
1,150,0	19.290	16.444	3	4	25.560	1.325	1.554
1,50,0	22.927	19.448	6	0	25.296	1.103	1.301
1,200,0	22.452	19.764	14	0	17.784	0.792	0.900
5,150,0	23.085	19.290	8	23	26.352	1.142	1.366
1,50,0.01	28.777	29.884	1	10	20.712	0.720	0.693
1,20,0	32.730	29.251	7	4	15.912	0.486	0.544
1,10,0	24.508	24.191	16	9	30.600	1.249	1.265
1,150,0.01	16.444	12.965	8	3	29.784	1.811	2.297
1,5,0	18.974	14.863	9	6	15.552	0.820	1.046
1,15,0	19.764	13.282	13	7	6.744	0.341	0.508

Table 5.4: Assessment of power of the rolling approach standard deviation in explaining the trading rule profit vs buy and hold returns for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.

“rule” is the trading rule applied. “Rule Return” and “BH Return” are the returns from the trading rule and the buy and hold strategy respectively. “TR σ rol” and “BH rol” are the standard deviation for the trading rule and the buy and hold both calculated using the rolling approach. “Sharpe (BH)” and “Sharpe (TR)” are the Sharpe ratios for the buy and hold returns and the trading rule returns respectively. Both ratios are calculated using their respective standard deviations “TR σ rol” and “BH σ rol” both calculated using the rolling approach. Column 8 contains counts of values t from 64 stocks to which each rule was applied that rejects the null of no predictability implied by equality of the two risk adjusted performance measures. The last column contains the breakeven transactions costs which is adjusted for risk using the rolling standard deviation.

rule	Rule Return (%)	BH Return (%)	TR σ rol (%)	BH rol (%)	Sharpe (BH) (%)	Sharpe (TR) (%)	$t > 1.96$	Break-even σ rol) %
1,150,0	25.560	18.458	19.290	19.040	1.122	1.325	12	0.92
1,50,0	25.296	15.124	22.927	19.179	0.068	1.103	8	0.16
1,200,0	17.784	17.415	22.452	18.977	0.056	0.792	14	1.35
5,150,0	26.352	16.358	23.085	18.759	0.041	1.142	3	1.53
1,50,0.01	20.712	18.163	28.777	19.179	0.038	0.720	4	-0.58
1,20,0	15.912	16.256	32.730	19.141	0.556	0.486	11	0.73
1,10,0	30.600	15.345	24.508	17.921	0.020	1.249	8	0.88
1,150,0.01	29.784	15.483	16.444	19.129	0.096	1.811	7	0.29
1,5,0	15.552	14.364	18.974	19.536	0.122	0.820	3	1.62
1,15,0	6.744	15.134	19.764	19.170	1.139	0.341	6	-0.37

Table 5.5: Analysis of the time varying trading rule performance for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.

“rule” is the trading rule applied. “# trades (no. of buy days)” is the number of days in long position. “Buy-Return” is the average daily return per trading rule across the 64 stocks in the sample obtained from taking long positions throughout the sample period. “Buy-TR_{ctrl}” is the standard deviation of returns from long positions. “Sharpe (Buy-TR)” is the Sharpe ratio of returns from long positions adjusted using the standard deviation of returns from long positions. “# trades (no. of sell days)” is the number of days in short positions. “sell-Return” is the average daily return per trading rule across the 64 stocks in the sample obtained from taking short positions throughout the sample period. “Short-TR_{ctrl}” is the standard deviation of returns from short positions. “Sharpe (Sell-TR)” is the Sharpe ratio of returns from short positions adjusted with the respective standard deviation of returns from short positions. “buy-sell” is the difference between return from buy and return from sell days for each strategy. Columns 11 and 12 contain counts of values of t from 64 stocks to which each rule was applied that rejects the null of no difference between the buy return and sell returns.

rule	# trades (no. of buy signals)	Buy - Return	Buy- TR _{ctrl}	Sharpe (Buy-TR)	# trades of sell signals)	Sell- Return	Sell- TR _{ctrl}	Sharpe (Sell-TR)	Buy-sell	$t > 1.96$	$t < 1.96$
1,150,0	1804	0.074	1.680	0.044	1202	0.009	1.660	0.005	0.065	33	0
1,50,0	1830	0.084	1.530	0.055	1292	0.069	1.550	0.044	0.015	28	6
1,200,0	636	0.147	1.250	0.118	2382	0.055	1.420	0.039	0.092	29	0
5,150,0	1572	0.158	1.040	0.152	1713	0.003	1.220	0.002	0.155	43	8
1,50,0.01	1830	0.101	1.910	0.053	1282	0.024	1.950	0.012	0.077	27	5
1,20,0	2304	0.109	1.480	0.074	792	0.002	1.520	0.001	0.107	21	4
1,10,0	972	0.107	1.790	0.060	2162	-0.032	1.890	-0.017	0.139	27	0
1,150,0.0	1904	0.078	1.220	0.064	1202	0.035	1.460	0.024	0.043	24	6
1,5,0	1344	0.101	1.890	0.053	1802	0.015	1.820	0.008	0.086	39	8
1,15,0	1764	0.065	2.140	0.031	1352	0.052	2.240	0.023	0.014	21	3
Average	1596	0.102	1.593	0.070	1518	0.023	1.673	0.014	0.079	292	40

Table 5.6: Results of testing excess profits from trading rules after adjusting for risk estimates for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.

“rule” is the trading rule applied. “Rule Return” and “BH Return” are the returns from the trading rule and the buy and hold strategy respectively. “Excess Trading rule return” is the average return obtained from dynamic trading throughout the sample period. “Xeff” is the Dacarogna et al.’s (2001) test statistic for risk adjusted trading rule returns. Column 8 contains counts of values z from 64 stocks to which each rule was applied that rejects the null of no positive Xeff statistic.

Rule	No. of trades	Rule Return (%)	BH Return (%)	Excess Trading rule return	Transaction costs	X _{eff}	t > 1.96
1	2	3	4	5	6	7	8
				(3 - 4)	(2 x 0.525%)	(5 - 6)	
1,150,0	15	25.56	18.458	7.102	7.84	-0.74	0
1,50,0	21	25.296	15.124	10.172	10.85	-0.68	0
1,200,0	1	17.784	17.415	0.369	0.45	-0.09	0
5,150,0	18	26.352	16.358	9.994	9.37	0.62	0
1,50,0.01	5	20.712	18.163	2.549	2.61	-0.07	0
1,20,0	1	15.912	16.256	-0.344	0.29	-0.64	0
1,10,0	31	30.6	15.345	15.255	16.08	-0.83	0
1,150,0.01	31	29.784	15.483	14.301	16.35	-2.05	0
1,5,0	4	15.552	14.364	1.188	2.02	-0.84	0
1,15,0	7	6.744	15.134	-8.39	3.80	-12.19	0

Chapter 6 Technical Analysis and Predictability of Asset Returns in African Markets

6.1 Introduction

Technical analysts have long relied on the premise of predicting market returns through identifying patterns in past stock market prices. Belief in past price patterns in security movements violates the random walk hypothesis and the weak form of stock market efficiency. According to efficient market theory, technical analysis should not produce significant abnormal returns because by default the markets are efficient.

The research of trading rules performance on mature markets of developed countries has recently found consistent predictability and some excess returns over the buy and hold strategy. In the recent literature, especially following increasing evidence of the presence of regularity in asset returns in speculative markets it is argued that it is not appropriate to investigate markets for their absolute efficiency or inefficiency. It is rather useful to consider the markets' efficiency in relative terms, for example, whether the efficiency of a certain market has improved or worsened after a certain event, or the comparative efficiency of market A relative to market B given certain differences in market conditions or environment. In this context the differences in the institutional setups of different markets should be reflected in their differences in the strength of regularities in their return series. Differences in the drivers or factors leading to inefficiency between markets set expectations for the magnitude of the differences in strength of regularities. In the same context, this

should be reflected in the difference in profitability of trading rule profits before transaction costs are considered. The motivation to study technical analysis in the African markets is motivated by the fact that the apparent high levels of risk in these markets can provide further insight into the relationship between time varying risk and return predictability

The study by Appiah-Kusi and Menyah (2003) concluded that some markets in Africa are weak-form efficient while some are not even weak-form efficient. They pointed at the institutional and infrastructural deficiencies as the drivers of market inefficiencies. Such deficiencies also reflect the level of risk involved in investing in such markets. Given that the presence of risk factors (together with data snooping) is emerging as a strong explanation for significant trading rule profits even after accounting for transaction costs, this chapter is motivated to compare the trading rule performance when applied to emerging markets against developed markets. The general hypothesis is that given that African small markets are considered to have higher levels of risk, then there should be more regularity in their stock return series compared to stock return series of more developed markets, and that should there be time-varying risk premium, then this should be more pronounced in the return series of the emerging markets compared to the developed markets.

The chapter employs simple moving average trading rules to exploit positive autocorrelations in the series of returns of ten African stock market indices for the period from January 1990 to December 2004. The results demonstrate, on average, that superior profits (after estimated trading costs) can be achieved by technical trading rules over a simple buy and hold strategy only in certain countries, mainly Namibia, Kenya and Zambia. Also consistent with Yadav, et al. (1999) I find that differences in institutional arrangements do not affect

the time series dynamics of stock returns. It is also concluded that technical trading rules do not yield results far different from those in developed markets. This means that the argument used to justify the co-existence of trading rule profits and weak form efficiency in literature may not be valid.

The remainder of the chapter is organized as follows. The objectives of this work are given in the next section. Section 6.3 briefly reviews the relevant previous literature on market efficiency and technical trading rules in developed and emerging markets. Section 6.4 presents a brief discussion of the institutional arrangements of African stock exchanges, setting the intuition for expecting results different from developed markets. Section 6.5 contains the methodology used including a brief review of the technical trading systems, testing procedures, hypotheses and data. The results of the tests are given in Section 6.6 while concluding remarks are offered in Section 6.7.

6.2 Research Objectives and Significance

An important reason to undertake this chapter is the fact that the proportion of financial transactions undertaken in African markets to the global financial transactions has been increasing steadily in the last two decades following a steady proliferation of new markets. In the course of these developments the financial markets (emerging economies) of numerous countries have been liberalized and therefore one would expect improved levels of their institutional infrastructure and reduced information inefficiencies. The importance of undertaking this study lies in the need to provide empirical evidence of the implications of including African assets in international portfolios.

A number of studies have been done on the efficiency of emerging markets in genera, but the current literature does not possess studies of technical analysis for African markets. It must be interesting to follow the intuition that the level of development of markets in Africa is small enough to attract inefficiency because (1) liquidity levels are severe, (2) in some markets, the organization of trading arrangements is still rudimentary; (3) the presence and enforcement of legislations protecting the investor and the functioning of the judiciary system provide ample room for poor corporate governance; and (4) there is poor transparency leading to potential lags in information diffusion. In terms of efficiency, there is a large contrast between large markets, like the London Stock Exchange or the Tokyo Stock Exchange and some African markets. In theory, this apparent efficiency difference can be reflected in the ability of technical trading rules to capitalize on information contained in past prices when the same rules are applied to each.

As discussed below, there is an insignificant difference between the distribution properties of the time series of large and small markets. They both exhibit the same typical characteristics of financial time series. Thus, in view of the apparent risk differentials, the research intends to examine the relative predictive ability of technical trading rules when applied to small markets and large markets respectively. The objective of this research, therefore, is to exploit this enormous apparent risk difference between these two market classes and examine their relative risk return relationship in the context of technical analysis.

The research, therefore, will examine the similarity or differences in the distributional properties of the return indices of these two market classes in order to determine whether such differences or similarities can be reflected in the differences in their level of informational efficiency. More important, since current literature

suggests that the presence of regularity in speculative asset return series and the subsequent trading rule profits are a compensation for bearing time varying risk premium, this research examines this issue further. The research compares the implied co-movement of the profits from trading rules and the associated risk between the two classes of markets.

6.3 Previous research

Stock returns have a non-normal distribution for both the developed and developing stock markets (see Bekaert and Harvey, 1997; Choudhry, 1996). This supports the general view that emerging markets may be characterized by a non-normal distribution (Richards, 1996) and points to similarities in distribution of returns for both the developed and developing markets. Volatility clustering is also evident in both the developed and developing markets. In another study Fraser and Power (1997) and Choudhry (1996) find evidence of volatility clustering, for both developed and emerging markets. Yadav, et al. (1999) find that stock returns exhibit significant non-linear dependence in UK, as in the US market, and conclude that differences in institutional arrangements do not affect the time series dynamics of stock returns.

Evidence from both the developed and developing markets also shows that stock returns responses to shocks are asymmetric; see, for example, Kuotmos (1999) and Fraser and Power (1997). Kuotmos (1999) tests for an asymmetric response in five emerging markets including, Korea, Malaysia, Philippines, Singapore and Taiwan. The EGARCH model is applied assuming the GED distribution to control for leptokurtic standardized residuals obtained from ARCH-type models. Results

show an asymmetric response of stock returns to past information. Fraser and Power (1997) studying the Pacific Rim, UK, and US markets also document substantial asymmetries in the dynamics of price changes both within and across financial markets. The findings by Shields (1997), however, demonstrate the non-existence of an asymmetric response in emerging markets.

Other studies show evidence of a time varying risk premium. Fraser and Power (1997) find a significantly negative coefficient for Malaysia investors which they interpret as showing that investors in Malaysia are predominantly risk-lovers. Choudhry (1996), using the GARCH-M model, confirms no time varying risk premium in several emerging markets and where it is significant, the sign is negative, indicating risk-averse investors.

The profitability of technical trading rules in emerging markets may be associated with the persistence of returns, or autocorrelation, in these markets. Harvey (1995a) finds that the autocorrelation in emerging markets is much higher than in developed markets. He also suggests that the level of autocorrelation is directly associated with the size and the degree of concentration of the market. Predictability has also been addressed by Harvey (1995b) who utilizes a pricing model. Harvey contends that emerging market returns seem to be predictable when using international and local risk factors. Erb et al. (1996) find that equity returns and volatility are predictable for a group of 48 countries by using credit risks obtained from Institutional Investor as the sole explanatory variable. Diamonte et al. (1996) indicate that political risk measures are capable of predicting the returns in emerging markets better than in developed markets.

Volatility clustering is also evident in both the developed and developing markets. De Santis and Imrohrolus (1997), using GARCH model and assuming

Generalized Error Distribution (GED) of the conditional density function, show predictability, clustering and persistence in conditional volatility of returns in emerging markets. Similarly, Fraser and Power (1997) and Choudhry (1996) find evidence of volatility clustering, for both developed and emerging markets. Yadav, et al. (1999) find that stock returns exhibit significant non-linear dependence in UK, as in US market, and conclude that differences in institutional arrangements do not affect the time series dynamics of stock returns.

The study by Appiah-Kusi and Menyah (2003) concluded that some markets in Africa are weak-form efficient while some are not weak-form efficient. They pointed at the institutional and infrastructural deficiencies as the drivers of market inefficiencies. Such deficiencies also reflect the level of risk involved in investing in such markets. Given that the presence of risk factors (together with data snooping) is emerging as a strong explanation for significant trading rule profits even after accounting for transaction costs, we are motivated to compare the trading rule performance when applied to emerging markets against developed markets. The hypothesis is that given that small African markets are considered to have higher levels of risk, then there should be more regularity in their stock return series compared to stock return series of more developed markets. Also the argument in current literature that the presence of trading rule profits in excess of the buy and hold profits is a compensation for bearing time varying risk premium should also be pronounced in a comparative study of this nature.

6.4 The institutional infrastructure of African markets

Emerging markets can be distinguished from the capital markets of developed economies with regard to the degree of information efficiency and

institutional infrastructure. A stock market's institutional infrastructure is generally characterized by the organization of the markets, the degree of relevant sophistication impacting on transparency and speed of information transmission, and aggregate participation of various potential investors to trading opportunities. The infrastructure can also be looked at in terms of liquidity, the legal environment and the quality of corporate government standards.

Despite the progress made by the emerging markets, differences still exist in the institutional set up and macroeconomic environment between the developed and emerging markets. These differences provide a basis for a comparative analysis of developed versus emerging markets, especially in terms of their microstructure characteristics as well as the corporate governance standards.

The S&P Emerging Markets Database (EMDB) monitors only 12 African stock markets available in the continent. The Johannesburg Stock Exchange (JSE) of South Africa dominates markets in Africa in both the size of capitalization and the degree of sophistication. It accounts for about 80% of total African stock market capitalization and is large by world standards¹⁹. The remaining markets are small. In the middle range there are the markets of Egypt, Morocco, Nigeria, Zimbabwe and Kenya. The reasonably small ones include the markets of Botswana, Ghana and Mauritius. There are other markets which are still in the embryonic stage and are yet to take off. These include the markets of Zambia, Tanzania, Malawi, and Uganda. Apart from South Africa, Africa stock markets account for about 0.2% of world stock market capitalization and only 2% of emerging market stock market capitalization (Jefferis and Smith, 2005).

Liquidity conditions of African markets remain very dull. Apart from South Africa with a turnover of about 44% (Janiffe and Smith, 2005) other markets' turnovers are less than 10% with most well below 5% per annum. This is partly because most of the shares listed are owned by controlling interests, often foreign parent companies leaving small proportions of shares available for public trading.

Foreign investment in African markets is somehow growing. This is particularly in response to the lifting of restrictions to foreign participation. For example, Tanzania has lifted its total restriction to foreign participation. Except for Egypt and The Ivory Coast where there are no restrictions to participation of foreign investors, the rest of the other countries impose some form of restrictions on foreign investors, for example individual foreign investors are allowed to participate in a stock from a minimum of 11% to a maximum of 40% in some countries. These restrictions contribute to the strained liquidity characterizing most of these markets. Other constraints of liquidity are a function of trading practices. Some countries have reduced the limit to some new levels such that 50% of the markets in Africa can be described as having free entry to foreign investors while the remaining 50% can be described as relatively free.

On the issue of transparency and quality of corporate governance, this is also very poor. At least all of the stock markets of emerging countries evaluated in this paper require consolidated and examined annual reports from listed companies. Further, in numerous countries quarterly or semi-annual reports from listed companies are required to be published.

19 S.A. was the 18th largest equity market in the world with a capitalization of US \$ 267 billion at the end of 2003. (Jefferis and Smith, 2005)

Table 6.6 contains a summary of trading arrangements of the ten markets used in this study (some are not). Most exchanges have limited trading hours and are closely time synchronous with other regional markets. There is little domestic stock market culture and awareness. Trading in the majority of the markets is overwhelmingly dominated by a handful of stocks. Weaknesses in broker capitalization also has adverse effects, reducing the ability to respond to arbitrage profits resulting from price differentials between rival stock markets where securities have double listing.

6.5 The methodology

Trading systems

A technical trading system is composed of a set of trading rules that can be used to generate trading signals. In general, a simple trading system has one or two parameters that are used to vary the timing of trading signals. Trading rules contained in a system are the results of the parameterizations. For example, the Dual Moving Average Crossover system with two parameters (a short moving average and a long moving average) can produce hundreds of trading rules by altering combinations of the two parameters. This study duplicates the trading rules that were used by Brock *et al.* (1992) and later on by Hudson *et al.* (1996).

Moving average based trading systems are the simplest and most popular trend-following systems among practitioners (Taylor and Allen (1992); Lui and Mole, 1998) . Moving average systems take different forms according to the method used to average past prices in the moving average calculations. For example, the simple moving average uses equal weighting on each past price considered, while the exponential moving average gives comparatively more weight to recent prices.

Their effect is to smooth out price actions, thereby avoiding false signals generated by erratic short-term price movements, and identifying the true underlying trend. In this study, we use the Dual Moving Average Crossover (DMC). The DMC system involves comparison of two moving averages, generating a buy (sell) signal when a short-term moving average rises (falls) above (below) a long-term moving average. This system is a reversing system that is always in the market, either long or short.

The Simple Moving Average with Percentage Price Band system literally uses a simple moving average with a price band centered around it. A trading signal is triggered whenever the closing price breaks outside the band, and an exit signal is triggered when the price re - crosses the moving average. The upper and lower price bands act as a neutral zone that has the effect of keeping traders out of the market during non-trending conditions. By standing aside and not trading while prices are fluctuating within the price bands and the market is seeking a direction, traders may significantly increase the probability of profitable trades.

According to Neftci,(1991) the (dual) moving average method is one of the few technical trading procedures that is statistically well defined, because it generates trading signals by depending only on data available at the present time. The Dual Moving Average Crossover system employs a similar logic to that of the Simple Moving Average with Percentage Price Band system by trying to find when the short-term trend rises above or falls below the long-term trend. The moving average method developed here is a reversing system that is always in the market, either long or out of the market (risk free asset). As market participants, such as brokers, money managers or advisers, and individual investors, were known to extensively use the Dual Moving Average Crossover system, many academics have tested this system since the early 1990s.

Statistical Tests

Most previous technical trading studies applied the traditional t -test, the standard bootstrap, or the model-based bootstrap to measure statistical significance of technical trading profits. However, the t -test and standard bootstrap methods, which assume independently and identically distributed (IID) observations, may not be relevant for high-frequency time series data that is highly likely to be time-dependent. The model-based bootstrap can also deliver inconsistent estimates if the structure of serial correlation is not tractable or is misspecified (Maddala and Li, p. 465). As a resampling procedure that is generally applicable to weekly dependent stationary time series, the stationary bootstrap preserves both enough of the dependence and stationarity of the original time series in the resampled pseudo-time series by resampling blocks of random length from the original series, where the block length follows a geometric distribution. Thus, the standard bootstrap can provide more improved statistical tests than the traditional statistical methods.

I use the same technical trading rules used by Brock et al. (1992) with a bootstrap technique. Focusing on variable length moving averages (VMA). Moving average trading models take advantage of positive serial correlation in equity returns. A trading signal usually follows a large movement in stock price under the assumption that the autocorrelation bias in the time series trend will continue in the same direction.

This research employs the Variable Moving Average (VMA) rules. The VMA rules analyzed are as follows: 1-50, 1-150, 5-150, 1-200, 2-200, where the 1, 2 and 5 represent the number of days in the short moving average, and the 50, 150 and 200 represent the number of days in the long moving average. A buy signal is given when the short moving average exceeds the long moving average.

The two short (S) and long (L) moving averages (MA) are calculated at time t using the most recent price information;

$$SMA_{t,s} = \frac{1}{S} \sum_{j=1}^s P_{t-s+j}, \quad LMA_{t,l} = \frac{1}{L} \sum_{j=1}^L P_{t-l+j}$$

Where $R_{i,t}$ is the daily return in period S (1,2 or 5 days) and $R_{i,t-1}$ is the return used to compute the long average over period L (50, 150 or 200 days). This test is repeated daily with the changing moving averages throughout the sample. The buy position is a long position in the index and is maintained until short moving average crosses the long moving average from above. With the sell signal, the investor invests in the risk-free rate²⁰. A rule is effective if the average buy minus sell (buy - sell) signal is positive, significant, and greater than a buy and hold alternative after trading costs.

Since the return distribution is non-normal, the trading models may simply capture the dependencies in the data. To address this issue, a bootstrap procedure is performed by scrambling the returns by sampling with replacement from the original series to form a simulated series. The trading strategies are then applied to the simulated series and the mean buy and sell returns are computed for each iteration. This process is repeated 500 times to form a distribution of mean returns. We calculate the proportion of returns that is greater than that computed with the actual series to produce simulated p-values²¹.

20 No short selling strategies are implemented in this research because such practices are prohibited in all the exchanges included in the sample

21 See Brock et al. (1992) and Bessembinder and Chan (1998) for a detailed description of this procedure.

This study differs from Brock *et al* (1992) and others who evaluate each rule with a trading band of zero and one percent of returns²². While this band may be reasonable for developed markets, it does not account for the large differences in volatility between the emerging markets. As a result, we employ a trading band of zero and one standard deviation of the actual return series. A zero band classifies each return to emit either a buy or sell signal, while a band of one standard deviation would emit a buy or sell signal only when the short moving average crosses the trading band.

Data

The sample consists of data from ten African emerging markets and the S&P500 and the NIKKEI 225. Daily local index closing levels are obtained for the stock exchanges of Ghana, South Africa, Botswana, Morocco, Nigeria, Egypt, Namibia, the Zimbabwe, Kenya, and Zambia. The Daily index levels are collected from January 1990 through December 2004, and are provided by each country's stock exchange and the online database, Perfect Analysis. The beginning period of January 1990 is selected arbitrarily. Exchanges of other countries like Tanzania, Malawi, Swaziland and Uganda are excluded because of their short period in business since establishment. They are still in such an infant stage and they may give results which may be biased. The indices for the United States (S&P 500) and Japan (Nikkei 225) are included for comparison purposes. For those exchanges which have not yet established an index, we computed (using a facility available in

22 Bessembinder and Chan (1995) use a zero and one percent trading band for Southeast Asian emerging markets. A trading band of one standard deviation would generate less trades, be more cost effective and accounts for the differences in country volatility more accurately than the one percent band

Perfect Analysis) a portfolio representing all listed companies in the exchange. These portfolios are based on market capitalization.

6.6 Transactions Costs

It is apparent that transaction costs are an important factor that influences net trading returns. Previous studies that have used transaction costs in emerging markets have considered them to be high due to significant inefficiencies. Matheussen and Satchel (1998) assume a two percent (2%) transaction cost for emerging markets. This may be on the lower side because the impact cost may be very high which incorporates liquidity cost for most of these exchanges.

We follow Hudson *et al.* (1996) to include as transaction costs both the stamp duty and brokerage commission but also the bid-ask spread, which is also referred to as execution costs, liquidity costs, or skid error. The transaction costs are expressed in percentage transaction cost per unit after dividing the currency unit transaction costs by the average value of the typical transaction in each market. The summary of the transaction costs are indicated in table 1 along with the descriptive statistics. We consider these transaction costs to be only indicative. Given the notorious illiquidity of most of the exchanges, the impact costs may be even higher.

6.7 Hypotheses tested

Hypothesis 1

1. The returns of emerging markets and the returns of developed markets have similar statistical properties.

Hypothesis 2

2. Technical trading rules are more effective when applied to markets with a weak institutional environment than in markets which are more mature. In this hypothesis we expect trading rules to give better results in terms of using information in the time series of emerging markets than when exploiting the time series of developed markets.

Hypothesis 3

3. Trading rule profits do not violate the efficient market hypothesis since they are a compensation for bearing time varying risk premium.

Table 6.1 presents the distribution properties of returns of selected African markets. The properties are found to have characteristics commonly found in most financial time series literature. The table reports daily means and standard deviations for the returns. Stocks in Ghana (0.03156), Namibia (0.04066), and Egypt (0.03513) contain the largest volatility of returns. The first autocorrelation is presented for each market, where significant autocorrelation suggests potential patterns in the data.

The larger the magnitude of the autocorrelation coefficient, the greater the potential for weak form market inefficiency. The autocorrelations for orders higher than one for all countries are significantly close to zero. Significant first-order autocorrelation is observed in all markets except Zimbabwe. The highest estimate for first-order autocorrelation is 0.9 for Ghana and the lowest is for Nigeria (0.01) and Zimbabwe (-0.01). All estimates of autocorrelation are positive except for Zimbabwe, South Africa and Nigeria. This implies that there is more continuation effect in these markets than there is reversal effects. This further justifies the use of moving average trading rules in favour of contrarian strategies. Non-normality of

the series is demonstrated as most of the kurtosis coefficients and most of the skewness coefficients are significant. To avoid exploiting the apparent dependencies in the data, a bootstrap procedure is utilized to form a simulated series of returns for each country.

6.8 Results

Table 6.2 reports the mean daily returns (%) of the buy and sell signals generated by the VMA trading models without a trading band. The difference in buy-sell returns are averaged for each trading rule and country over time. For the trading rule to be effective, the average buy return must be significantly larger than the average sell return. Out of fifty VMA rules tested for all African markets (ten countries with five models each), 14 models (or 28% of the models) have buy returns significantly larger than sell returns. For the developed markets, only one rule (in Japan) out of ten (two countries with five models each) is significant. This result is not unexpected given the greater predictability of emerging markets indicated by Harvey (1995b), among others. The moving average models identify significant buy/sell differences in seven countries. Kenya, Zambia and Namibia demonstrate the most consistent potential profits across trading rules. Japan, Nigeria, Egypt and the Zimbabwe present only one significant rule. The US, Morocco, Ghana, South Africa and Botswana do not profit from any of the trading rules, as their buy-sell differences are insignificant. The length of each moving average trading rule (i.e., 1, 2, 5 and 50, 150, 200 days) does not appear to influence the significance of the models. Our results are consistent with those of

Bessembinder and Chan (1995) for Taiwan and Thailand, and with Ready (1997) for the US²³.

While trade profitability with standard statistical significance levels demonstrate some profit potential, the results in Table 6.2 also indicate that technical trading strategies are mostly correct regarding the movements of the market when we disregard statistical significance. Forty-six out of 50 rules in the African markets have average buy signal returns greater than average sell returns, which is 92% of the rules. Even in Japan four out of five rules have average buy signals that are greater than sell signals. Only the US presents no evidence of predictability. While profitability is not guaranteed, investors may still use the information conveyed by technical trading rules.

Table 6.3 reports the buy/sell differences of the trading rules when a trading band of one standard deviation is imposed. The trading band filters out small fluctuations in the data and provides a cleaner signal that a trend is occurring.

In this model, the current position (either in or out of the market) is maintained until the short moving average crosses the long moving average and the trading band. While there are 15 significant VMA buy/sell signals with no trading band, there are only eight significant signals here, all of them in emerging markets. Of the three countries that previously contained the most consistent significant results, Kenya and Namibia continue to demonstrate potential trading rule benefits with two significant VMA models each, while Zambia, Nigeria and Japan no longer have any significant VMA rules. The Zimbabwe now

23 Ready (1997) reports technical trading profits from NYSE stocks prior to 1980, but does not find trading profits subsequent to 1980.

has two significant trading rules, and Egypt still offers one significant VMA rule. South Africa is the exception, presenting one significant VMA rule with the trading band, while it had none without the trading band. When we examine only the average returns of the buy and sell signals, without their statistical significance, 31 out of 50 rules in all emerging markets contain average buy signal returns greater than the sell signals (62% of the rules). Interestingly, two out of the five trading rules in both Japan and the US indicate price changes in the correct direction for the market indices.

Our results for Africa diverge from those of Bessembinder and Chan (1995) due to the larger trading band we impose because of the higher volatility. While their band was one percent across all countries, we use one standard deviation to reflect the disparate volatilities between the markets. Therefore, our trading band leads to more conservative results. Our study differs from Bessembinder and Chan in several ways, as we consider very small emerging markets of Africa such as Morocco, Zimbabwe, Botswana, Zambia and Kenya.

To verify if the significant trading rules would overcome trading costs, we provide Tables 6.4 and 6.5 below. Table 6.4 provides summary information of the five VMA trading models with no trading band. For each rule, the number of trades, buy signals and sell signals are reported. In addition, the potential returns of the VMA trading rules after trading costs are compared with a simple buy and hold strategy. The cost per trade figures represent estimates of one-way transactions

costs and are assumed constant throughout the sample period²⁴. The trading costs for each country are estimated by reducing the average VMA return earned by the cost per trade (%) multiplied by the number of trades executed.

Without a trading band, an enormous number of trades must be conducted, increasing as the long moving average (200-, 150-, 50-days) shortens. Although there are no other discernible patterns, the longest moving average model (2- 200-day) does appear to have the highest overall pre- and post-trading cost returns. Trading costs only change our previous results for the 1-50 rule in Egypt, all the other rules remain significant after trading costs.

Of particular interest are the last three rows of Table 6.4. Here the average VMA returns across models (with and without trading costs) are compared with a buy and hold strategy. With the exception of Ghana and South Africa, the average VMA model produces superior results relative to the buy and hold returns. However, after imposing trading costs, the superior returns are only realized in Nigeria, Kenya, Zambia and Namibia. In each of these cases, the trading rule that performed highest did show a significant buy-sell difference in Table 6.2. The average VMA rule for Kenya after trading costs is 32.14%, compared with 17.59% with the buy and hold. Zambia's average VMA also shows a substantial improvement over the buy and hold (25.05% vs. 15.36%). Namibia (20.52% vs. 19.53%) and Nigeria (9.78% vs. 8.63%) demonstrate only marginal gains.

²⁴ Trading costs for Japan, Nigeria, Egypt, Zambia and Kenya are provided by Rhee et al. (1990), including brokers fee and taxes. Price (1994) provides the costs in Ghana (excludes fees and taxes). Costs for Morocco and the Zimbabwe are provided by Birinyi Associates. Costs for South Africa (excludes fees and taxes), Botswana and Namibia are provided by the individual local exchanges. The costs for trading in the US are the 2003 costs of trading with discount broker Charles Schwab

The summary data for the VMA trading rules with a one standard deviation trading band are reported in Table 6.5. As expected, there are far fewer trades conducted with the trading band than without it. Before trading costs are considered, the average VMA returns exceed the buy and hold returns in seven out of the ten emerging market countries. After trading costs are factored in, VMA returns outperform the buy and hold returns in only four countries: Nigeria (14.31% vs. 8.63%), the Zimbabwe (18.16% vs. 9.52%), Kenya (32% vs. 17.59%), and Namibia (30.13% vs. 19.53%). The results for Nigeria and Kenya are consistent with those in Table 6.4 when a null trading band was considered. Namibia, given its greater trading costs and the lower number of trades with the larger trading band, now presents a wider difference between its average net VMA return and the buy and hold strategy. The results appear to be the same with Zimbabwe, now showing larger technical trading rule profitability given its greater trading costs. However, trading rules in Zambia, with its low trading costs, probably benefit from more frequent trading and do not perform well with a larger trading band.

Microstructure issues at the country level may explain why technical trading is profitable in one country and not in another, even though they demonstrate comparable market inefficiencies. Trading bands tend to produce higher VMA returns where trading costs are high, because they signal fewer trades. Namibia, for example, requires a high cost for each trade. Although Namibia has four significant VMA rules without a trading band (from Table 6.2), the models produced only modest gains against the buy and hold strategy. With a trading band imposed, technical trading in Namibia achieved substantial excess profits.

Very low trading costs may explain why the Nigerian VMA models are profitable when none of their buy - sell differences are significant. In contrast,

high trading costs in Egypt may account for the poor performance (7.01% vs. 8.34%) there, even though they do have one significant VMA buy/sell model. Relatively high trading costs in the Zimbabwe may also explain why the trading rules are profitable with a trading band, but unprofitable without one.

6.9 Conclusions

The objective of this chapter was to compare the profitability of trading rules when applied to the emerging markets and the developed markets. The general hypothesis was that emerging markets are more riskier compared to the developed ones, thus the time series of the returns of the former are more predictable than of the later. This study has applied five moving average models to test the effectiveness of technical trading in ten small equity markets of Africa from January 1990 through December 2004. The US and Japan are also examined for comparison purposes. The current study differs from prior technical trading studies in two ways: we examine African markets not previously tested and apply a trading band that accounts for differences in volatility between markets. The significance of the moving average buy/sell signals are assessed through a bootstrap simulation.

Emerging markets are known for persistency in their return series as indicated by the significant autocorrelations found in previous research (Harvey, 1995). Emerging markets are also less liquid and present more concentrated trading than many developed markets. Finally, cases of insider trading and manipulation scandals are notorious. Thus, it would be natural to expect that inefficiencies could be more easily exploited in these markets.

First the results for developed markets of the US and Japan are consistent with what is already documented in literature. The stocks returns for developed

markets are predictable but this regularity can not be exploited to make abnormal profits. We also find that trading using simple moving average trading rules results can capture future stock price movements in most of the emerging markets. It is demonstrated that standard statistical significance for 11 rules out of 50 rules tested (five rules for each one of the ten emerging markets) before considering trading costs and for 21 trading rules after trading costs. However, for some countries these profits appear to disappear when transaction costs are incorporated. Even though our results indicate that trading rule profitability after transaction costs is limited to one-fifth of the rules tested, mostly concentrated in four markets (Namibia, Kenya, Zambia and the Zimbabwe), the trading rules applied to virtually all emerging markets present forecasting ability. In fact, 41 rules out of the 50 rules tested provide the correct indication of the index return change in emerging markets when we disregard statistical significance. This finding is consistent with Bessembinder and Chan (1998) for the US after they factor in break-even trading costs. The hypothesis that trading rule profitability is higher in emerging markets compared to developed markets due to weak institutional arrangements (inefficiency) can therefore be accepted when using technical analysis.

All rules present buy signals greater than sell signals in Namibia, Egypt, and Zimbabwe, four out of five rules present the same evidence in South Africa and Kenya, four of five rules in Botswana, three out of five in Zambia, and three out of five rules in Nigeria and Japan. Bessembinder and Chan (1998) argue that a Bayesian investor could alter his asset allocation in response to this information, even if they could not profit from the buy and sell signals. This indicates that

regardless of the classical statistical significance, the previous results may have important economic implications.

I believe that further research should explore microstructure issues to explain why most statistically significant and profitable trading strategies are concentrated in a handful of countries. South Africa has the lowest trading costs and the highest turnover of all markets with a significant first order autocorrelation. This environment is friendly to trading strategies such as those examined in this paper. However for most of the other countries, the illiquidity of the markets makes the trading opportunities virtually unexploitable. However, the results still give important implications to the debate regarding the profitability of trading rules. Disregarding statistical significance, the technical trading rules correctly predict return series' changes, consistent with recent findings for the US by Bessembinder and Chan (1998).

Further research may be directed into a more comprehensive understanding of the nature of the return generating process among these world's smallest emerging equity markets. In this particular regard, it may be useful to examine the return using popular models for example, the GARCH and its family of models.

The next chapter gives a summary of findings and the conclusions of this dissertation.

6.10 Appendix 4

Table 6.1: Summary of Statistics of the daily returns of 10 African markets, Jan 1990 – Dec 2004.

“Country” is the name of the country in which the exchange is operating, the second column “Mean” is the daily mean return of the index for each exchange. “1-order Autocorr” is the autoregressive coefficient at lag 1 for each exchange. “Skewness” and “kurtosis” stands for skewness and kurtosis respectively. “Trans cost” is the estimated one way trip transaction cost at an exchange. “code” in the second column is the country code used in subsequent tables.

Country	code	Mean	Std Dev	1-order AutoCorr	Skew ness	Kurtosis	Trans. Cost ²
Morocco	MOR	0.000241	0.00783	0.26*	0.12	2.04*	3.25
Nigeria	NIG	0.000215	0.01513	0.01	-7.72	143.32	2.11
Egypt	EGY	0.000812	0.03513	0.22*	0.33	4.17	4.4
Zimbabwe	ZIM	0.001024	0.12322	-0.01	-1.72*	19.94*	2.5
Kenya	KEN	0.000567	0.01758	0.05*	-7.24*	201.42*	3.15
Zambia	ZAM	0.001078	0.01830	0.13*	1.52*	65.83*	5.5
Ghana	GHA	0.000442	0.03156	0.90*	-4.45	72.58	2.16
South Africa	SA	0.000386	0.01438	0.21	-0.83*	8.50*	1.5
Botswana	BOT	0.000551	0.02046	0.23*	-1.22	27.93	3.2
Namibia	NAM	-0.000140	0.04066	0.21*	-0.21	26.81	4.8

1 * indicates significance at the 5% level.

2. The costs of trading for the emerging markets were estimated from information provided by the individual local exchanges.

Table 6.2: Returns from trading rule strategies applied to 10 African markets for the sample period Jan 1990 – Dec 2004.

The mean daily returns of buy and sell signals are for a band of 0 standard deviations. Buy and sell signals are generated by variable moving average (VMA) trading rules. Rules are defined as "(short, long, standard deviation)" where short and long represent the moving average length in days, and the standard deviation is the trading band of 0 standard deviations of each country's return series. Column one "rule" is the trading rule applied, Co is the code for the country, "buy" and "sell" are the mean daily returns from buy and sell signals respectively for each rule applied. "p-value" are p values of the difference between buy and sell signals.

Rule	(1,50,0)			(1,150,0)			(5,150,0)			(1,200,0)			(2,200,0)		
Co.	buy	sell	p-value	buy	sell	p-value	buy	sell	p-value	buy	sell	p-value	buy	sell	p-value
JAP	0.035	0.033	0.483	0.025	0.03	0.457	0.05	0.008	0.186	0.04	0.015	0.304	0.077	-0.018	0.027*
USA	0.03	0.038	0.415	0.031	0.052	0.314	0.035	0.052	0.351	0.02	0.067	0.15	0.038	0.044	0.447
MOR	0.047	0.05	0.473	0.054	0.075	0.322	0.076	0.045	0.251	0.032	0.071	0.207	0.077	0.021	0.123
NIG	0.043	0.033	0.396	0.047	0.02	0.274	0.055	0.017	0.197	0.038	0.031	0.437	0.085	-0.005	0.025*
EGY	0.058	-0.031	0.012*	0.046	-0.01	0.101	0.034	-0.002	0.207	0.069	-0.008	0.052	0.066	-0.011	0.056
ZIM	0.065	-0.049	0.004*	0.053	0.001	0.148	0.047	0.018	0.28	0.049	0.017	0.273	0.055	0.017	0.235
KEN	0.11	0.043	0.05*	0.092	0.036	0.114	0.12	0.012	0.011*	0.114	0.044	0.084	0.136	0.018	0.009*
ZAM	0.075	0.004	0.046*	0.102	-0.018	0.005*	0.128	-0.042	0.0000*	0.103	0.001	0.021*	0.092	0.014	0.059
GHA	0.005	-0.022	0.279	0.005	-0.022	0.298	0.01	-0.032	0.209	0.037	-0.032	0.105	0.023	-0.023	0.201
SA	0.058	-0.007	0.074	0.022	-0.003	0.304	-0.018	0.028	0.18	0.021	-0.018	0.237	0.012	-0.008	0.357
BOT	0.041	0.005	0.19	0.089	0.025	0.078	0.071	0.047	0.304	0.074	0.041	0.252	0.079	0.038	0.204
NAM	0.146	0.016	0.001*	0.121	-0.007	0.003*	0.076	0.044	0.245	0.123	0.001	0.006*	0.106	0.008	0.021*

4. Indicates p-values at the 5% significant level .

Table 6.3: Returns from trading rule strategies applied to 10 African markets for the sample period Jan 1990 – Dec 2004.

The mean daily returns of buy and sell signals are for a band of 1 standard deviations. Buy and sell signals are generated by variable moving average (VMA) trading rules. Rules are defined as "(short, long, standard deviation)" where short and long represent the moving average length in days, and the standard deviation is the trading band of 0 standard deviations of each country's return series. Column one "rule" is the trading rule applied, Co is the code for the country, "buy" and "sell" are the mean daily returns from buy and sell signals respectively for each rule applied. "p-value" are p values of the difference between buy and sell signals.

Rule	(1,50,1)			(1,150,1)			(5,150,1)			(1,200,1)			(2,200,1)		
	buy	sell	p-value	buy	sell	p-value	buy	sell	p-value	buy	sell	p-value	buy	sell	p-value
JAP	0.021	0.033	0.412	0.029	0.02	0.448	0.031	0.033	0.323	0.032	0.031	0.498	0.017	-0.022	0.307
USA	0.061	0.038	0.311	0.029	0.099	0.144	0.003	-0.015	0.465	0.008	0.121	0.047	0	0.049	0.3
MOR	0.045	0.051	0.463	0.063	0.181	0.048	0.057	0.201	0.157	0.068	0.145	0.146	0.063	-0.075	0.158
NIG	0.093	0.033	0.124	0.059	0.078	0.377	0.038	0.145	0.306	0.057	0.061	0.477	0.044	0.097	0.258
EGYP	0.029	-0.032	0.122	0.014	-0.015	0.343	0.043	-0.123	0.164	0.024	-0.03	0.23	0.07	-0.109	0.026*
ZIM	0.12	-0.049	0.001*	0.051	-0.068	0.083	0.086	-0.202	0.029*	0.067	-0.04	0.117	0.053	0.024	0.394
KEN	0.141	0.043	0.049*	0.118	0.02	0.096	0.023	0.109	0.189	0.152	0.02	0.04*	0.112	0.053	0.247
ZAM	-0.399	0.003	0.009	0.034	-0.002	0.43	-0.09	0.937	0.153	0.034	-0	0.43	-0.06	0.083	0.31
GHA	-0.148	-0.022	0.035	-0.038	0.078	0.166	0.014	0.628	0.122	-0.013	0.078	0.241	-0.04	0.11	0.214
SA	0.094	-0.007	0.034*	0.014	-0.052	0.166	0.001	-0.015	0.453	0.008	-0.02	0.335	-0.001	-0.092	0.153
BOT	0.006	0.005	0.497	0.064	0.114	0.247	0.051	-0.132	0.217	0.075	0.098	0.391	0.054	-0.104	0.108
NAM	0.187	0.016	0.002*	0.106	0.042	0.237	0.038	-0.125	0.101	0.097	-0.07	0.033*	0.117	-0.031	0.078

* Indicates p-values at the 5% significant level

Table 6.4: Summary of VMA trading rule statistics using returns and a trading band of 0 standard deviations. January 1990 – Dec2004.

Strategy/Parameter	JAP	USA	MOR	NIG	EGYP	ZIM	KEN	ZAM	GHA	SA	BOT	NAM
(1,50,0) # trades	1235	1255	1230	1220	1110	1115	1155	1120	1170	1155	1165	1055
# buy signals	1280	1340	1230	1235	1210	1235	1345	1330	1100	1260	1300	1270
# sell signals	1240	1180	1290	1285	1310	1285	1175	1190	1420	1260	1220	1250
Annualized VMA return	9.04%	7.77%	12.50%	11.36%	15.49%	17.56%	31.77%	20.70%	1.33%	15.56%	10.88%	44.09%
Returns less trading cost	-1.09%	3.51%	-2.87%	3.92%	-0.05%	0.83%	30.04%	15.10%	-0.54%	9.78%	-12.42%	25.10%
(1,150,0) # trades	965	980	1040	935	910	960	925	855	910	985	940	910
# buy signals	985	1085	1055	975	975	1015	1080	1070	890	995	1075	985
# sell signals	1035	935	965	1045	1045	1005	940	950	1130	1025	945	1035
Annualized VMA return	6.41%	8.18%	14.51%	12.41%	12.18%	14.09%	25.82%	29.08%	1.19%	5.73%	25.04%	35.27%
Returns less trading cost	-1.50%	4.85%	1.51%	6.71%	-0.56%	-0.31%	24.43%	24.80%	-0.27%	0.80%	6.24%	18.89%
(5,150,0) # trades	395	470	395	315	310	360	285	260	335	425	310	290
# buy signals	960	1045	1055	850	1080	1005	980	1055	910	945	1105	1050
# sell signals	1040	955	945	1150	920	995	1020	945	1090	1055	895	950
Annualized VMA return	13.29%	9.26%	20.81%	14.68%	8.90%	12.36%	35.02%	37.73%	2.47%	-4.47%	19.44%	20.93%
Returns less trading cost	10.05%	7.66%	15.87%	12.76%	4.56%	6.96%	34.60%	36.43%	1.93%	-6.59%	13.24%	15.71%
(1,200,0) # trades	790	875	915	840	780	825	810	770	780	860	825	770
# buy signals	885	955	900	820	910	865	970	950	755	865	965	855
# sell signals	885	815	870	950	860	905	800	820	1015	905	805	915
Annualized VMA return	10.47%	5.05%	8.23%	10.05%	18.74%	13.07%	32.90%	29.36%	9.62%	5.38%	20.31%	36.11%
Returns less trading cost	3.99%	2.07%	-3.20%	4.93%	7.82%	0.69%	31.69%	25.51%	8.37%	1.08%	3.81%	22.25%
(2,200,0) # trades	555	665	555	485	460	505	430	510	580	480	495	535
# buy signals	835	920	880	770	985	855	950	935	795	895	940	895
# sell signals	930	845	885	995	780	910	815	830	970	870	825	870
Annualized VMA return	21.13%	10.05%	21.32%	23.54%	18.00%	14.66%	40.58%	25.98%	5.97%	3.01%	21.81%	30.28%
Returns less trading cost	16.58%	7.79%	14.39%	20.58%	11.56%	7.09%	39.93%	23.43%	5.04%	0.61%	11.91%	20.65%
Cost per trade	0.82%	0.34%	1.25%	0.61%	1.40%	1.50%	0.15%	0.50%	0.16%	0.50%	2.00%	1.80%
Average VMA return	12.07%	8.06%	15.48%	14.41%	14.66%	14.35%	33.22%	28.57%	4.11%	5.04%	19.50%	33.34%
VMA return less cost	5.61%	5.18%	5.14%	9.78%	4.66%	3.05%	32.14%	25.05%	2.91%	1.14%	4.56%	20.52%
Buy & Hold Return	5.90%	7.70%	14.55%	8.63%	8.34%	9.52%	17.59%	15.36%	32.08%	22.91%	11.26%	19.53%

Table 6.5: Summary of VMA trading rule statistics using i returns and a trading band of 1 standard deviation. January 1990 – Dec 2004.

Strategy/Parameter	JAP	USA	MOR	NIG	EGYP	ZIM	KEN	ZAM	GHA	SA	BOT	NAM
(1,50,1) # trades	410	460	350	440	440	390	360	60	320	530	470	365
# buy signals	465	570	315	475	430	505	480	35	275	655	520	460
# sell signals	1240	1180	1285	1285	1305	1285	1175	1185	1415	1260	1220	1250
Annualized VMA return	5.34%	16.45%	11.87%	26.02%	7.42%	35.04%	42.42%	-63.11%	-30.92%	26.46%	1.45%	59.78%
Returns less trading cost	1.98%	14.88%	7.49%	23.34%	1.26%	29.19%	41.88%	-63.41%	-31.43%	23.81%	-7.95%	53.21%
(1,150,1) # trades	280	260	210	280	190	230	250	30	160	300	220	110
# buy signals	1075	1150	1090	875	1305	1080	780	645	1160	910	1100	615
# sell signals	275	220	205	360	200	240	300	55	160	360	235	170
Annualized VMA return	7.46%	7.63%	16.94%	15.76%	3.56%	13.68%	34.27%	8.99%	-8.98%	3.66%	17.31%	30.35%
Returns less trading cost	5.16%	6.74%	14.31%	14.05%	0.90%	10.23%	33.89%	8.84%	-9.23%	2.16%	12.91%	28.37%
(5,150,1) # trades	10	20	30	30	30	20	40	10	20	50	20	10
# buy signals	210	590	725	1360	1425	795	625	60	1470	1250	850	1200
# sell signals	105	30	30	35	50	100	140	10	10	80	30	45
Annualized VMA return	-7.43%	0.78%	15.20%	9.98%	11.40%	24.05%	6.04%	-20.19%	3.64%	0.25%	13.50%	10.01%
Returns less trading cost	-7.51%	0.72%	14.83%	9.80%	10.98%	23.75%	5.98%	-20.24%	3.61%	0.00%	13.10%	9.83%
(1,200,1) # trades	270	250	170	290	190	210	220	30	110	280	180	90
# buy signals	1065	995	970	745	1110	1155	730	645	905	785	915	520
# sell signals	265	215	180	370	195	230	300	55	130	330	200	125
Annualized VMA return	8.26%	1.89%	18.39%	15.30%	6.27%	18.14%	46.34%	8.99%	-3.17%	2.00%	20.68%	27.32%
Returns less trading cost	6.05%	1.04%	16.27%	13.53%	3.61%	14.99%	46.01%	8.84%	-3.35%	0.60%	17.08%	25.70%
(2,200,1)#trades	100	90	50	130	60	110	100	10	40	130	100	20
# buy signals	515	790	1385	625	815	1135	590	75	1090	860	980	530
# sell signals	205	120	65	200	145	165	205	45	65	210	100	75

Table 6.5 Continued

Strategy/Parameter	JAP	USA	MOR	NIG	EGYP	ZIM	KEN	ZAM	GHA	SA	BOT	NAM
Annualized VMA return	4.46%	0.09%	17.11%	11.60%	19.14%	14.28%	32.38%	-13.96%	-9.59%	-0.20%	14.50%	33.90%
Returns less trading cost	3.64%	-0.22%	16.48%	10.81%	18.30%	12.63%	32.23%	-14.01%	-9.66%	-0.85%	12.50%	33.54%
Cost per trade	0.82%	0.34%	1.25%	0.61%	1.40%	1.50%	0.15%	0.50%	0.16%	0.50%	2.00%	1.80%
Average VMA return	3.62%	5.37%	15.90%	15.73%	9.56%	21.04%	32.29%	-15.86%	-9.80%	6.43%	13.49%	32.27%
VMA return less cost	1.86%	4.63%	13.88%	14.31%	7.01%	18.16%	32.00%	-16.00%	-10.01%	5.14%	9.53%	30.13%
Buy & Hold Return	5.90%	7.70%	14.55%	8.63%	8.34%	9.52%	17.59%	15.36%	32.08%	22.91%	11.26%	19.53%

Summary of the Institutional and Trading Arrangements of the Sample African Stock Markets

Table 6.6: Trading arrangements of African Markets in the Sample

Market	Trading Days	Trading Hours	Trading Arrangements
Botswana Stock Exchange	Monday to Friday	Times of call over are: 09.00 and 15.00h	Open Outcry
The Casablanca Stock Exchange	Monday to Friday	08.30 to 12.30h	Electronic order driven trading for the most liquid stocks. Fixing basis for the less liquid stocks
The Egyptian Stock Exchange	5 days: Sunday to Thursday	11.30 to 15.30	Electronic order driven trading
Ghana Stock Exchange	Mondays, Wednesdays and Fridays	10.00 to 13.00h	Call over with a limited auction
Johannesburg Stock Exchange	Monday to Friday	09.00 to 16.00h	Open outcry, continuous auction on a trading floor, order driven. Electronic Trading link
The Stock Exchange of Mauritius	Official Market: Monday to Friday OTC Market: Tuesday and Thursday	Official Market: 10.00 to 11.00h OTC market: 14.00 to 15.00h	Open outcry, order driven and single price auction system
Nairobi Stock Exchange	Monday to Friday	10.00 – 12.00h	Open outcry

Table 6.6 continued

Market	Trading Days	Trading Hours	Trading Arrangements
The Nigerian Stock Exchange	Monday to Friday	Daily, from 11.00h onwards until all bids are done	Call-over system
The Swaziland Stock Exchange	Monday to Friday	10.00 to 12.00h	Matched bargains basis. Broker acts as agent
Zimbabwe Stock Exchange	Monday to Friday	08.00 to 16.00h	Open outcry
Namibia		9.00am – 4p.00pm	Electronic Trading Link
Zambia		10.00m – 12.00 noon	Call-over system

Source: The Africa Stock Exchange Association

Table 6.7: Foreign Investment Regulations of the sample African stock Markets

Country	Restriction
Botswana	Foreign investors collectively may not own more than 40% of a publicly quoted company's shares.
Egypt	No restrictions
Ghana	Foreign investors collectively may not own more than 74% of the shares in a quoted company. A non-resident portfolio investor may not own more than 11% of shares in a company. Resident investors may invest without any limit.
Cote d Ivoire	Restricted
Kenya	Foreign investors as a group may not own more than 40% of the shares in a company. Individual foreign investors may not own more than 5% of shares in a single company
Mauritius	Not more than 15% in a sugar company may be owned by a foreigner. Foreign investors may participate in unit trusts and mutual funds with approved limits.
Morocco	No Restrictions
Nigeria	Foreign investors collectively may not own more than 40% of shares in some industrial sectors which were incorporated in 1990, Since the industrial policy act of 1989; foreigners can incorporate companies as sole owners as they wish.
South Africa	Total foreign ownership is limited to 15% for banks and 25% for insurance companies. There are no restrictions to foreign investors in other areas.
Swaziland	Prior approval of central bank required before investment is undertaken if the investor wishes to buy 20% or more of a company
Zimbabwe	Foreign investors collectively may not own more than 40% of the shares in a company. Individual foreign investors may not own more than 5% of shares in a company

Table 6.8: Key Performance Statistics of the sample African Stock Markets

COUNTRY	Market Capitalization 2002 (US\$ millions)	Market Cap/GDP	No. of Listed Companies (2002)
Algeria	145	0.3%	3
Botswana	1,717	31.9%	19
Cote d'Ivoire	1,329	14.2%	38
Egypt	26,245	26.6%	1,151
Ghana	382	7.4%	24
Kenya	1,676	16.2%	50
Malawi	107	6.1%	8
Mauritius	1,324	30.2%	40
Morocco	8,319	24.9%	56
Namibia	201	5.8%	13
Nigeria	5,989	14.6%	195 (261)
South Africa	182,616	145.1%	472
Swaziland	146	11.6%	5
Tanzania	695	7.4%	5(6)
Tunisia	1,810	9.3%	46
Uganda	52	0.9%	3
Zambia	231	8.8%	11
Zimbabwe	11,689	158.1%	77
Total Africa	244,673		2,216

2004 Comparative Analysis of Key Performance Statistics for African Stock Markets	
Africa	195,202
All Emerging Markets	2,572,064
Developed Markets	25,242,554
World Total	27,818,618
Africa/Emerging Markets	7.59%
Africa/World	0.70%

Source: African Stock Markets Handbook, UNDP, 2003; Emerging Markets Fact book, Standard & Poor, 2004

Table 6.9: Sub Saharan African Markets - Selected statistics (US \$ millions), ranked by year established

Country	Year	GDP	Market Capitalization	Market Cap/GDP(%)	Traded Value (pa)	Turnover ratio (%)	Number of Stocks
South Africa (1887)	1992	130,553	103,537	79.32	7,767.00	7.50	683
	1998	133,461	170,252	127.57	58,347.00	34.27	668
Zimbabwe (1946)	1992	6,752	628	9.31	20.00	3.18	62
	1998	6,338	1,310	20.67	186.00	14.20	67
Kenya (1954)	1992	8,002	637	7.96	12.00	1.88	57
	1998	11,579	2,024	17.48	79.00	3.90	58
Nigeria (1961)	1992	32,710	1,221	3.73	14.00	1.15	153
	1998	41,353	2,887	6.98	160.00	5.54	186
Botswana (1989)	1992	4,147	295	7.11	15.00	5.08	11
	1998	4,876	724	14.80	70.00	9.67	14
Ghana (1989)	1992	6,413	84	1.31	0.40	0.48	15
	1998	7,501	1,384	18.45	59.50	4.30	21
Mauritius (1989)	1992	3,189	416	13.05	10.00	2.40	22
	1998	4,199	1,849	44.04	101.00	5.46	40
Swaziland (1990)	1992	967	111	11.47	0.36	0.33	3
	1998	1,221	85	6.96	0.21	0.25	5
Namibia (1992)	1992	2,823	15,084		0.15	0.01	6
	1998	3,044	333,916		1,035.00	0.70	40

Chapter 7 Summary and Conclusions

7.1 Summary of findings

The controversy over the plausibility or implausibility of the presence of significant excess returns from technical analysis has important and far reaching implications to many stakeholders of the various types and forms of the finance community. The interested parties range from investors to academic researchers to finance professionals and regulatory authorities. The importance of the argument that the markets are efficient despite the empirically found regularities and excess trading rules profits is reflected by numerous discussions²⁵.

Proof of the rejection of the Random Walk Hypothesis suggests the presence of predictable elements in the speculative markets. This in turn gives green light for practices that capitalise on such predictability to make superior investment returns through active investment management. The proof can also cast serious doubt on the use of popular paradigms whose theoretical foundation is the Random Walk Hypothesis, for example the policy portfolio (also known as strategic asset allocation). The use of policy portfolio has been challenged recently, apparently as a

²⁵ for example the Spring 2004 Q-Group seminar and the panel discussion on 'changing views of policy portfolio'. Both forums were attended by senior officers of leading academics and practitioners alike.

result of the steep rise in stock prices during the 1990's and followed by the steep decline.

Extant literature indicates that the empirical explanations of technical trading rule profits have focused on market microstructure deficiencies, order flows, temporary market inefficiencies, central bank intervention (for foreign exchange markets), data snooping and risk premium. The main focus of this dissertation has been the empirical examination of the risk premium (risk view) as a plausible explanation for excess trading rules profits based on conditioning on information contained in past prices. It is important to underline the fact that the scientific process of investigating this line of research is plagued with numerous factors that the debate doesn't seem to be approaching a clear conclusion. Lo and MacKinlay (1999) writes;

“...the efficient market hypothesis, by itself, is not a well-defined and empirically refutable hypothesis. To make it operational one must specify additional structure, investor's preferences, information structure, business conditions, etc...” Lo and MacKinlay (1999) pp 6

The studies carried out and documented in this dissertation have relied on intuition and insightful works of previous authors as well as developments on the practitioner's side. Arguments and views raised in previous works reflect the fact that in the recent past, the resolves on each side of the argument has hardened rather than softened despite an increase in the quantity of research output in this area. On the other hand the increased output signifies the importance and the differences in opinions regarding the topic.

Theoretical discussions and empirical results documented in different chapters are summarised as follows.

Chapter 2 has provided a synopsis of various aspects of the theoretical issues that seek to investigate the link between risk factors and the efficacy of trading rules. The material in this fundamental chapter include a brief review of the theoretical development of the efficient market hypothesis, a discussion of the developments in both the theoretical and empirical findings from studies of the information content of current and past prices via technical analysis in the recent past (twenty years or so) that has led to renewed momentum and interest in technical analysis.

The material in this chapter also contains a brief review of; 1) the alternative theoretical basis of empirical questions and studies suggesting that a market or its segment(s) may not be weak form efficient, 2) a brief review of the empirical models, various testing procedures, including their strengths and shortcomings. In general, chapter two has documented that the rate of increase in technical analysis research output is increasing very rapidly. It has grown from about 6 studies for the six year period (1960- 1965) to about 45 studies for a similar period (2000 – 2005). The chapter also documents the fact that an increasing proportion of technical analysis studies is now taking the view that technical analysis as a practice can be useful. However, numerous obstacles still stand on the way of research in this area, making definitive conclusions to remain remote. Such obstacles include differences in data frequencies, pricing model specifications, technical trading systems, market proxies and other aspects of testing procedures.

Of the various empirical explanations of excess profits from trading rules, data snooping and risk premium are emerging as the most frequently given explanations. A few studies have actually tested whether trading rules can be

explained by the time varying risk premium and results are still very mixed. For example Sweeney (1986), Taylor (1992) and Okunev and White (2003) conclude that the time varying risk premium cannot explain profits. While Kho (1996), Sapp (2004) and Neely (2001) on the other hand, conclude that the time varying risk premium is able to explain profits. Overall, the background of chapter 2 forms the foundation for further analytical and empirical relations explored in chapters three, four, five, and six.

In chapter 3, formal tests regarding the link between the book-to-market ratio of a stock and its return predictability is carried out. Focusing on the documented evidence that book-to-market ratios can be used to predict both cross sectional and time series returns, the dissertation answers the question whether profits from conditioning on information contained in the book-to-market ratio can be construed to be caused by temporary market mis-pricing captured by the book-to-market ratio. In other words, the dissertation answers the question whether profits from trading rules based on the book-to-market ratios is a compensation for bearing time varying risk premium.

The tests are carried out using the simple standard model for testing the efficacy of trading rules as well as the various consideration points that have become part of technical analysis studies. As in all empirical studies, the validity of the inferences in chapter 3 are subject to the caveat that our empirical proxies for risk arising from technical trading reasonably captures the risk level inflicted to the investor by such trading activities. This is particularly with respect to the specifications used in the Fama and French factor models as well as the GARCH model. Subject to this caveat, chapter 3 documents results consistent with Bokhari

et al. (2005) although Bokhari *et al.*'s (2005) study focused on sized based portfolios.

This evidence is consistent with the finding in the finance literature that, in general, stocks in the higher risk bracket have higher returns where the return differential is a compensation for bearing additional risk. This additional risk is caused by the imprecision of news and information about the stock because of its lower analytic coverage and the fact that they are generally off the spotlight. Given that stocks with high book-to-market bracket are growth stocks.

The findings and conclusions from this chapter are not consistent with Lakonishok *et al.*'s (1994) model, which posits an inefficient market where the book-to-market ratio uncovers stocks with prices which are different from their fundamental values. In this model a period of time passes while the market works through the pricing mechanism to remove pricing errors²⁶. This period of mispricing is associated with the delay (lag) that it takes for information to be encapsulated into prices and it differs with the size of the book-to-market ratio. This period of temporal mispricing implies the presence of inefficiency in the market.

Chapter 4 concerns microstructure explanations of trading rule profits. The empirical study carried out in this chapter is motivated by previous evidence that statistics of liquidity dynamics contain information that can be conditioned to generate excess profits. Brown *et al.* (1997) provide theory and evidence that the relative size of the bid-ask spread given by specialists provides information about future price movements. Kavadjecz and White (2004) also found that moving averages were able to reveal information about the relative depth on the order book.

Chapter 4 therefore extends this research by investigating whether liquidity as a risk factor explains trading rules profits in the UK market for the period 1990-2004. Factor models (CAPM, Fama and French (1992); Fama and French three factor model and the Fama and French extended four factor model are used to test whether liquidity can explain profits from trading rules.

Even after controlling for the four risk factors suggested in previous documented studies, namely the market risk, the Fama & French three factor model; the size factor and the liquidity factor, the formal tests conducted in chapter four still reveal that (1) price movements for assets with lower liquidity as measured by the bid-ask spread is significantly predictable than price movements for assets with higher liquidity (2) the trading rule profits generated from these assets with lower liquidity can not be explained by the three models tested in this chapter. A significant amount of profits remains unaccounted by the models used to control for the risk factors.

Chapter five examined potential biases in evaluating the efficacy of trading rules profits that could be caused by statistical testing errors. In this chapter an examination of whether the computation of the standard deviation and its subsequent use as a risk adjustment factor applied to the excess profits when evaluating technical trading rules significantly affects the results. An alternative rolling approach to computing the standard deviation is used and then applied to compute the Sharpe ratio and in the adjustment of profits from conditioning on current and past prices.

The alternative rolling approach is found to be able to capture the stability in the portfolio returns that is a direct consequence of using a dynamic strategy. However,

²⁶ Pricing errors exist while higher excess returns are obtained from stocks with higher book-to-

the approach does not give strong indications that trading rules are more profitable than the buy and hold strategy. The alternative approach does not give evidence in support of the notion that risk from active trading is lower than risk from buy and hold strategy. Nevertheless, we are able to conclude that the use of rolling windows in estimating risk results in risk figures that are lower than risks estimated from traditional standard deviations.

In chapter 6 we look at emerging markets. The main idea in this chapter is to further understanding on the connection between the risk premium and the profitability of trading rules by comparing returns on assets from markets operating in environments with significant risk differentials. Theoretically, the absence of the appropriate and comprehensive institutional setups that support financial markets in most emerging markets suggests that prices will be more predictable. Relying on other studies of predictability of returns in emerging markets, we set out to establish whether the excess trading rules returns from emerging markets can be explained as compensation for risk. The choice of small emerging markets of Africa is motivated by first the fact that this block of economies is under-researched, but second the institutional environment in which these markets are operating attracts inefficiencies.

7.2 Scope for future research

The central result of this dissertation has been that the risk view can explain profits from trading rules. Despite this general conclusion, we acknowledge the fact

that several issues remain unresolved as regards the evaluation of trading rules profits. These issues can potentially attract bias into the conclusions. To gain further understanding of the efficacy of technical analysis, more research is needed in this area. For example, while we have considered the deficiencies of the standard deviation and the Sharpe ratio as risk estimates for evaluating trading rules, this thesis only considered profit and loss clustering in a limited manner. Further research can be carried out to incorporate the measures that use lower partial moments (LPMs). Downside risk considerations can be used to improve the X_{eff} statistic that is adapted from Dacorogna *et al* (2001) and used in this thesis. This incorporation of downside risk can make the estimation of risk for technical analysis more realistic as it will capture only the price volatilities that actually matter to the investor.

BIBLIOGRAPHY

- Acar, E. and S. E. Satchell. (1997). "A theoretical analysis of trading rules: an application to the moving average case with Markovian returns." *Applied mathematical Finance*, 4, 165-180
- Akemann, C. A., and W. E. Keller. (1977) "Relative Strength Does Persist." *Journal of Portfolio Management*, Fall, 38-45.
- Alexander, S. S. (1961). "Price Movements in Speculative Markets: Trends or Random Walks." *Industrial Management Review*, 27-26.
- Alexander, S. S. (1964). "Price Movements in Speculative Markets: Trends or Random Walks No. 2." *Industrial Management Review*, 5, 25-46.
- Allen, F., and R. Karjalainen. (1999). "Using Genetic Algorithms to Find Technical Trading Rules." *Journal of Financial Economics*, 5, 1245-271.
- Andreou, E., N. Pittis, and A. Spanos. (2001). "On Modeling Speculative Prices: The Empirical Literature." *Journal of Economic Surveys*, 15, 187-220.
- Ang, A. and G. Bekaert, (2001). "Stock Return Predictability: Is it there?", *Working Paper*, Columbia Business School.
- Antoniou, A., N. Ergul, P. Holmes, and R. Priestley. (1997). "Technical Analysis, Trading Volume and Market Efficiency: Evidence from an Emerging Market." *Applied Financial Economics*, 7, 361-365.
- Arnott, R. D. (1979). "Relative Strength Revisited." *Journal of Portfolio Management*, Spring, 19-23.
- Bachelier, L. *Théorie de la Spéculation*. (1900). Doctoral Dissertation in Mathematics, University of Paris Translated into English by Cootner, P. H. (ed.) (1964):17-78.
- Banz, R. W. (1981). "The Relationship Between Return and Market Value of Common Stocks." *Journal of Financial Economics*, 93-18.
- Beja, A., and M. B. Goldman. (1980): "On the Dynamic Behavior of Prices in Disequilibrium." *Journal of Finance*, 3, 5235-248.

- Bessembinder H., and K. Chan. (1995): "The Profitability of Technical Trading Rules in the Asian Stock Markets." *Pacific-Basin Finance Journal*, 3, 257-284.
- Bessembinder H., and K. Chan. (1998), "Market Efficiency and the Returns to Technical Analysis." *Financial Management*, 27, 5-17.
- Brunnermeier, M. K. and Nagel, S. (2004) Hedge funds and the technology bubble. *Journal of Finance*, 59, 2013-2040.
- Billingsley, R. S., and D. M. Chance. (1996) "Benefits and Limitations of Diversification Among Commodity Trading Advisors." *Journal of Portfolio Management*, 65-80.
- Bird, P. J. W. N. (1985), "The Weak Form Efficiency of the London Metal Exchange." *Applied Economics*, 17, 571-587.
- Black, F. , (1986) "Noise." *Journal of Finance*, 4, 529-543.
- Blume, L., D. Easley, and M. O'Hara. (1994) "Market Statistics and Technical Analysis: The Role of Volume." *Journal of Finance*, 49, 153-181.
- Bokhari, J., Cai, C., Hudson, R. and K. Keasey (2005), "The predictive ability and profitability of technical trading rules: does company size matter?," *Economics Letters*, 86(1), January, 21-27.
- Bohan, J. (1981) "Relative Strength: Further Positive Evidence" *Journal of Portfolio Management*, 36-39.
- Brock, W., J. Lakonishock, and B. LeBaron. (1992) "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *Journal of Finance*, 47, 1731-1764.
- Brorsen, B. W., and S. H. Irwin. (1987), "Futures Funds and Price Volatility." *The Review of Futures Markets*, 6, 118-135.
- Brown, G. W; R B. Cohen, and C K. Polk; (1997). Does quoted depth predict intraday stock returns?: theory and evidence, <http://www.people.hbs.edu/rcohen>, 27/04/2006
- Brown, D. P., and R. H. Jennings. (1989), "On Technical Analysis." *Review of Financial Studies*, 2, 527-551.
- Brunnermeier, M. K. (2001) *Asset Pricing under Asymmetric Information - Bubbles, Crashes, Technical Analysis, and Herding*. Oxford, UK: Oxford University Press.

- Brush, J. S. (1986) "Eight Relative Strength Models Compared." *Journal of Portfolio Management*, 21-28.
- Brush, J. S., and K. E. Boles. (1983) "The Predictive Power in Relative Strength and CAPM." *Journal of Portfolio Management*, 20-23.
- Caginalp, G., and H. Laurent. (1998) "The Predictive Power of Price Patterns." *Applied Mathematical Finance*, 181-205.
- Campbell, J. Y., and J. H. Cochrane. (1999), "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." *Journal of Political Economy*, 107, 205-251.
- Campbell, J. Y., A. W. Lo, and A. C. MacKinlay. (1997) *The Econometrics of Financial Markets*. Princeton, NJ: Princeton University Press,
- Chang, P. H. K., and C. L. Osler. (1999) "Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts." *Economic Journal*, 109, 636-661.
- Cheung, Y. W., and M. D. Chinn. (2001) "Currency Traders and Exchange Rate Dynamics: A Survey of the US Market." *Journal of International Money and Finance*, 20, 439-471.
- Cheung, Y. W., and C. Y. P. Wong. (1997), "The Performance of Trading Rules on Four Asian Currency Exchange Rates." *Multinational Finance Journal*, 1, 1-22.
- Cheung, Y. W., and C. Y. P. Wong. (2000) "A Survey of Market Practitioners' Views on Exchange Rate Dynamics." *Journal of International Economics*, 51, 401-419.
- Cheung, Y. W., M. D. Chinn, and I. W. Marsh. (2000) "How Do UK-Based Foreign Exchange Dealers Think Their Market Operates?" NBER Working Paper, No. 7524.
- Chopra, N. J. Lakonishok and J. R. Ritter. (1992), "Measuring Abnormal Performance: Do Stocks Overreact?" *Journal of Financial Economics* 31, 235-68.
- Chordia, Tarun, Roll, Richard W. and Subrahmanyam, Avaniidhar. (2006), "Liquidity and Market Efficiency", Available at SSRN: <http://ssrn.com/abstract=794264>
- Clyde W. C., and C. L. Osler. (1997), "Charting: Chaos Theory in Disguise?" *Journal of Futures Markets*, 17, 489-514.
- Cochrane, J. H. (2001), *Asset Pricing*. Princeton, NJ: Princeton University Press

- Constantinides, G. M., and D. Duffie. (1996) "Asset Pricing with Heterogeneous Consumers." *Journal of Political Economy*, 104, 219-240.
- Cooper, M., and H. Gulen. (2003), "Is Time-Series Based Predictability Evident in Real-Time?" Working Paper, Krannert Graduate School of Management, Purdue University.
- Cootner, P. H. "Stock Prices. (1962), Random vs. Systematic Changes." *Industrial Management Review*, 3, 24-45.
- Cootner, P. H. (1964), *The Random Character of Stock Market Prices*. Cambridge, MA: MIT Press
- Corrado, C. J., and S. H. Lee. (1992), "Filter Rule Tests of the Economic Significance of Serial Dependencies in Daily Stock Returns." *Journal of Financial Research*, 15, 369-387.
- Cornell, W. B., and J. K. Dietrich. (1978) "The Efficiency of the Market for Foreign Exchange under Floating Exchange Rates." *Review of Economics and Statistics*, 60, 111-120.
- Coutts, J. A., and K. Cheung. (2000), "Trading Rules and Stock Returns: Some Preliminary Short Run Evidence from the Hang Seng 1985-1997." *Applied Financial Economics*, 10, 579-586.
- Curcio, R., C. Goodhart, D. Guillaume, and R. Payne. (1997), "Do Technical Trading Rules Generate Profits? Conclusions from the Intra-Day Foreign Exchange Market." *International Journal of Finance and Economics*, 2, 267-280.
- Dacorogna, M. M., R. Gençay, U. A. Müller, and O. V. Pictet. (2001), "Effective Return, Risk Aversion and Drawdowns." *Physica A*, 289, 229-248.
- Dale, C., and R. Workman. (1980), "The Arc Sine Law and the Treasury Bill Futures Market." *Financial Analysts Journal*, 36, 71-74.
- Dale, C., and R. Workman. (1981), "Measuring Patterns of Price Movements in the Treasury Bill Futures Market." *Journal of Economics and Business*, 33, 81-87.

- Davutyan, N., and J. Pippenger. (1989), "Excess Returns and Official Intervention: Canada 1952-1960." *Economic Inquiry*, 27, 489-500.
- Dawson, E. R., and J. Steeley. (2003), "On the Existence of Visual Technical Patterns in the UK Stock Market." *Journal of Business Finance & Accounting*, 30, 263-293.
- Day, T. E., and P. Wang. (2002), "Dividends, Nonsynchronous Prices, and the Returns from Trading the Dow Jones Industrial Average." *Journal of Empirical Finance*, 9, 431-454.
- Daniel, K., D. Hirshleifer and A. Subrahmanyam. (1998), "Investor Psychology and security market under and over reaction." *The Journal of Finance*, LIII, 6, 1839-1885
- De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. (1990), "Noise Trader Risk in Financial Markets." *Journal of Political Economy*, 98, 703-738.
- De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. (199), "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance*, 45, 379-395.
- De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. (1991), "The Survival of Noise Traders in Financial Markets." *Journal of Business*, 64, 1-19.
- Denton, F. T. "Data Mining as an Industry. (1985), " *Review of Economics and Statistics*, 67, 124-127.
- Dewachter, H. (2001), "Can Markov Switching Models Replicate Chartist Profits in the Foreign Exchange Market?" *Journal of International Money and Finance*, 20, 25-41.
- Donchian, R. D. (1957), "Trend-Following Methods in Commodity Price Analysis." *Commodity Year Book*, 35-47.
- Donchian, R. D. (1960), "High Finance in Copper." *Financial Analysts Journal*, 133-142.
- Dryden, M. (1969), "A Source of Bias in Filter Tests of Share Prices." *Journal of Business*, 42, 321-325.
- Dryden, M. (1970), "Filter Tests of U.K. Share Prices." *Applied Economics*, 1, 261-275.

- Dryden, M. (1970), "A Statistical Study of U.K. Share Prices." *Scottish Journal of Political Economy*, 17, 369-389.
- Fama, E.F; The Behaviour of Stock Market Prices, (1965), *Journal of Business*, xxx viii, 34-105
- Fama, E. F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance*, 25, 383-417.
- Fama, E. F. "Efficient Capital Markets, (1991), : II." *Journal of Finance*, 46, 1575-1617.
- Fama, E. F. (1998) "Market Efficiency, Long-Term Returns, and Behavioral Finance. " *Journal of Financial Economics*, 49, 283-306.
- Fama, E. F., and M. E. Blume. (1966), "Filter Rules and Stock Market Trading." *Journal of Business*, 39, 226-241.
- Fama, E. F., and K. R. French. (1993), "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33, 3-56.
- Fang, Y., and D. Xu. (2003), "The Predictability of Asset Returns: An Approach Combining Technical Analysis and Time Series Forecasts." *International Journal of Forecasting*, 19, 369-385.
- Farrell, C. H., and E. A. Olszewski. (1993), "Assessing Inefficiency in the S&P 500 Futures Market." *Journal of Forecasting*, 12, 395-420.
- Fernández-Rodríguez, F., C. González-Martel, and S. Sosvilla-Rivero. (2000), "On the Profitability of Technical Trading Rules Based on Artificial Neural Networks: Evidence from the Madrid Stock Market." *Economic Letters*, 69, 89-94.
- Fernández-Rodríguez, F., S. Sosvilla-Rivero, and J. Andrada-Félix. (2003), "Technical Analysis in Foreign Exchange Markets: Evidence from the EMS." *Applied Financial Economics*, 13, 113-122.
- Fleming, J., B. Ostdiek, and R. E. Whaley. (1996), "Trading Costs and the Relative Rates of Price Discovery in Stock, Futures, and Option Markets." *Journal of Futures Markets*, 16, 353-387.

- Frankel, J. A., and K. A. Froot. "Chartist, Fundamentalists, and Trading in the Foreign Exchange Market." *American Economic Review*, 80, 181-185.
- French, K. R. and R. Roll. (1986), "Stock Return Variances: The Arrival of Information and the Reaction of Traders." *Journal of Financial Economics*, 17, 5-26.
- Froot, K. A., D. S. Scharfstein, and J. C. Stein. (1992), "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation." *Journal of Finance*, 47, 1461-1484.
- Fyfe, C., J. P. Marney, and H. F. E. Tarbert. (1999), "Technical Analysis versus Market Efficiency - A Genetic Programming Approach." *Applied Financial Economics*, 9, 183-191.
- Gençay, R. (1998), "Optimization of Technical Trading Strategies and the Profitability in Security Markets." *Economic Letters*, 59, 249-254.
- Gençay, R. (1999), "Linear, Non-linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules." *Journal of International Economics*, 47, 91-107.
- Gençay, R., and T. Stengos. (1998), "Moving Average Rules, Volume and the Predictability of Security Returns with Feedforward Networks." *Journal of Forecasting*, 17, 401-414.
- Goldbaum, D. (1999), "A Nonparametric Examination of Market Information: Application to Technical Trading Rules." *Journal of Empirical Finance*, 6, 59-85.
- Goodacre, A., and T. Kohn-Speyer. (2001), "CRISMA Revisited." *Applied Financial Economics*, 11, 221-230.
- Goodacre, A., J. Boshier, and A. Dove. (1999), "Testing the CRISMA Trading System: Evidence from the UK Market." *Applied Financial Economics*, 9, 455-468.
- Goyenko, R. (2005), "Stock and Bond Pricing with Liquidity"
<http://www.kelley.iu.edu/finance/> 25/05/2006

- Gray, R. W., and S. T. Nielsen. (1963), "Rediscovery of Some Fundamental Price Behavior Characteristics." Paper Presented at the Meeting of the Econometric Society, Cleveland, Ohio, September.
- Group of Thirty. (1985), *The Foreign Exchange Market in the 1980s*. New York, NY: Group of Thirty.
- Grossman, S. J., and J. E. Stiglitz. (1976), "Information and Competitive Price Systems." *American Economic Review*, 66, 246-253.
- Grossman, S. J., and J. E. Stiglitz. (1980), "On the Impossibility of Informationally Efficient Markets." *American Economic Review*, 70, 393-408.
- Grundy, B. D., and M. McNichols. (1989), "Trade and the Revelation of Information through Prices and Direct Disclosure." *Review of Financial Studies*, 2, 495-526.
- Guillaume, D. M. (2000), *Intradaily Exchange Rate Movements*. Boston, MA: Kluwer Academic Publishers.
- Gunasekarage, A., and D. M. Power. (2001), "The Profitability of Moving Average Trading Rules in South Asian Stock Markets." *Emerging Markets Review*, 17-33.
- Hansen, P. R. (2003), "Asymptotic Tests of Composite Hypotheses." Working Paper, Department of Economics, Brown University
- Hansen, P. R. "A Test for Superior Predictive Ability. 92004)" Working Paper, Department of Economics, Brown University,
- Hausman, J. A., A. W. Lo, and A. C. MacKinlay. (1992) "An Ordered Probit Analysis of Transaction Stock Prices." *Journal of Financial Economics*, 31, 319-379.
- Hellwig, M. (1982), "Rational Expectations Equilibrium with Conditioning on Past Prices: A Mean-Variance Example." *Journal of Economic Theory*, 26, 279-312.
- Houthakker, H. (1961), "Systematic and Random Elements in Short-Term Price Movements." *American Economic Review*, 51, 164-172.
- Hudson, R., M. Dempsey, and K. Keasey. (1996), "A Note on the Weak Form Efficiency of Capital Markets: The Application of Simple Technical Trading Rules to UK Stock Prices - 1935 to 1964." *Journal of Banking & Finance*, 20, 1121-1132.

- Irwin, S. H., and B. W. Brorsen. (1987), "A Note on the Factors Affecting Technical Trading System Returns." *Journal of Futures Markets*, 7, 591-595.
- Irwin, S. H., and J. W. Uhrig. (1984), "Do Technical Analysts Have Holes in Their Shoes?" *Review of Research in Futures Markets*, 3, 264-277.
- Irwin, S. H., C. R. Zulauf, M. E. Gerlow, and J. N. Tinker. (1997), "A Performance Comparison of a Technical Trading System with ARIMA Models for Soybean Complex Prices." *Advances in Investment Analysis and Portfolio Management*, 4, 193-203.
- James, F. E. Jr. (1968), "Monthly Moving Averages - An Effective Investment Tool?" *Journal of Financial and Quantitative Analysis*, 315-326.
- Jegadeesh, N.(2000), "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation - Discussion." *Journal of Finance*, 55, 1765-1770.
- Jegadeesh, N. and S. Titman. (1993). "Returns to buying winners and selling losers: implications for stock market efficiency", *Journal of Finance*, 48, 65-91
- Jegadeesh, N. and W. Kim. (2006), "Value of Analyst Recommendations: International Evidence" <http://faculty.fuqua.duke.edu/areas/finance/papers/analysts.pdf>,
- Jensen, M. C. (1967), "Random Walks: Reality or Myth - Comment." *Financial Analysts Journal*, 23, 77-85.
- Jensen, M. C. (1978), "Some Anomalous Evidence Regarding Market Efficiency." *Journal of Financial Economics*, 6, 95-101.
- Jensen, M. C., and G. A. Benington. (1970), "Random Walks and Technical Theories: Some Additional Evidence." *Journal of Finance*, 25, 469-482.
- Kaufman, P. J. (1998), *Trading Systems and Methods*, New York, NY: John Wiley & Sons,
- Kho, B. (1996), "Time-Varying Risk Premia, Volatility, and Technical Trading Rule Profits: Evidence from Foreign Currency Futures Markets." *Journal of Financial Economics*, 41, 249-290.

- Kidd, W. V., and B. W. Brorsen. (2004), "Why Have the Returns to Technical Analysis Decreased?" *Journal of Economics and Business*, 56, 159-176.
- Kavajecz, A. K. (1999), "The specialist's quoted depth and limit order book." *The Journal of Finance*, 52, 747-771
- Kavajecz, A. K. and Odders-White, E. (2004), "Technical Analysis and Liquidity Provision." *Review of Financial Studies*, 17, 1043 - 1071
- Korczak, J., and P. Roger. (2002), "Stock Timing Using Genetic Algorithms." *Applied Stochastic Models in Business and Industry*, 18(2002):121-134.
- Koza, J. (1992), *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. Cambridge, MA: MIT Press, 1992.
- Kwan, J. W. C., K. Lam, M. K. P. So, and P. L. H. Yu. (2000), "Forecasting and Trading Strategies Based on a Price Trend Model." *Journal of Forecasting*, 19, 485-498.
- Kwon, K., and R. J. Kish. (2002), "Technical Trading Strategies and Return Predictability: NYSE." *Applied Financial Economics*, 12, 639-653.
- Lakonishok, J, Shleifer A, and Vishniy, R. W. (1994), "Contrarian Investment, Extrapolation and Risk" *The Journal of Finance* 49
- Lakonishok, J., and S. Smidt. (1988), "Are Seasonal Anomalies Real? A Ninety-Year Perspective." *Review of Financial Studies*, 1(1988):403-425.
- LeBaron, B. (1999), "Technical Trading Rule Profitability and Foreign Exchange Intervention." *Journal of International Economics*, 49, 125-143.
- Lee, C. I., and I. Mathur. (1996), "Trading Rule Profits in European Currency Spot Cross-Rates." *Journal of Banking & Finance*, 20, 949-962.
- Lee, C. I., and I. Mathur. (1996), "A Comprehensive Look at the Efficiency of Technical Trading Rules Applied to Cross-Rates." *European Journal of Finance*, 2, 389-411.
- Lee, C. I., K. C. Gleason, and I. Mathur. (2001), "Trading Rule Profits in Latin American Currency Spot Rates." *International Review of Financial Analysis*, 10, 135-156.

- Lee, C. I., M. Pan, and Y. A. Liu. (2001), "On Market Efficiency of Asian Foreign Exchange Rates: Evidence from a Joint Variance Ratio Test and Technical Trading Rules." *Journal of International Financial Markets, Institutions and Money*, 11, 199-214.
- Lehman, B. N. "Fads, (1990), Martingales, and Market Efficiency." *Quarterly Journal of Economics*, 105,1 , 1-28.
- Leigh, W., N. Modani, R. Purvis, and T. Roberts. (2002), "Stock Market Trading Rule Discovery Using Technical Charting Heuristics." *Expert Systems with Applications*, 23, 155-159.
- Leigh, W., N. Paz, and R. Purvis. (2002), "Market Timing: A Test of a Charting Heuristic." *Economic Letters*, 77, 55-63.
- LeRoy, S. F. (1989), "Efficient Capital Markets and Martingales." *Journal of Economic Literature*, 27, 1583-1621.
- Leuthold, R. M. (1972), "Random Walk and Price Trends: The Live Cattle Futures Market." *Journal of Finance*, 27(1972):879-889.
- Leuthold, R. M., J. C. Junkus, and J. E. Cordier. (1989), *The Theory and Practice of Futures Markets*. Lexington, MA: Lexington Books
- Levich, R. M., and L. R. Thomas. (1993), "The Significance of Technical Trading Rule Profits in the Foreign Exchange Market: A Bootstrap Approach." *Journal of International Money and Finance*, 12, 451-474.
- Levy, R. A. (1967), "Random Walks: Reality or Myth." *Financial Analysts Journal*, 23, 69-77.
- Levy, R. A. (1971), "The Predictive Significance of Five-Point Chart Patterns." *Journal of Business*, 44 , 316-323.
- Lo, A., and A. C. MacKinlay. (1990), "Data Snooping Biases in Tests of Financial Asset Pricing Models." *Review of Financial Studies*, 3, 431-467.

- Lo, A., and A. C. MacKinlay. (1988), "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test." *The Review of Financial Studies*, 1,1, 41-66
- Lo, A., and A. C. MacKinlay. (1999), *A Non-Random Walk Down Wall Street*. Princeton, NJ: Princeton University Press.
- Lo, A., H. Mamaysky, and J. Wang. (2000), "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation." *Journal of Finance*, 55 , 1705-1765.
- Locke, P. R., and P. C. Venkatesh. (1997), "Futures Market Transaction Costs." *Journal of Futures Markets*, 17, 229-245.
- Logue, D. E., and R. J. Sweeney. (1977), "'White-Noise' in Imperfect Markets: The Case of the Franc/Dollar Exchange Rate." *Journal of Finance*, 32, 761-768.
- Logue, D. E., R. J. Sweeney, and T. D. Willett. (1978) "The Speculative Behavior of Foreign Exchange Rates during the Current Float." *Journal of Business Research*, 6, 159-174.
- Lovell, M. C. "Data Mining. (1983), " *Review of Economics and Statistics*, 65, 1-12.
- Lui, Y. H., and D. Mole. (1998), "The Use of Fundamental and Technical Analyses by Foreign Exchange Dealers: Hong Kong Evidence." *Journal of International Money and Finance*, 17, 535-545.
- Lukac, L. P., and B. W. Brorsen. (1989), "The Usefulness of Historical Data in Selecting Parameters for Technical Trading Systems." *Journal of Futures Markets*, 9, 55-65.
- Lukac, L. P., and B. W. Brorsen. (1990), "A Comprehensive Test of Futures Market Disequilibrium." *Financial Review*, 25, 593-622.
- Lukac, L. P., B. W. Brorsen, and S. H. Irwin. (1988), "A Test of Futures Market Disequilibrium Using Twelve Different Technical Trading Systems." *Applied Economics*, 20, 623-639.
- Lukac, L. P., B. W. Brorsen, and S. H. Irwin. (1988), "Similarity of Computer Guided Technical Trading Systems." *Journal of Futures Markets*, 8(1988):1-13.

- Lukac, L. P., B. W. Brorsen, and S. H. Irwin. (1990), *A Comparison of Twelve Technical Trading Systems*. Greenville, SC: Traders Press, Inc.
- Maillet, B., and T. Michel. (2000), "Further Insights on the Puzzle of Technical Analysis Profitability." *European Journal of Finance*, 6, 196-224.
- Malkiel, B. G. (1996), *A Random Walk Down Wall Street*. New York: W. W. Norton,
- Mandelbrot, B. (1963), "The Variation of Certain Speculative Prices." *Journal of Business*, 36, 394-419.
- Mandelbrot, B. (1966), "Forecasts of Future Prices, Unbiased Markets, and 'Martingale' Models." *Journal of Business*, 39, 242-255.
- Marsh, I. W. (2000), "High-Frequency Markov Switching Models in the Foreign Exchange Market." *Journal of Forecasting*, 19, 123-134.
- Martell, T. F. (1976), "Adaptive Trading Rules for Commodity Futures." *Omega*, 4, 407-416.
- Martell, T. F., and G. C. Phillipatos. (1974), "Adaptation, Information, and Dependence in Commodity Markets." *Journal of Finance*, 29, 493-498.
- Martin, A. D. (2001), "Technical Trading Rules in the Spot Foreign Exchange Markets of Developing Countries." *Journal of Multinational Financial Management*, 11, 59-68.
- Menkhoff, L. (1997), "Examining the Use of Technical Currency Analysis." *International Journal of Finance and Economics*, 2, 307-318.
- Menkhoff, L., and M. Schlumberger. (1997), "Persistent Profitability of Technical Analysis on Foreign Exchange Markets?" *Banca Nazionale del Lavoro Quarterly Review*, No. 193, 189-216.
- Merton, R. C. "On the Current State of the Stock Market Rationality Hypothesis. (1987), " In Dornbusch R., S. Fischer, and J. Bossons, (ed.), *Macroeconomics and Finance: Essays in Honor of Franco Modigliani*, Cambridge, MA: MIT Press,
- Mills, T. C. (1997), "Technical Analysis and the London Stock Exchange: Testing Trading Rules Using the FT30." *International Journal of Finance and Economics*, 2, 319-331.

- Neely, C. J. (1997), "Technical Analysis in the Foreign Exchange Market: A Layman's Guide." Review, Federal Reserve Bank of St. Louis, September/October, . 23-38.
- Neely, C. J. (2002), "The Temporal Pattern of Trading Rule Returns and Exchange Rate Intervention: Intervention Does Not Generate Technical Trading Profits." *Journal of International Economics*, 58, 211-232.
- Neely, C. J. (2003), "Risk-Adjusted, Ex Ante, Optimal Technical Trading Rules in Equity Markets." *International Review of Economics and Finance*, 12, 69-87.
- Neely, C. J., and P. A. Weller. (1999), "Technical Trading Rules in the European Monetary System." *Journal of International Money and Finance*, 18, 429-458.
- Neely, C. J., and P. A. Weller. (2001), "Technical Analysis and Central Bank Intervention." *Journal of International Money and Finance*, 20, 949-970.
- Neely, C. J., and P. A. Weller. (2003), "Intraday Technical Trading in the Foreign Exchange Market." *Journal of International Money and Finance*, 22, 223-237.
- Neely, C. J., P. A. Weller, and R. Dittmar. (1997), "Is Technical Analysis Profitable in the Foreign Exchange Market? A Genetic Programming Approach." *Journal of Financial and Quantitative Analysis*, 32, 405-426.
- Neftci, S. N. (1991), "Naïve Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of 'Technical Analysis.'" *Journal of Business*, 64, 549-571.
- Neftci, S. N., and A. J. Policano. (1984), "Can Chartists Outperform the Market? Market Efficiency Tests for 'Technical Analysis.'" *Journal of Futures Markets*, 4, 465-478.
- Nison, S. (1991), *Japanese Candlestick Charting Techniques*. New York Institute of Finance, New York, 1991.
- Oberlechner, T. (2001), "Importance of Technical and Fundamental Analysis in the European Foreign Exchange Market." *International Journal of Finance and Economics*, 6, 81-93.
- Olson, D. (2004), "Have Trading Rule Profits in the Currency Markets Declined over Time?" *Journal of Banking and Finance*, 28, 85-105.

- Osler, C. L. (2002), "Support for Resistance: Technical Analysis and Intraday Exchange Rates." *Economic Policy Review*, Federal Reserve Bank of New York, 6, 53-65.
- Osler, C. L. (2003), "Currency Orders and Exchange Rate Dynamics: An Explanation for the Predictive Success of Technical Analysis." *Journal of Finance*, 58, 1791-1819.
- Osler, C. L., and P. H. K. Chang. (1995), "Head and Shoulders: Not Just a Flaky Pattern." Federal Reserve Bank of New York, Staff Reports, 4,
- Parisi, F., and A. Vasquez. (2002), "Simple Technical Trading Rules of Stock Returns: Evidence from 1987 to 1998 in Chile." *Emerging Markets Review*, 1, 152-164.
- Peterson, P. E., and R. M. Leuthold. (1982), "Using Mechanical Trading Systems to Evaluate the Weak form Efficiency of Futures Markets." *Southern Journal of Agricultural Economics*, 14, 147-152.
- Poole, W. (1967), "Speculative Prices as Random Walks - An Analysis of Ten Time Series of Flexible Exchange Rates." *Southern Economic Journal*, 33, 468-478.
- Poterba, J; and L. Summers. (1986), "The Persistence of Volatility and Stock Market Fluctuations." *American Economic Review*, 76 , 1142- 1151.
- Porteba, J. M. and L. H. Summers. (1988), "Mean Reversion in Stock Prices: Evidence and Implications." *Journal of Financial Economics*, 22 , 27-59.
- Pont, J. and L. Schall. (1998), "Book-to-market ratios as predictors of market returns." *Journal of Financial Economics*, 141-160
- Praetz, P. D. (1975), "Testing the Efficient Markets Theory on the Sydney Wool Futures Exchange." *Australian Economic Papers*, 14, 240-249.
- Pring, M. J. (2002) *Technical Analysis Explained*. New York, NY: McGraw-Hill
- Pruitt, S. W., and R. E. White. (1988), "The CRISMA Trading System: Who Says Technical Analysis Can't Beat the Market?" *Journal of Portfolio Management*, 55-58.
- Pruitt, S. W., and R. E. White. (1989), "Exchange-Traded Options and CRISMA Trading." *Journal of Portfolio Management*, 55-56.

- Pruitt, S. W., K. S. Maurice Tse, and R. E. White. (1992), "The CRISMA Trading System: The Next Five Years." *Journal of Portfolio Management*, 22-25.
- Qi, M., and Y. Wu. (2002) "Technical Trading-Rule Profitability, Data Snooping, and Reality Check: Evidence from the Foreign Exchange Market." Working Paper,.
- Ratner, M., and R. P. C. Leal. (1999). "Tests of Technical Trading Strategies in the Emerging Equity Markets of Latin America and Asia." *Journal of Banking & Finance*, 23, 1887-1905.
- Raj, M. (2000) "Transactions Data Tests of Efficiency: An Investigation in the Singapore Futures Markets." *Journal of Futures Markets*, 20, 687-704.
- Raj, M., and D. Thurston. (1996), "Effectiveness of Simple Technical Trading Rules in the Hong Kong Futures Markets." *Applied Economics Letters*, 3, 33-36.
- Ready, M. J. "Profits from Technical Trading Rules. (2002), " *Financial Management*, 31, 43-61.
- Reinganum, M. R; and J. K. Smith, (1993), Investor preference for large firms: New evidence on economies of size, *Journal of Industrial economics*, 32, 231-227
- Roberts, M. C. (2003), "Technical Analysis in Commodity Markets: Risk, Returns, and Value." Paper Presented at the NCR-134 Conference, St. Louis, Missouri.
- Roll, R. (1984), "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance*, 39, 1127-1139.
- Saacke, P. (2002), "Technical Analysis and the Effectiveness of Central Bank Intervention." *Journal of International Money and Finance*, 21, 459-479.
- Samuelson, P. (1965), A. "Proof That Properly Anticipated Prices Fluctuate Randomly." *Industrial Management Review*, 6, 41-49.
- Sapp, S. (2004), "Are All Central Bank Interventions Created Equal? An Empirical Investigation." *Journal of Banking & Finance* 28, 443-474.
- Schmidt, A. B. (1999), "Modeling the Demand-Price Relations in a High-Frequency Foreign Exchange Market." *Physica A*, 271, 507-514.

- Schmidt, A. B. (2002), "Modeling the Birth of a Liquid Market." *Physica A*, 283, 479-485.
- Schmidt, A. B. (2002), "Why Technical Trading May Be Successful? A Lesson from the Agent-Based Modeling." *Physica A*, 303, 185-188.
- Schulmeister, S. (1988). "Currency Speculation and Dollar Fluctuations." *Banca Nazionale del Lavoro Quarterly Review*, No. 167, 343-365.
- Schwager, J. D. (1985), "Alternative to Sharpe Ratio Better Measure of Performance." *Futures*, 56-58.
- Schwager, J. D. (1996). *On Futures: Technical Analysis*. New York, NY: John Wiley & Sons
- Schwert, G. W. (2003), "Anomalies and Market Efficiency." *Handbook of the Economics of Finance*, eds. George Constantinides, Milton Harris, and René Stulz, North-Holland , 937-972.
- Sharpe, W. F. (1996), "Mutual fund performance.", *Journal of Business*, 39 , 119-138
- Shiller, R. J. (1990), "Speculative Prices and Popular Models." *Journal of Economic Perspectives*, 4 , 55-65.
- Shiller, R. J. (2003), "From Efficient Markets Theory to Behavioral Finance." *Journal of Economic Perspectives*, 17, 83-104.
- Shleifer A., and L. H. Summers. (1990), "The Noise Trader Approach to Finance." *Journal of Economic Perspectives*, 4, 19-33.
- Silber, W. L. (1994), "Technical Trading: When It Works and When It Doesn't." *Journal of Derivatives*, 1, 39-44.
- Skouras, S. (2001), "Financial Returns and Efficiency as Seen by an Artificial Technical Analyst." *Journal of Economic Dynamics & Control*, 25, 213-244.

- Smidt, S. (1965a), *Amateur Speculators*. Ithaca, NY: Graduate School of Business and Public Administration, Cornell University,
- Smidt, S. (1965b), "A Test of Serial Independence of Price Changes in Soybean Futures." *Food Research Institute Studies*, 5, 117-136.
- Smith, T., and R. E. Whaley. (1994), "Estimating the Effective Bid/Ask Spread from Time and Sales Data." *Journal of Futures Markets*, 14, 437-455.
- Solt, M. E., and P. J. Swanson. (1981), "On the Efficiency of the Markets for Gold and Silver." *Journal of Business*, 54, 453-478.
- Sosvilla-Rivero, S., J. Andrada-Félix, and F. Fernández-Rodríguez. (2002), "Further Evidence on Technical Trade Profitability and Foreign Exchange Intervention." *Applied Economics Letters*, 9, 827-832.
- Stevenson, R. A., and R. M. Bear. (1970), "Commodity Futures: Trends or Random Walks?" *Journal of Finance*, 25, 65-81.
- Stewart, B. (1949), "An Analysis of Speculative Trading in Grain Futures." Technical Bulletin, No. 1001, US Department of Agriculture, Washington, D.C..
- Sullivan, R., A. Timmermann, and H. White. (1999), "Data Snooping, Technical Trading Rule Performance, and the Bootstrap." *Journal of Finance*, 54, 1647-1691.
- Sullivan, R., A. Timmermann, and H. White. (2001), "Dangers of Data-Mining: The Case of Calendar Effects in Stock Returns." *Journal of Econometrics*, 105, 249-286.
- Sullivan, R., A. Timmermann, and H. White. (2003) "Forecast Evaluation with Shared Data Sets." *International Journal of Forecasting*, 19, 217-227.
- Sweeny, R. J. (1986), "Beating the Foreign Exchange Market." *Journal of Finance*, 41, 163-182.

- Sweeny, R. J. (1988), "Some New Filter Rule Tests: Methods and Results." *Journal of Financial and Quantitative Analysis*, 23, 285-300.
- Sweeny, R. J., and P. Surajaras. (1989), "The Stability of Speculative Profits in the Foreign Exchanges." In R. M. C. Guimaraes et al., (ed.), *A Reappraisal of the Efficiency of Financial Markets*, Heidelberg: Springer-Verlag,
- Szakmary, A. C., and I. Mathur. (1997), "Central Bank Intervention and Trading Rule Profits in Foreign Exchange Markets." *Journal of International Money and Finance*, 16, 513-535.
- Takens, F. (1981), "Detecting Strange Attractors in Turbulence." In *Dynamical Systems and Turbulence*, Rand, D. A., and L. S. Young, (ed.), Berlin: Springer,
- Taylor, M. P., and H. Allen. (1992) "The Use of Technical Analysis in the Foreign Exchange Market." *Journal of International Money and Finance*, 11, 304-314.
- Taylor, S. J. (1980), "Conjectured Models for Trends in Financial Prices, Tests and Forecasts." *Journal of the Royal Statistical Society, A* 143, 338-362.
- Taylor, S. J. (1983), "Trading Rules for Investors in Apparently Inefficient Futures Markets." In *Futures Markets - Modeling, Managing and Monitoring Futures Trading*, Oxford, UK: Basil Blackwell,
- Taylor, S. J. (1985), "The Behaviour of Futures Prices over Time." *Applied Economics*, 17, 713-734.
- Taylor, S. J. (1986), *Modelling Financial Time Series*. Chichester, England: John Wiley & Sons.
- Taylor, S. J. (1988), "How Efficient are the Most Liquid Futures Contracts?" A Study of Treasury Bond Futures." *Review of Futures Markets*, 7, 574-592.
- Taylor, S. J. (1992), "Rewards Available to Currency Futures Speculators: Compensation for Risk or Evidence of Inefficient Pricing?" *Economic Record*, 68, 105-116.

- Taylor, S. J. (1994), "Trading Futures Using a Channel Rule: A Study of the Predictive Power of Technical Analysis with Currency Examples." *Journal of Futures Markets*, 14, 215-235.
- Taylor, S. J. (2000), "Stock Index and Price Dynamics in the UK and the US: New Evidence from a Trading Rule and Statistical Analysis." *European Journal of Finance*, 6, 39-69.
- Taylor, S. J., and A. Tari. (1989), "Further Evidence against the Efficiency of Futures Markets." In R. M. C. Guimaraes et al., (ed.), *A Reappraisal of the Efficiency of Financial Markets*, Heidelberg: Springer-Verlag
- Thompson, S. R., and M. L. Waller. (1987), "The Execution Cost of Trading in Commodity Futures Markets." *Food Research Institute Studies*, 20, 141-163.
- Timmermann, A., and C. W. J. Granger. (2004), "Efficient Market Hypothesis and Forecasting." *International Journal of Forecasting*, 20, 15-27.
- Tomek, W. G., and S. F. Querin. (1984), "Random Processes in Prices and Technical Analysis." *Journal of Futures Markets*, 4, 15-23.
- Treynor, J. L., and R. Ferguson. (1985), "In Defense of Technical Analysis." *Journal of Finance*, 40, 757-773.
- Van Horne, J. C., and G. G. C. Parker. (1967), "The Random-Walk Theory: An Empirical Test." *Financial Analysts Journal*, 23, 87-92.
- Van Horne, J. C., and G. G. C. Parker. (1968), "Technical Trading Rules: A Comment." *Financial Analysts Journal*, 24, 128-132.
- Wang, J. (2000), "Trading and Hedging in S&P 500 Spot and Futures Markets Using Genetic Programming." *Journal of Futures Markets*, 20, 911-942.
- White, H. (2000), "A Reality Check for Data Snooping." *Econometrica*, 68, 1097-1126.

- Wilder, J. W. Jr. (1978), *New Concepts in Technical Trading Systems*, Trend Research, Greensboro, NC: Hunter Publishing Company.
- Wong, M. C. S. (1995), "Market Reactions to Several Popular Trend-Chasing Technical Signals." *Applied Economics Letters*, 2, 449-456.
- Wong, W. K., M. Manzur, and B. K. Chew. (2003), "How Rewarding Is Technical Analysis? Evidence from Singapore Stock Market." *Applied Financial Economics*, 13, 543-551.
- Working, H. (1934), "A Random-Difference Series for Use in the Analysis of Time Series." *Journal of the American Statistical Association*, 29, 11-24.
- Working, H. (1949), "The Investigation of Economic Expectations." *American Economic Review*, 39, 150-166.
- Working, H. (1958), "A Theory of Anticipatory Prices." *American Economic Review*, 48, 188-199.
- Working, H. (1962), "New Concepts Concerning Futures Markets and Prices." *American Economic Review*, 52, 431-459.
- Zhou, X., and M. Dong. (2004), "Can Fuzzy Logic Make Technical Analysis 20/20?" *Financial Analysts Journal*, 60, 54-75.