MACQUARIE UNIVERSITY

Doctoral Thesis

Statistical Testing of Technical Trading Rule Profitability

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Declaration of Authorship

I, Jung-Soo PARK, declare that this thesis titled, 'Statistical Testing of Technical Trading Rule Profitability' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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Signed: JUNG-SOO PARK

Date: 10/12/2015

"Whom do I call educated? First, those who manage well the circumstances they encounter day by day. Next, those who are decent and honorable in their intercourse with all men, bearing easily and good naturedly what is offensive in others and being as agreeable and reasonable to their associates as is humanly possible to be... those who hold their pleasures always under control and are not ultimately overcome by their misfortunes... those who are not spoiled by their successes, who do not desert their true selves but hold their ground steadfastly as wise and sober – minded men."

Socrates

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Abstract

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Doctor of Philosophy

Statistical Testing of Technical Trading Rule Profitability

by Jung-Soo PARK

The profitability of technical trading rules has been widely studied in the literature and many researchers have found evidence that technical trading rules are able to generate profits in excess of those available from a simple buy-and-hold strategy. Taken at face value, this contradicts the Efficient Market Hypothesis and suggests that much of the classical theory of finance needs to be revised. However, despite the large volume of empirical literature on the subject, no clear consensus on the profitability of trading rules has emerged. Studies of US equity markets tend to find that trading rules were profitable prior to the mid-1980s, but there is little evidence of profitability after that time. Studies of other countries present mixed results – with evidence of profitability being found for some countries by some authors, but no evidence of profitability being found for many markets.

There are a number of potential shortcomings of the existing literature which may explain its failure to provide consistent conclusions about the profitability of technical trading rules. Previously published papers have almost all focussed on a narrow range of technical trading rules. In fact, the majority of trading rules that feature in the *practicioner's* literature on technical trading have received little or no attention in the *academic* literature. Similarly, the academic literature has focussed on a narrow range of markets. Not surprisingly, the US equity markets, and the other major markets, have received the largest share of academic attention. Several studies of non-major markets also exist, but they tend to concentrate on relatively small numbers of Asian and Latin American markets. Authors often neglect to report precisely which parameterizations of which rules are found to be profitable, and there are a number of variations of methodology used, making it difficult to draw firm conclusions from the literature. Furthermore, the fact that the academic literature has considered only a small subset of all trading rules over narrow ranges of markets raises the possibility that interesting results are still waiting to be discovered.

The credibility of many of the findings of trading rule profitability in the literature is compromised by frequent poor selection of statistical methodology. There exist many different classes of technical trading rules, and most rules can be paramaterised in any number of ways. Financial theory gives little guidance on which paramterisations of which rules should be profitable, so it is inevitable that empirical research must consider a large number of different rules. This raises statistical challenges. The classical methods of hypothesis testing control the probability of rejecting a true null hypothesis and are appropriate for testing a single hypothesis. When applied to multiple hypotheses, the probability of rejecting at least one true null hypothesis is likely to be greater than the nominal significance level of the test. In cases in which a large number of hypotheses are tested, the probability of rejecting at least one true null hypothesis is unknown, but may be close to 1. This is referred to as data snooping. Its consequence is that studies that apply classical hypothesis testing to a large number of different parameterizations of different trading rules, perhaps for different assets and/or in different countries, and report the rejection of some hypotheses are not statistically valid.

With the above comments in mind, the main objective of this thesis is to provide a comprehensive study of the profitability of technical trading rules which covers a broad set of rules over a wide range of markets, employing a consistent methodology and utilizing recent advances in multiple hypothesis testing that provide control of well-defined error rates when testing large numbers of hypotheses.

The thesis is structured as follows. Chapter 1 provides the background and outline of this thesis. Chapter 2 then surveys the relevant literature and discusses the motivations behind the development of the three key research questions addressed in Chapter 3 through 5, respectively.

Chapter 3 examines the the profitability of technical trading rules in Australian financial markets (stock, currency and interest market) using tests which provide weak control of the family-wise error rate.

In Chapter 4, we consider the US equity market over a period of more than a century using 54 different classes of technical trading rule. I use statistical methods which provide strong control of the family-wise error rate and allow us to identify sets of profitable trading rules.

Chapter 5 presents a cross-country study of technical trading rule profitability, in which the 54 trading rules introduced in Chapter 4 are applied to the equity markets of 39 different countries, 21 of which are classed as emerging markets by MCSI. In order to enhance power, we employ techniques that control generalized family-wise error rates and the false discovery proportion.

Chapter 6 summarizes the key findings of this thesis along with some recommendations for future research.

This thesis makes two distinct contributions to the literature on technical trading rules. Firstly, to my knowledge, it is the most comprehensive empirical study of technical trading rule profitability to date. It employs a wide range of technical trading rules, most of which have received little or no attention in the prior academic literature. These are applied to US data dating back as far as the late 1800's and to more recent data from 39 different equity markets. Secondly, I provide an illustration of the application of a number of recently developed statistical techniques for multiple hypothesis testing which are appropriate for the empirical analysis of technical trading rules. In particular, to my knowledge, this is the first study of technical trading rule profitability to control generalized family-wise error rates and the false discovery proportion. In each chapter of the thesis, I also produce results using standard hypothesis testing procedures and find many apparently spurious positive results. This illustrates the dangers of data-snooping in the analysis of trading rule profitability, and demonstrates the importance of the selection of appropriate testing methodologies.

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Contents

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Abbreviations

BLL	The paper of **B**rock,**L**akonishok and **L**eBaron (1992)
DJIA	**D**ow **J**ones **I**ndustrial **A**verage
FDP	**F**alse **D**iscovery **P**ortion
FDR	**F**alse **D**iscovery **R**ate
FWER	**F**amily-**W**ise **E**rror **R**ate
GFWER	**G**eneralized **FWER**
GSRC	**G**eneralized **S**tepwise **R**eality **C**heck
GSSPA	**G**eneralized **S**tepwise **S**uperior **P**redictive **A**bility
IID	**I**ndependent and **I**dentically **D**istributed.
NASDAQ	**N**ational **A**ssociation of **S**ecurities **D**ealers **A**utomated **Q**uotations
NYSE	**N**ew **Y**ork **S**tock **E**xchange
RC	White's **R**eality **C**heck
S&P	**S**tandard and **P**oor's 500 Index
SMA	**S**imple **M**oving **A**verage
SPA	Hansen's **S**uperior **P**redictive **A**bility
SRC	**S**tepwise **R**eality **C**heck
SSPA	**S**tepwise **S**uperior **P**redictive **A**bility
STW	The paper of **S**ullivan, **T**immerman and **W**hite (1999)

For the memory of my parents who always watch me from heaven,

and thanks to my wife and two daughters, Ji-Hye and Ji-Hyun for their dedicated love to me.

...

Chapter 1

Introduction

The profitability of technical trading rules been widely studied in the literature and many researchers claim to have found evidence that trading rules are able to generate profits in excess of those available from a simple buy-and-hold strategy. However, this predictability contradicts economic orthodoxy the Efficient Market Hypothesis and ,due to a number of criticisms that may apply to many of the published studies of trading rule profitability, the matter is still controversial.

The empirical literature of technical trading rules is vast, covering different trading rules applied to a range of different markets (stock markets, currency markets, futures markets, etc), in different countries, over different time periods, with returns measured at different frequencies. A number of different approaches are taken to performance measurement and statistical analysis. In spite of its abundance, the limitations of the previous literature are threefold.

Firstly, many of the previous academic studies consider only a couple of different types of technical trading rule, and few consider more than a handful. The research literature has focused largely on the rules considered in the seminal works of Brock et al. (1992) and Sullivan et al. (1999), which cover 2 and 5 rules respectively. This is in contrast to books and websites aimed at practitioners, in which scores of trading rules are presented. The Brock et al. (1992) and Sullivan et al. (1999) rules were well-known in the 1960s and many other rules have been devised since then. As Clements (2010) and Neely and Weller (2011) have mentioned, there are no academic studies which consider the newer range of technical trading rules. Secondly, while the dangers of data-snooping are well-recognized in the empirical finance literature, most studies of technical trading rule profitability take no effective steps to mitigate this problem. Consequently, their findings lack a sound statistical foundation and may be spurious. The last two decades have seen the development of a number of statistical techniques for controlling error rates that are sensible for applications in which there are a large number of hypotheses to test. I argue that these tests constitute the statistical toolbox that should be used when considering trading rule profitability. Thirdly, the existing literature focuses strongly on the US market and a few other advanced markets. Relatively few studies have considered other markets. In light of the above comments, the main objective of this research was to measure the predictive ability of a comprehensive set of technical trading rules, most of which have never been addressed in the literature before, using state-of-the-art statistical approaches that are designed for testing large numbers of hypotheses. As (Lo et al., 2000, P. 1708) suggested , academia's role is

> to bridge the gulf between technical analysis and quantitative finance, by developing a systematic and scientific approach to the practice of technical analysis and by employing the new-standard methods of empirical analysis to gauge the efficacy of technical indicators over time and across securities.

This statement provides the direction for my research.

In the remainder of this chapter I provide some details of the contents of each chapter. Chapter 2 surveys the relevant literature and discusses the motivations behind the development of the three key research questions addressed in Chapter 3 through 5, respectively. This thesis is based on a thesis by publication format with three papers and these three papers form the content of chapters 3, 4 and 5. The content of Chapter 3 has already been published in the journal literature as Park and Heaton (2014).

A paper titled "Technical Trading Rules in Australian Financial Markets" provides the material for Chapter 3. According to the World Federation of Exchanges (WFE), the Australian stock market (ASX) is one of the world's top 10 and Asia-Pacific's top 5 exchange market measured in USD based market capitalisation as of the end of 2010. Nonetheless, the Australian markets have attracted little attention in the technical trading rule literature and this chapter is the 1st Australian study of technical trading rules that controls the family-wise error rate.

In Chapter 3 the 7,846 technical trading rules considered by Sullivan et al. (1999) are applied to a stock index, some individual stocks, some currencies and some interest rate futures contracts traded in the Australian financial markets, and I test for profitability relative to a buy-and-hold strategy. Size distortions due to data-snooping are avoided by using the Reality Check test of White (2000) and the Superior Predictive Ability test of Hansen (2005). However, I find no evidence that technical trading rules provide trading profits in excess of those available from a simple buy-and-hold strategy.

A paper titled "The Profitability of a New Generation of Technical Trading Rules : Evidence from the Equity Market" provides the material for Chapter 4. Most of the existing literature on technical trading rule profitability focuses on a handful of technical trading rules that have been in use since the early 1960s. This chapter investigates the profitability of over 20,000 different parameterizations of 49 newer technical trading rules on the Dow Jones Industrial Average, most of which have not previously been considered in the academic literature. I employ a stepwise multiple hypothesis testing methodology that provides strong control over the family-wise error rate, and therefore allows us to identify sets of profitable trading rules in different time periods. My findings support the proposition that the decline in trading rule profitability reported in the prior literature is due to improvements in market efficiency rather than to traders learning which rules are profitable.

A paper titled "A Cross-Country Study of Technical Trading Rule Profitability" provides the material for Chapter 5. This chapter describes a comprehensive cross-sectional study of technical trading predictability in equity markets in 39 countries, including 18 developed and 21 emerging markets. I strictly controlled the risk of data snooping with the latest methodologies (their first use in the empirical economic analysis literature), and used them to detect more profitable trading rules. The stepwise multiple testing methodology we employed is more powerful than single-step approaches, and this paper is the first study of technical trading rules to use these techniques. With the same rules we introduced in Chapter 4, I found one profitable developed market and seven profitable emerging markets (before transaction costs and data snooping bias tests). With additional statistical tests of return predictability, I found first-order autocorrelation is the best explanation for the technical trading profitability of these markets.

Chapter 6 summaries the key findings and gives recommendations for future research. Additionally, two appendixes are included to provide further details to help the reader. Appendix A describes the technical trading rules applied in this thesis. Appendix B further presents some of the code that I wrote to produce the results in this thesis. I have made extensive use of Kevin Sheppard's Oxford MFE Matlab toolbox, toolboxes provided by MathWorks, various packages in R, Professor Michael Wolf's homepage, and many authors who were kind enough to send me the code used for their papers.

Chapter 2

Review on Previous Studies

Chapters 3, 4 and 5 of this thesis each contain separate papers which are largely self-contained and include their own literature reviews. The intention of this chapter is to provide a more general review of the literature which is relevant to all three of the subsequent chapters.

There is a great deal of literature available on technical trading rules and readers who are interested in learning more about technical analysis methods should consult textbooks such as Pring (1985), Murphy (1998), Bulkowski (2005) and Kirkpatrick and Dajlquist (2011). In addition, academic journal articles such as Menkhoff (2007); Park and Irwin (2007) provide excellent surveys of the literature, and Neely and Weller (2011) provide good coverage of the currency market.

2.1 Practitioners' use of technical analysis

A number of surveys have been conducted to measure the extent to which technical analysis is used in the financial industry. In his pioneering work, Smidt (1965) surveys amateur traders in the United States' (US) commodity market, and his later surveys cover most of the major financial markets or trading centres: Germany (Menkhoff (1997); Gehrig and Menkhoff (2006)); Hong Kong (Lui and Mole (1998)); North America (Cheung and Chinn (2001); Oberlechner and Osler (2012)), the United Kingdom (Cheung et al. (2004)), Austria and Switzerland (Oberlechner (2001)), Japan and Singapore (Cheung and Wong (2000)).

The common findings from the surveys are as follows:

Firstly, foreign exchange dealers rely on both technical and fundamental analysis as complementary ways to forecast exchange rate movements. However, they prefer technical analysis for short-run forecasts and fundamental analysis for long-term forecasts. Secondly, surveys show that at least 30% of foreign exchange traders around the world believe that technical analysis is the major factor determining exchange rates in the short-run up to six months. Thirdly, surveys show that the use of technical analysis has become more prevalent in recent years as market participants attribute a growing role to technical analysis (e.g., Cheung and Chinn (2001); Gehrig and Menkhoff (2006)). Fourthly, surveys found that technical analysts are more concerned with the psychological factors of the market (market sentiment) (e.g., Taylor (1992); Menkhoff (1997); Oberlechner (2001); Gehrig and Menkhoff (2006); Menkhoff (2010)).

In addition, Menkhoff (1997) searched for relations between the preferred use of technical analysis and institutional factors, such as age (Professionals preferring technical analysis are younger than other participants), position (Junior professionals prefer technical analysis than seniors), company size (Small institutions use more technical analysis than large) and education (Lower level of education prefers technical analysis than higher education) from foreign exchange professionals in Germany. Cheung et al. (2004) found that the use of technical analysis by traders increased to 32.7% from 13.8% five years ago. Finally, Menkhoff (2010) was the first researcher to conduct an extensive survey of fund managers in five countries. Results from the survey show that the use of technical analysis by fund managers is less than that of currency traders, but technical analysis is an important tool for short-term analysis. Specifically, Menkhoff (2010) also found that compared to peer groups, technical analysts are equal with regard to qualifications, experience, education and decision-making.

2.2 Debates on the profitability of technical trading rules

2.2.1 The First Debate: Efficient Market Hypothesis (1960-1988)

Cowles (1933) appears to be the first researcher to conduct an empirical study on technical analysis to be published in an academic journal, and active publication on this subject can be seen from early 1960s. However, whether technical trading techniques indeed result in significant profit has been a long-debated issue since Fama and Blume (1966). Early studies investigated several technical trading rules, including filter rules (Alexander (1961, 1964); Fama and Blume (1966); Sweeney (1988), stop-loss orders (Houthakker (1961); moving averages (Cootner (1962); Horne and Parker (1967, 1968); James (1968); Dale and Workman (1980); channels (Donchian (1960); and the relative strength index (Levy (1967); Jensen and Benington (1970)). The majority of early technical trading studies on foreign exchange markets and futures markets found substantial net profits, but studies on stock markets show that trading rules based on moving averages or relative strength indexes are not profitable over the "Buy and Hold" strategy (Fama and Blume (1966); Horne and Parker (1967, 1968); James (1968); Jensen and Benington (1970)). Specifically, Fama and Blume (1966) found no evidence that filter rules could earn abnormal profits in the stock market. The researchers concluded that excess profits on long transactions over the buy-and-hold strategy may be negative in practice if trading related costs are taken into account. These results suggest that stock markets were more efficient than foreign exchange markets or futures markets before the mid-1980s. Nonetheless, several studies suggested that technical rules are capable of generating profits after inclusion of transaction costs (Poole (1967); Leuthold (1972); Logue et al. (1978); Cornell and Dietrich (1978); Sweeney (1986, 1988)).

2.2.2 The Second Debate: Reliability of the profitability (1988-1999)

The empirical studies during the 1980s may suggest technical rules possess predictive power, although the excess returns from trading tend to be largely reduced after the inclusion of transaction costs. Three seminal papers by Brock et al. (1992); Sullivan et al. (1999); White (2000) also find evidence for the profitability of technical analysis. Brock et al. (1992) applied the model-based bootstrap approach to overcome the weaknesses of conventional t-tests and provide strong evidence on the profitability of technical trading. They applied two technical trading systems, a moving average oscillator and a trading range break-out, and found strong support for the ability of several widely used technical rules to predict the Dow Jones Industrial Average index over the period 1897-1986.

The profitability of technical trading rules after allowance for transactions costs is provided by, among others, Sweeney (1988); Corrado and Lee (1992); Levich and Thomas (1993); Bessembinder and Chan (1995); Kho (1996); Raj and Thurston (1996); Neely (1997); Mills (1997); Szakmary and Mathur (1997); Neely (1997); Neely and Weller (1999); Gencay (1999); Ito (1999); Ratner and Leal (1999),and LeBaron (1999).

In addition, while fewer in number, studies of futures markets also reported the profitability of various technical trading strategies over time (e.g., Lukac and Brorsen (1990); Silber (1994); Brock et al. (1992))

Moreover, some researchers claimed that earlier studies did not conduct statistical tests on the significance on technical trading returns. Although several studies

(James (1968); Bird (1985); Sweeney (1986)) measure statistical significance under the assumption that trading rule returns are normally distributed, Lukac and Brorsen (1990) reported that technical trading returns are positively skewed and leptokurtic. Thus, the researchers argued that past applications of t-tests to technical trading returns may be biased.

Lukac et al. (1988)'s work substantially improved early studies by conducting out-of-sample verification for optimized trading rules. Additionally, ample literature insists the performance of technical trading rules is highly unstable and gains from technical trading tends to decline over time (Levich and Thomas (1993); Hudson et al. (1996); Mills (1997); Bessembinder and Chan (1998); Ito (1999); LeBaron (1999)).

2.2.3 The Third Debate: Methodological Innovation (2000-current)

(Lovell, 1983, p.11) wrote "Unfortunately, inspection of Social Science Citation Index indicates that applied researchers are slow to adopt improved procedures", and (Lo and MacKinlay, 1990, p.465) warned "It is widely acknowledged that incorrect conclusions may be drawn from procedures violating the assumptions of classical statistical inference, but the nature of these violation is often as subtle as it is profound". White (2000, p. 1098) mentioned "it is dangerous practice to be avoided but researchers still routinely data snoop" and (Sullivan et al., 1999, p.1647) noted "an important issue generally encountered, but rarely directly addressed when evaluating technical trading rules, is data snooping". However, we have surveyed 75 papers published since White (2000) advocated the use of tests that account for data snooping and found only 15.4% included one or some of the aforementioned formal data snooping bias tests.[1]

To deal with data snooping problems, White (2000) proposed a Reality Check (RC) test to formally test whether there exists a superior predictive model or profitable trading rule within a large collection of models/rules. Sullivan et al. (1999) applied the unpublished version of White's RC to the data and methods of Brock et al. (1992). They found Brock et al's findings to be robust to data snooping biases, although they found that technical trading rules lose their predictive power for major U.S. stock indices after 1987-1996. Also, Sullivan et al. (2001) demonstrated that the well-known calendar effect is insignificant based on the RC test. Sullivan et al. (2003) enlarged the full set of trading rules by combining their earlier set of technical trading rules with calendar frequency trading rules first tested by Sullivan et al. (2001). Qi and Wu (2006) also applied White (2000)'s methodology to seven foreign exchange rates during 1973-1998 and found that

[1] see Appendix Table 4.7 and 5.7 for the list

technical trading rules generated substantial profits (7.2%-12.2%) in five of the seven markets even after adjustment for transaction costs and systematic risk.

At this juncture, Hansen (2005) proposed a more powerful superior predictive ability (SPA) test. This test improves the power of the RC test by correcting the bias from models with negative population means. Based on the SPA test, Hansen et al. (2005) found significant calendar effects, which is contrary to the results reported in Sullivan et al. (2001). Hsu and Kuan (2005) applied both White's and Hansen's tests to four main stock indexes, DJIA, S&P 500, NASDAQ Composite, and Russell 2000, over 1989-2002. Their in- and out of sample results indicated that technical trading rules were profitable in relatively new markets (NASDAQ Composite and Russell 2000) but not in matured markets (DJIA and S& P 500) after reflecting transaction costs. They also found that the SPA test was more powerful than the RC test. Park and Irwin (2010) investigated the profitability of technical trading rules in US futures markets during the years 1985-2004 using White's Bootstrap Reality Check and Hansen's SPA tests, and demonstrated that technical trading rules generally have not been profitable in the US futures markets.

In addition, Romano and Wolf (2005) noted that White's RC test was a joint testing method and was suboptimal in testing whether an individual model/rule outperforms the benchmark. They proposed a stepwise multiple testing procedure for White's RC test (SRC hereafter) that was optimal in a multiple testing framework, and, accordingly, was more powerful than the RC test. Romano and Wolf (2005), and Romano et al. (2008) applied this test to examine the performance of hedge funds and concluded that some hedge funds do produce significant profits. Finally, Hsu et al. (2010) constructed the stepwise SPA (SSPA) test and tested the predictive ability of trading rules on emerging market indices. The researchers found predictive ability but noted that the emergence of exchange traded funds appeared to weaken the phenomenon. Still, the debate on the profitability of technical analysis is inconclusive.

2.3 Other literature on technical analysis

2.3.1 Profitability on chart patterns

Levy (1971) investigated the profitability of chart patterns (five extrema formations) for the NYSE securities and found that none of the 32 patterns generated greater than average profits for any holding period after taking into account the transaction costs. Dempster and Jones (2001) drew the same conclusions regarding the non-profitability of the trading rules related to chart patterns. Curcio et al. (1997) and Lucke (2003) showed limited evidence of the profitability of technical patterns in foreign exchange markets, with trading profits from the patterns declining over time. Moreover, Chang and Osler (1999) constructed an algorithm to identify head-and-shoulders patterns in currency markets. They found evidence to suggest that these patterns have predictive ability in some markets. In particular, Lo et al. (2000) developed an automated pattern detection algorithm based on kernel regression. They applied this methodology to identify a variety of technical price patterns including 'head-and-shoulders' in the US stock market over the period 1962-1996. They found statistical evidence that there was potentially useful information contained in most of the patterns they considered. In addition, Dawson and Steeley (2003) applied Lo et al. (2000)'s approach to UK stock data and showed that the 'informativeness' of the chart patterns does not necessarily lead to trading profits.

Omrane and Van Oppens (2008) applied the chart patterns in Euro/Dollar intraday foreign exchange markets and found the existence of significant predictability of some chart patterns in the currency market. Except for the Euro, the kernel regression methodology has yet to be applied to the foreign exchange market. Savin et al. (2007) extended the analysis of Lo et al. (2000) by calibrating the pattern recognition algorithm using price patterns identified by a practicing technical analyst. The researchers found evidence that the head-and-shoulders pattern has significant predictive power for stock returns over periods up to three months. Leigh et al. (2002) found that bull flag patterns generate positive excess returns (before transaction costs) for the NYSE Composite Index over a buy-and-hold strategy.

2.3.2 System trading algorithm trading

Allen and Karjalainen (1999) were among the first to apply genetic programming to test the profitability of technical trading rules. Out-of-sample results indicate that trading rules optimized by genetic programming failed to generate consistent excess returns over a simple buy-and-hold strategy after adjustment for transaction costs. Similarly, Wang (2000) and Neely (2003) reported that genetically optimized trading rules failed to outperform a buy-and-hold strategy in both S&P 500 spot and futures markets.

Neely and Weller (2001) reported mixed results on trading profits net of transaction costs for four major foreign exchange rates, ranging from 1.7% to 8.3% per year over the period 1981-1992. The results were near zero or negative, except for the yen, over the period 1993-1998. Ready (2002) compared the performance of technical trading rules formed by genetic programming to Brock et al. (1992)'s moving average rules for dividend adjusted DJIA data. The researcher concluded that the apparent success (after transaction costs) of the Brock et al. (1992) moving average rules is a spurious result due to data snooping. Using intraday data for 1996 and realistic trading hours and transaction costs, Neely (2003) generated break-even transaction costs of less than 0.02% for most major foreign exchange rates using genetic trading rules. They found no evidence of positive excess returns. Similarly, Kozhan and Salmon (2008), using high frequency (tick-by-tick) data, found that trading rules derived from a genetic algorithm were profitable in 2003, but that this was no longer true in 2008. Gencay (1999) and others have similarly employed neural networks as 'black-box' methods for generating trading rules with positive results. Hong and Lee (2003), for instance, found strong nonlinearity in the conditional mean as well as volatility clustering in exchange rate returns, and that technical rules based on nonlinear models exhibited superior forecast power. Fernandez-Rodriguez et al. (2003) similarly found that technical trading rules based on nearest-neighbour (NN) nonlinear predictors generate net returns that dominate the buy-and-hold net returns.

2.3.3 Central Bank Intervention

In the literature on technical analysis many authors such as Levich (1986), Dooley and Shafer (1984), Sweeney (1986), Lukac et al. (1988),Davutyan and Pippenger (1989), Levich and Thomas (1993) are of the opinion that technical trading profits are correlated with central bank intervention. In recent years, this idea has been formally tested with direct and indirect intervention data. Szakmary and Mathur (1997) used monthly foreign exchange reserves held by central banks as a proxy for intervention and found that profits for moving average rules in major foreign exchange markets may be explained by a 'leaning against the wind' policy of central banks.

LeBaron (1999) used daily official intervention series to show that when a typical moving average rule generates buy signals for a foreign exchange rate, the Federal Reserve tends to support the dollar the next period. Saacke (2002) extended LeBaron (1999)'s analysis to Deutsche Bundesbank and confirmed the researchers findings. In addition, Sapp (2004) found that market uncertainty, measured by spread and volatility, is high before interventions and lower afterwards. This indicates that profits earned by technical analysis during these periods are a compensation for risk. Reitz and Taylor (2008) analysed the interaction of chartism, fundamentalism, and central bank intervention and provided evidence that intervention is most likely to occur and to be effective after a period of sustained trending away from the equilibrium level suggested by purchasing power parity. However, Neely (2002) used high-frequency returns and intervention to show that the timing and direction of trading are inconsistent with the idea that central bank intervention generates technical trading rule profits.

2.3.4 Other Studies

Studies have found some links between Markov regime switching models and technical trading rules (Vigfusson (1996); Dewachter (2001). However, profitability does not seem to be better than for simple moving average rules (Dueker and Neely (2007), although an advantage may be gained by the fact that profits remain more stable over time. Alternatively, Kozhan and Salmon (2008) employed the Knighthan Uncertainty model[2] algorithm to illustrate the inertia or uncertainty parameter which followed from the Bewley's preferences for decision-making under uncertainty with composite technical trading rules which emulate market practice of practitioners. The researchers found profitability of technical trading rules after imposing transaction costs and White's RC test.

With high frequency data, Schulmeister (2009) shows S&P500 daily technical trading profitability has decreased since 1960 and unprofitable since 1990s but with 30-minute data, both full and sub-data series shows positive returns. He insists profitability of technical trading rules are shifting from daily to high frequency data. However, using 5-minute Standard and Poor's Depository Receppts(SPDR) of 2002-2003, Marshall et al. (2008) find no evidence that Sullivan et al. (1999)'s 5 rules are profitable.[3]

[2] `http://news.mit.edu/2010/explained-knightian-0602`

[3] refer Andersen et al. (2005)for importance of the data cleaning in high frequency studies.

Chapter 3

Technical Trading Rules in Australian Financial Markets

3.1 Introduction

Despite the scepticism of some in the academic community, technical analysis and technical trading rules continue to be widely used in the finance industry. In a recent survey of 682 fund managers in five different countries, Menkhoff (2010) found that 87% of respondents place at least some importance on technical analysis, and in a survey of foreign exchange dealers in Germany and Austria, Gehrig and Menkhoff (2006) found that over 95% made some use of technical analysis.[1]

In this chapter I consider the profitability of a large number of alternative parameterisations of 5 classes of technical trading rule using data from the Australian financial markets. In total, I consider 7,846 different rules[2]. These are tested against a benchmark buy-and-hold strategy. To avoid spurious results due to data-snooping, for each asset I test the null hypothesis that the most profitable rule is no more profitable than the benchmark strategy using both the Reality Check test due to White (2000) and the Superior Predictive Ability test of Hansen (2005). While previous studies have considered the profitability of technical trading rules in the Australian markets, they have typically focused on a small number of trading rules. To my knowledge, this is the first study of Australian financial markets to consider such a wide range of trading strategies using established statistical testing methodologies that are robust to data-snooping.

[1]See also Section 3 of Menkhoff (2007) for a review of similar surveys.
[2]The set of rules that I consider is that used by Sullivan et al. (1999) in their analysis of the Dow Jones Industrial Index.

The remainder of this paper is organized as follows: Section 2 discusses the existing literature on technical analysis with particular emphasis on studies of the Australian markets. Section 3 provides an outline of the methodology of the research. Section 4 presents the empirical results of the study. Finally, conclusions are presented in Section 5.

3.2 Previous Studies

The academic research literature has a long history of investigating the profitability of technical trading rules, stretching back at least as far as Cowles (1933). Park and Irwin (2007) provide a comprehensive review of much of this literature which I recommend to the interested reader.[3] Of the 95 studies that they considered, Park and Irwin (2007) found that 56 yielded positive results, 20 studies found negative results, and 19 found mixed results. Accordingly, on face value, the balance of evidence might be taken to favour the proposition that technical trading rules have predictive power. However, it should be noted that many existing studies are open to criticism. In particular, given the wide range of rules that may be tested for any particular financial asset, the charge that much of the apparent evidence in favour of technical trading rule profitability is in fact the result of data-snooping must be taken seriously. In recent years new approaches to multiple hypothesis testing that control the family-wise error rate (Note 4) have been developed. In particular, White (2000) developed the Reality Check test and Hansen (2005) developed the Superior Predictive Ability test. These tests work by considering a large number of test statistics simultaneously, and computing the distribution of the largest statistic. Consequently, they avoid the spurious positive results that occur when standard pairwise tests of equal predictive ability are used over multiple pairs of rules, with evidence of profitability claimed if any individual null hypothesis is rejected. A number of studies of technical trading rule profitability have utilised these tests. Some (e.g.,Hsu and Kuan (2005) ; Metghalchi et al. (2008a)) still find evidence of profitability when data snooping is accounted for. Others (e.g., Marshall et al. (2008)) find no evidence of profitability. A common finding for US markets (e.g., Shynkevich (2012); Qi and Wu (2006); Sullivan et al. (1999)) is that evidence exists of profitability in the first half of the sample, but the evidence is much weaker, or non-existent, in the latter half of the sample.

In contrast to the wealth of studies that have considered technical trading rules in the context of the large northern hemisphere markets, relatively few past studies have considered the Australian markets. The profitability of technical trading rules for Australian

[3]See also Section 4 of Menkhoff (2007).

stock market indices has been considered by Ball (1978); Batten and Ellis (1996); Ellis and Parbery (2005) and Loh (2004). None of these studies found evidence in favour of technical rules. Pavlov and Hurn (2012) consider moving average rules for a cross-section of Australian stocks and report evidence of losses, which they interpret as a contrarian profit. Lento et al. (2007) considers three different parameterizations for three different trading rules for an Australian stock index and finds evidence that two of the nine rules considered generate excess profits. Lee et al. (2001); Olson (2004) and Hawtrey and Nguyen (2006) have considered technical trading rules for the Australian dollar. Lee et al. (2001) found no evidence of profitability. Olson (2004) and Hawtrey and Nguyen (2006) found evidence of profitability in the early part of their samples, but no evidence in the later data.

Overall, the literature provides little empirical support for the contemporary use of technical trading rules in Australian markets. However, it should be noted that the Australian studies cited above each consider a narrow range of trading rules. Theory provides relatively little guidance about the types of rules and parameter values that should be profitable. Consequently, the body of evidence on the profitability of technical trading rules is not complete until a wide range of trading rules and parameterizations have been considered.

The present chapter contributes to the literature on technical trading rules by providing a far more comprehensive empirical analysis of the profitability of technical trading rules than currently exists for the Australian financial markets. I consider the 7,846 different trading rules that were used by Sullivan et al. (1999) in their analysis of the Dow Jones Industrial Index. These consist of a range of parameterizations of each of 5 well-known technical trading rules. I apply each of these rules to a value-weighted stock index, 6 individual stocks (3 large-cap; 3 small-cap), 3 exchange rates relative to the Australian dollar, and 3 interest rate futures contracts over the time period January 1993 to December 2012 and to 4 sub-periods. In each case I use the Reality Check test of White (2000) and the Superior Predictive Ability test of Hansen (2005) to compute the probability that the most profitable trading rule generates profits no better than a buy and hold strategy.

3.3 Methodogy

In this section, I describe the data that I used in the study, the trading rules that I considered, and the statistical methodology that I applied.

3.3.1 Data

My data set spans the period 1st, January 1993 to 31st December 2012[4]. In addition to considering the complete span of data, I also conduct the analysis for 4 sub-periods: 1st January 1993 to 31st December 1997, 1st January 1998 to 31st December 2002, 1st January 2003 to 31st December 2007, and 1st January 2008 to 31st December 2012. A common finding in the literature (e.g., Sullivan et al., 1999; Taylor, 2014) is that the profitability of technical trading rules varies over time in the US market. A consideration of sub-periods allows for this possibility in the Australian markets. My variables are as follows:

ASX: The ASX200 value-weighted stock index of the largest 200 firms by capitalisation listed on the Australian Securities Exchange.

BHP: BHP Billiton Limited (single stock, large-cap).

CBA: Commonwealth Bank of Australia (single stock, large-cap).

WES: Wesfarmers Limited (single stock, large-cap).

APN: APN News and Media Limited (single stock, small-cap).

BPT: Beach Energy Limited (single stock, small-cap).

PPT: Perpetual Limited (single stock, small-cap).

USD: Australian dollar / US dollar exchange rate.[5]

JPY: Australian dollar / Japanese Yen exchange rate.

GBP: Australian dollar / British Pound exchange rate.

BB90: ASX 90 Day Bank Accepted Bill Futures.

TB3Y: ASX 3 Year Treasury Bond Futures.

TB10Y : ASX 10 Year Treasury Bond Futures.

The large-cap stocks were all in the top 20 stocks on the Australian market by capitalization. The small-cap stocks all lie outside the top 100 stocks by capitalization. All data are taken from the Thomson-Reuters Datastream database[6].

[4]Our data set starts on 1st of January 1993. We use the first 250 days to generate the trading signals for the first trading day of our simulation, which is the 16/Dec/1993. This rule applied to sub-period analysis

[5]The interest rate differential between two countries is reflected on the trading return calculations . See pp.8-9 of the Hsu and Taylor (2014) and p.2141 of the Qi and Wu (2006).

[6]The family-wise error rate is defined as the probability of rejecting at least one true null hypothesis in a set of multiple hypothesis tests.

3.3.1.1 Trading rules

The trading rules that I use are those considered by Sullivan et al. (1999). I provide a description of each class of rule below. For more precise details, including the range of parameters used for each class of rule and references, the reader is referred to Sullivan et al. (1999) Section III and their Appendix A.

Filter rules: Filter rules require the investor to buy and hold an asset if its daily closing price moves up by more than a predefined threshold (x). The position is held until the daily closing price falls beneath the subsequent highest price by x. At that point, the asset is simultaneously sold and shorted.[7] The short position is maintained until the price increases by more than x from its subsequent lowest daily closing price, at which point the short position in reversed and the asset purchased. Three variations on the basic filter rule are also considered:

[1] Allow for neutral positions to be held if the increase or decrease in the price is more than another predefined threshold (y, where y<x).

[2] Force each position to be held for a predefined minimum number of days (c).

[3] Redefine high (low) prices to be higher (lower) than the prices for the previous e days, where e is a predefined number.

In the tables of results in Section IV, the parameterised filter rules are denoted FR(x,e,c,y). In total, I consider 497 different filter rules made up from all possible combinations of parameters considered by Sullivan et al. (1999).[8]

Moving average rules: A moving average rule is implemented by constructing two moving averages[9]-a short-ordered moving average and a long-ordered moving average-where the long-ordered moving average is necessarily of higher order than the short-ordered moving average. Buy and sell signals are generated when the short-ordered moving average crosses the long-ordered moving average. Thus, when the short-ordered moving average is greater than the long-ordered moving average, the investor should be long, and when the short-ordered moving average is less than the long-ordered moving average, the investor should be short in the asset. Note that the short-ordered moving

[7] Note that the small-cap stocks that I consider are not available for short-selling on the ASX. However, at the time of writing, there exist private firms that offer contracts for difference which allow an investment equivalent to a short position on these stocks to be held

[8] See their Appendix A for a list of all the parameter combinations considered.

[9] The moving average of order n is the arithmetic mean of the closing prices from the previous n days including the current day.

average could be of order 1, in which case the trading signals are generated when the asset price crosses the long-ordered moving average. Three variations on the basic moving average rule are considered:

[1] Instead of the trading signal being generated at the time that the two moving averages cross, it is generated when the moving averages have crossed and now differ by more than a fixed amount (b).

[2] The trading signal is only generated when the moving averages cross and remain crossed for a predefined number of days (d).

[3] All changes in positions may be held for a minimum of c days irrespective of the trading signals generated during that time.

In the tables of results in Section IV, the parameterised moving average rules are denoted MA(n,m,b,d,c). In total, I consider 2,049 different moving average rules.

Support and resistance rules: Rules based on support and resistance lines involve buying the asset when the closing price exceeds a local maximum and shorting when the closing price is less than a local minimum. The maxima (minima) may be defined as the maximum (minimum) price over the previous n days. Alternatively, the maxima (minima) may be defined as the most recent closing price that is greater (less) than the previous e closing prices. Other variations on the rule are:

[1] To require that any position is held for a minimum of c days.

[2] To ignore a signal until it has been maintained for a minimum of d days.

[3] To require the difference between the price and the maximum or minimum to exceed a predefined percentage (b) before a trading signal is recorded.

In the tables of results in Section IV, the parameterised support and resistance rules are denoted SAR(n,e,b,d,c). In total, I consider 1,220 support and resistance rules.

Channel breakout rules: A channel is defined as a situation in which the highest closing price over the previous n days is within x percent of the lowest closing price over the previous n days. A channel breakout occurs when the current closing price lies outside the channel. A buy signal occurs when the current price exceeds the channel. A sell signal occurs when the current price is less than the channel. All positions are held for a fixed number of days (c). A variation on the basic channel breakout rule is to require that the difference between the current price and the border of the channel is more than b percent before a trading signal is recorded. In the tables of results in Section IV, the parameterised channel breakout rules are denoted CBO(n,x,b,c). I consider a total of 2,040 channel breakout rules.

On-balance volume: An on-balance volume indicator is constructed by taking the cumulative sum of volumes from days in which the closing price increases and subtracting the cumulative sum of volumes from days in which the closing price decreases. The moving average rules described above are then applied to the on-balance volume indicator to generate trading signals. In the tables of results in Section IV, the parameterised on-balance volume rules are denoted OBV(n,m,b,d,c) where the parameters refer to the construction of the moving averages and are defined above. In total, I consider 2,040 on-balance volume moving averages.

3.3.1.2 Statistical Methodology

Each of the above trading rules is applied to every asset over the complete sample and for each sub-sample and the returns are computed. In cases where a trading rule dictates that the position should be neither short nor long, the funds in the portfolio are invested at an interest rate equal to the overnight cash rate that is targeted by the Reserve Bank of Australia. Similarly, when an asset is shorted, it is assumed that the cost of maintaining the short position is equal to the overnight cash rate. The data for the cash rate are taken from Thomson-Reuters Datastream. I assume that all other trading costs are zero. While this assumption is somewhat unrealistic, it simplifies the analysis since it circumvents the fact that trading costs may vary between traders, across assets and over time. Furthermore, the effect of trading costs on profitability is only of interest once it has been established that trading rules are indeed profitable, which has not yet been done conclusively for the Australian markets. The returns are also computed for a benchmark portfolio that consists of buying and holding an asset until the end of the (sub-) sample period.

For each asset in each sub-sample, and for the complete sample, I compute three statistics. The first statistic is the p-value for the Diebold and Mariano (1995) test for equal predictive ability. The null hypothesis for the Diebold-Mariano test that I conduct is

$$H_0 : E(r_{max,t+1} - r_{0,t+1}) = 0$$

where $r_{max,t+1}$ is the return of the most profitable trading rule and $r_{0,t+1}$ is the return from the benchmark buy-and-hold strategy. The test statistic is

$$d = \frac{|(r_{max,t+1} - r_{0,t+1})|}{\sqrt{var(r_{max,t+1} - r_{0,t+1})}}$$

The p-value `p_DM` is then computed by integrating the relevant t-distribution beyond ±d. Note that, my application of the Diebold-Mariano test involves choosing the most profitable of the 7,846 trading strategies, and comparing its returns to the benchmark strategy. Consequently, it is likely to be oversized, and it is computed only to determine whether data-snooping bias leads to misleading results in these applications.

The second statistic that I compute is White's Reality Check statistic. The null hypothesis for this test is

$$H_0 : \max_{k=1,\ldots,M} \mu_k \leq 0 \tag{3.1}$$

where $\mu_k = E(r_{max,t+1} - r_{0,t+1})$. The test statistic is constructed by first computing for each trading rule the performance measure

$$f_{k,t+1} = r_{k,t+1} - r_{0,t+1} \tag{3.2}$$

for $k = 1, \ldots M$, where M is the number of trading rules. The test statistic is computed as

$$\bar{V}_n = \max_{k=1,\ldots,M} \sqrt{n}\bar{f}_k \tag{3.3}$$

where$\bar{f}_k$=$\sum_{t=1}^{n} f_{k,t}/n$ and n is the number of observations in the sample.

To find an asymptotic p-value for $\bar{V}_n$, White (2000)suggested implementing the stationary bootstrap method of Politis and Romano (1994). In the stationary bootstrap, each pseudo-sample is constructed by randomly drawing contiguous blocks of observations from the time series and joining them together to form a series of the same length as the observed time series. Excess observations in the last drawn block are discarded. The starting index for each block is drawn from a uniform distribution, and the block length is independently drawn from a geometric distribution. Following Sullivan et al. (1999), I parameterise the geometric distribution so that the expected block length is 10. Several authors report results that are quite insensitive to the value chosen for the expected block length (e.g., Sullivan et al. (1999); Hsu and Kuan (2005); Metghalchi et al. (2008a); Hsu et al. (2010)). Consequently, I do not experiment with this value. I set the number of bootstrap(B) is 1000[10].For each bootstrap sample, the returns from the benchmark buy-and-hold strategy $r^*_{0,t+1}$ and from each of the technical trading rules $r^*_{k,t+1}$, $k = 1, \ldots, M$ are calculated over the relevant sample period and for each trading rule I compute the bootstrapped performance statistic.

$$f^*_{k,t+1} = r^*_{k,t+1} - r^*_{0,t+1} \tag{3.4}$$

Denote $\bar{f}^*_k(b)=\sum_{t=1}^{n} f^*{}_{k,t}(b)/n$. I estimate the empirical distribution of $\bar{V}^*_n$ with the relations:

$$\bar{V}^*_n(b) = \max_{k=1,\ldots,M} \sqrt{n}\,(\bar{f}^*_k(b) - \bar{f}_k), \tag{3.5}$$

where $b = 1, \ldots, B$ and B is the number of bootstrap simulations. White's reality check p-value is estimated by

$$p_{RC} \equiv \sum_{b=1}^{B} \frac{\mathbf{1}(\bar{V}^*_n > \bar{V}_n)}{B} \tag{3.6}$$

where $\mathbf{1}(\cdot)$ takes a value of 1 when its argument is true, and zero otherwise. The null hypothesis is rejected if the p-value is less than a given significance level.

The third statistic that I compute is the p-value for the Superior Predictive Ability test of Hansen (2005). Hansen observed that the null hypothesis of White's Reality Check statistic is a composite hypothesis and that the null probability density function of the test statistic is computed under the configuration that is least favorable to the alternative hypothesis. This causes the test to perform poorly in cases in which the analysis includes many poorly performing models in addition to some that perform well. Accordingly, Hansen (2005)proposed two modifications of the Reality Check test.

Firstly Hansen (2005) proposed that a studentized test statistic be used.

$$\tilde{V}_{SPA} = \max(\max_{k=1,\ldots,M} \frac{\sqrt{n}\,\bar{f}_k}{\hat{\omega}_k}, 0), \tag{3.7}$$

where $\hat{\omega}^2_k$ is a consistent estimator of $var(\sqrt{n}\,\bar{f}_k)$, computed from the stationary bootstrap. Secondly, he proposed a sample-dependent computation of the null distribution that results in the following bootstrap statistics.

[10]We follow ,most of the literature by setting B=1000 (see, e.g.White (2000),Bajgrowicz and Scaillet (2012) and Hsu et al. (2014)

$$\tilde{V}^*_{SPA}(b) = \max(\max_{k=1,\dots,M} \frac{\sqrt{n}\,(\bar{f}^*_k - \bar{f}_k)\mathbf{1}(\bar{f}_k - \omega_k\sqrt{2log\,log\,n})}{\hat{\omega}_k}, 0), b = 1, \dots, B. \quad (3.8)$$

By counting $\bar{V}^*_{SPA} > \bar{V}_{SPA}$, p-value can be calculated as

$$p_{SPA} \equiv \sum_{b=1}^{B} \frac{\mathbf{I}(\bar{V}^*_{SPA} > \bar{V}_{SPA})}{B} \quad (3.9)$$

3.4 Empirical Results

The results for the full sample period with zero transactions costs are presented in Table 3.1. The column "Return" provides the return earned by the most profitable of the 7,846 trading rules over the sample period.[11] The column "Best rule" indicates which rule generated the highest return. The notation used for the rules is explained in Section 3.3. The column "Bench" provides the return earned by the benchmark buy-and-hold strategy. For the 13 assets considered, a technical trading rule was more profitable than the benchmark strategy over the sample period for 8 assets. For 3 of the 5 assets for which the benchmark strategy is superior, a filter rule was the most profitable of the technical trading rules. In the (more interesting) cases in which a technical trading rule was most profitable a filter rule was superior for 3 assets, an on-balance volume rule was superior for 2 assets, channel breakout rules were the most profitable for 2 assets and a support and resistance rule was superior for the remaining asset. It should be noted however that for only 2 assets (CBA and APN) was the pairwise difference in the returns of the best technical rule and the benchmark strategy statistically significantly different from zero at the 5% significance level according to the Diebold-Mariano test (the column pDM contains the p-values for this test). Furthermore, since the p-values for the Reality Check (pRC) and the Superior Predictive Ability (pSPA) test are all quite large, it is clear that once data snooping is considered in the construction of the test, there is no evidence that any of the trading rules outperforms the benchmark. This constitutes the main finding of this chapter that while it is possible to find technical trading rules that have been profitable relative to a benchmark buy-and-hold strategy for some assets over the sample period, once the effects of data snooping are properly accounted for, there is no evidence that any of the 7,846 technical trading rules that I consider outperform the benchmark buy-and-hold strategy[12].

[11] Daily log return is converted into annualized return and every return on this thesis is annualized.

[12] Since the alternative hypotheses are one-sided, and the null hypotheses are not rejected, the addition of transactions costs would not change the results of the hypothesis tests. For this reason, transactions costs were not considered in the simulations.

Table 3.1: Full period : Jan. 1993 to Dec. 2012

Indice Name	Best Rule	Bench	Return	pDM	pRC	pSPA
ASX	AFR(0.005,3,0,0)	4.22	8.37	0.1823	0.9001	0.9081
BHP	OBV(250,75,1,0.001)	4.94	20.25	0.1001	0.7010	0.8751
CBA	SAR(0,4,1,0.01)	10.23	25.19	0.0220	0.3918	0.4616
WES	AFR(0.035,0,50,0)	8.93	15.71	0.2108	0.9639	0.9745
APN	MA(100,5,0,2)	-8.37	25.99	0.0013	0.0723	0.1432
BPT	OBV(150,100,1,0.04)	15.07	47.76	0.0195	0.6925	0.5048
PPT	OBV(150,152,1,0.01)	10.20	20.44	0.1511	0.8816	0.9089
GBP	MA(30,10,1,0.05)	1.67	6.05	0.0417	0.8335	0.6012
JPY	AFR(0.12,4,0,0,)	2.13	7.40	0.0526	0.7158	0.5897
USD	CBO(20,0.03,50,0.01)	0.95	10.29	0.0277	0.4492	0.4023
BB90	AFR(0.05,4,0,0,)	0.00	0.01	0.0166	0.3854	0.3186
TB3Y	OBV(200,1,0,0,)	0.00	0.01	0.0789	0.7244	0.7682
TB10Y	OBV(200,150,10,0)	0.00	0.01	0.1129	0.7976	0.8359

We applied Sullivan et al. (1999)'s five rules; AFR(Alexander's Filter Rule), CBO(Channel Breakouts), MA(Moving Average), SAR(Support and Resistance Rule), OBV(On Balance Volume). Best rule means name of the outperforming rule and it's input parameters. Bench and Return denote annual mean returns (%) after adjustment for transaction costs, respectively. pRC and pSPA denote White's and Hansen's nominal p-values, while pDM is obtained from applying only to the best rule or a single rule, thereby ignoring the effect of data snooping.

Table 3.2 provides the results for each of the subsamples assuming zero transactions costs. As was the case for the full sample, in the subsamples the best trading rule often generated a superior profit to the buy-and-hold benchmark strategy, but the pairwise Diebold-Mariano test rejects the null hypothesis that the superior technical trading rule is no better than the benchmark strategy in only a few cases. Note that there is little consistency across the subsamples and the full sample with respect to the best trading rules for each asset and whether the best trading rule is superior to the benchmark. Furthermore, there is only a single asset in a single subsample for which the Reality Check and Superior Predictive Ability tests reject the null hypothesis that the best technical trading rule beats the benchmark at the 5% significance level (a channel breakout rule for APN in the last subsample). Since for both tests the p-values are greater than 0.01 and, since I have conducted multiple tests for multiple assets, I do not interpret the result as evidence in favour of technical trading rule profitability relative to the benchmark strategy.

3.5 Conclusions

By considering 7,846 different technical trading rules applied to 13 different Australian financial assets, the research reported in this chapter provides a far more comprehensive consideration of the profitability of technical trading rules in the Australian markets than is available in the prior literature. Nonetheless, my results are consistent with prior

Table 3.2: P-values by Subsample Periods

	Best rule	Bench	Return	pDM	pRC	pSPA
Subsample period 1: Jan. 1993 to Dec. 1997						
ASX	MA(150,15,1,0.03,0)	5.75	16.97	0.0902	0.7664	0.7977
BHP	OBV(250,75,1,0.03,0)	6.41	32.61	0.0326	0.5127	0.6755
CBA	AFR(0.005,1,0,0,0)	16.26	36.53	0.0238	0.6331	0.5248
WES	AFR(0.005,4,0,0,0)	15.38	32.08	0.1086	0.8674	0.8694
BPT	OBV(150,20,1,0.015,0)	13.10	89.52	0.0920	0.7146	0.5633
PPT	OBV(200,125,1,0.03,0)	15.40	24.81	0.1960	0.9652	0.9639
APN	OBV(100,20,0,0,4)	9.57	26.14	0.0765	0.8952	0.8368
GBP	CBO(5,0.03,50,0.02,0)	-3.93	10.00	0.0134	0.4910	0.3806
JPY	MA(30,1,1,0.05,0)	-1.09	8.33	0.0284	0.4797	0.3087
USD	CBO(25,0.03,50,0,0)	3.20	19.16	0.0169	0.5109	0.2978
BB90	AFR(0.005,2,0,0,0)	0.00	0.02	0.0501	0.3884	0.6242
TB3Y	MA(200,150,0,0,4)	0.00	0.02	0.0356	0.5459	0.5298
TB10Y	MA(100,30,0,0,5)	0.00	0.02	0.0672	0.6638	0.7192
Subsample period 2: Jan. 1998 to Dec. 2002						
	Best rule	Bench	Return	pDM	pRC	pSPA
ASX	CBO(10,0.03,25,0.001,0)	3.44	14.16	0.0957	0.7196	0.7891
BHP	OBV(250,200,1,0.03,0)	-11.23	55.26	0.0544	0.2002	0.5407
CBA	MA(150,15,1,0.03,0)	11.44	29.09	0.1153	0.8348	0.8821
WES	MA(150,100,1,0.04,0)	21.58	37.22	0.0926	0.9202	0.8645
APN	MA(75,5,0,0,2)	5.51	23.52	0.1603	0.9089	0.9112
BPT	OBV(150,20,1,0.015,0)	44.74	143.01	0.0153	0.5299	0.2895
PPT	MA(150,15,1,0.03,0)	23.07	37.41	0.1786	0.9604	0.9608
GBP	MA(125,15,1,0.015,0)	-1.32	14.73	0.0182	0.5303	0.3152
JPY	MA(150,30,50,0,0)	-2.02	10.63	0.0725	0.552	0.5003
USD	CBO(15,0.03,50,0,0)	-1.81	14.27	0.0311	0.4906	0.3879
BB90	OBV(100,10,0,0,5)	0.00	0.01	0.0116	0.3564	0.2808
TB3Y	SAR(0,200,5,0.015,0)	0.00	0.02	0.0481	0.4921	0.4203
TB10Y	OBV(250,1,1,0.01,0)	0.00	0.01	0.0191	0.5938	0.5006
Subsample period 3: Jan. 2003 to Dec. 2007						
	Best rule	Bench	Return	pDM	pRC	pSPA
ASX	OBV(250,1,50,0,0)	16.17	16.64	0.4192	0.9999	0.9987
BHP	OBV(10,2,50,0,0)	32.95	37.97	0.2891	0.9974	0.9917
CBA	SAR(25,0,5,0,4)	18.86	24.73	0.1701	0.9833	0.9501
WES	SAR(25,0,10,0,0)	10.48	26.37	0.0769	0.8477	0.8401
APN	MA(125,1,0,0,3)	-5.65	27.39	0.0183	0.2261	0.3544
BPT	OBV(250,200,1,0.005,0)	31.76	58.56	0.1436	0.9211	0.9419
PPT	OBV(200,75,1,0.001,0)	15.67	27.17	0.1852	0.9613	0.9744
GBP	MA(30,25,1,0.005,0)	0.55	6.97	0.1207	0.8974	0.8004
JPY	MA(10,2,10,0,0)	4.11	9.28	0.2072	0.9339	0.9214
USD	MA(30,10,1,0.04,0)	4.96	12.57	0.1762	0.8782	0.9387
BB90	MA(75,2,0,0,5)	0.00	0.01	0.004	0.0721	0.0748
TB3Y	SAR(150,0,5,0.05,0)	0.00	0.01	0.0063	0.1685	0.2453
TB10Y	SAR(150,0,5,0.05,0)	0.00	0.01	0.0295	0.5164	0.5703
Subsample period 4: Jan. 2008 to Dec. 2012						
	Best rule	Bench	Return	pDM	pRC	pSPA
ASX	AFR(0.01,10,0,0,0)	6.14	21.32	0.0709	0.7756	0.7281
BHP	AFR(0.01,15,0,0,0)	8.19	46.06	0.0166	0.5245	0.4848
CBA	SAR(0,4,1,0.01,0)	10.32	39.42	0.0724	0.6036	0.7477
WES	OBV(150,20,1,0.015,0)	15.14	28.50	0.2318	0.9627	0.9810
APN	SAR(25,0,1,0.005,0)	-34.01	79.02	0.0018	**0.0308**	0.0620
BPT	OBV(150,15,1,0.005,0)	15.55	47.52	0.1651	0.8881	0.9432
PPT	SAR(0,200,1,0.015,0)	2.19	43.73	0.0862	0.6851	0.7225
GBP	MA(5,2,1,0.01,0)	8.91	11.54	0.3258	0.9933	0.9818
JPY	MA(30,20,0,0,5)	10.45	12.72	0.4179	0.9908	0.9885
USD	AFR(0.015,15,0,0,0)	9.15	24.01	0.0640	0.7605	0.7802
BB90	OBV(50,30,50,0,0)	0.00	0.01	0.0512	0.6912	0.6145
TB3Y	SAR(50,0,10,0,3)	0.00	0.02	0.0175	0.4744	0.4708
TB10Y	OBV(250,5,0,0,2)	0.00	0.01	0.0672	0.6762	0.7730

We applied Sullivan et al. (1999)'s five rules; AFR(Alexander's Filter Rule), CBO(Channel Breakouts), MA(Moving Average), SAR(Support and Resistance Rule), OBV(On Balance Volume). Best rule means name of the outperforming rule and it's input parameters. Bench and Return denote annual mean returns (%) after adjustment for transaction costs, respectively. pRC and pSPA denote White's and Hansen's nominal p-values, while pDM is obtained from applying only to the best rule or a single rule, thereby ignoring the effect of data snooping.

studies, both for Australian markets and for those of other countries, that have either found no evidence of profitability (e.g.,Ball (1978); Batten and Ellis (1996); Ellis and Parbery (2005); Loh (2004); Marshall et al. (2008) or have found some evidence, but not in recent time periods (e.g., Olson (2004); Hawtrey and Nguyen (2006); Shynkevich (2012); Qi and Wu (2006); Sullivan et al. (1999)). For each asset that I considered, I was able to find a technical trading rule that provided a superior profit to the buy-and-hold strategy in at least one sub-sample or the whole sample. This may be the reason that technical trading rules continue to be used widely in the Australian finance industry. Nonetheless, as the results presented above show, for the cases that I have considered, once the range of models that one must search to find profitable rules has been properly accounted for in the construction of statistical tests, there is no statistically significant evidence that technical trading rules generate superior returns to a simple buy-and-hold strategy at conventional levels of significance in the Australian markets.

Chapter 4

The Profitability of a New Generation of Technical Trading Rules : Evidence from the Equity Market

4.1 Previous Studies on Technical Trading Rules

According to Park and Irwin (2007) and Fang et al. (2014) studies on equity markets published before the early 1990s failed to find profitability from technical trading rules[1].

However, Brock et al. (1992)(BLL) found profitabiliy in trading rules applied to the Dow Jones Industrial Average (DJIA) from 1897 to 1986, with 26 trading strategies based on the moving average rule and trading range break rules. With the addition of three more rules (channel breakouts, on balance volume, support and resistance rules) on top of the Brock et al. (1992) rules, Sullivan et al. (1999) (STW) generated a universe of 7,846 trading strategies and revisited the DJIA to investigate whether findings of trading rule profitability were due to data-snooping. They found Brock et al. (1992)'s findings of predictability were robust with respect to data snooping. They also found their best trading rule was superior to that of Brock et al. (1992), but was not profitable for the out-of-sample period, possibly due to the enhanced market efficiency of the later period.[2]

[1]See Section 3.1 of Park and Irwin (2007) and p.31 of Fang et al. (2014)

[2]On the last paragraph of the Sullivan et al. (1999)'s conclusion, they mentioned "Third, it is possible that, historically, the best technical trading rule did indeed produce superior performance, but that, more recently, the markets have become more efficient and hence such opportunities have disappeared."

As Brock et al. (1992) didn't include transaction costs in their study, Bessembinder and Chan (1998) studied whether the return predictability identified by Brock et al. (1992) was attributable to measurement errors (e.g, transaction costs and non-synchronous trading[3]) and explained the reason for the predictability of the Brock et al. (1992) was not from the non-synchronous trading but from the absence of transaction costs in their trading simulation. Using the Brock et al. (1992) rules, Day and Wang (2002) also investigated the non-synchronous trading issue on the DJIA and found the non-synchronous trading risk existed from 1962 to 1986 but disappeared in a later sub-period (1987 to 1997) due to the increased liquidity in the USA market after 1980s.

Bajgrowicz and Scaillet (2012) re-investigated the profitability of the Sullivan et al. (1999) rules for the DJIA using a range of transactions costs and a statistical methodology that controls the false discovery rate, and found that technical trading rules did not outperform a buy-and-hold benchmark after 1986. Persistence analysis using out-of-sample tests confirmed this lack of net profitability.

In addition, numerous studies that have controlled for data-snooping have found evidence of trading rule profitability. Marshall et al. (2008) investigated markets for 15 US commodities (three grains, four softs[4], three metals, two energy, soy-bean oil, live cattle and feeder cattle) and found one (oats futures) with data-snooping-free profit from the full $(1984 - 2005)$ and the first sub-period$(1984 - 1994)$ but no profitability from the second sub-period$(1995 - 2005)$. Hsu and Kuan (2005) tested the DJIA, S&P500,NASDAQ and Russell2000 index and found significant profitable rules in young markets (NASDAQ, Russell2000) but not in mature markets (DJIA, S& P 500). Park and Irwin (2010) tested 17 US commodity futures (three grains, two meats, three softs, two metals, three currencies, two interest rates, crude oil and the S&P 500) markets and found only the Eurodollar and the Yen were profitable in the full period $(1985 - 1994)$. Yamamoto (2012) tested 207 individual stocks in the Nikkei225 and found no data-snooping-free outperforming rules in the Japanese equity market. Bajgrowicz and Scaillet (2012) found no profitability of DJIA with Sullivan et al. (1999) rules, after application of the transaction costs, using a methodology that controls the False Discovery Rate (FDR).Shynkevich (2012) tested the predictability of the small cap sector and technology industry sector sub-indices in the US equity market. With no application of transaction costs, they found data snooping robust profitability of six small cap

[3]One of the key assumptions of technical trading rules is that transactions must be executed whenever trading signals are generated (i.e., synchronous trading). In practice, there exists the possibility of failure in execution due to the illiquidity of the market; this is so called non-synchronous trading. In general, the likelihood of non-synchronous trading on advanced markets included in the DJIA is very low compared to emerging markets.

[4]In commodity futures market, the term softs typically means grown products, such as coffee, cocoa, sugar, corn, wheat, soybean and fruit.

sector indices and two technology industry indices for the first sub-period (18/10/1995 – 25/02/2003) but none for the second period (26/02/2003 – 30/06/2010.

Numerous authors (White (2000); Ready (2002); Hsu and Kuan (2005); Neely et al. (2009); Schulmeister (2009); Park and Irwin (2010); Neely and Weller (2011)) have asserted that the elimination of profitability during the 1980s is due to the markets' adaptation to specific rules. Once the profitability of a trading rule becomes widely known and its use becomes widespread, the market anomaly that it exploits vanishes. This proposition highlights the importance of research that considers a wide range of technical trading rules. If trading rule profitability self-destructs once it becomes widely known that it exists, then rules that have received little or no attention in the research literature might be expected to retain their profitability after the well-researched classical rules have lost theirs. As detailed in the next section, the literature to date has largely focussed on a narrow set of technical trading rules, so the extent to which the decline in profitability is shared across rules is unknown. The primary motivation of the present chapter is to consider a much broader range of rules than has appeared in the prior literature, and to determine whether the documented elimination of profitability that occured during the 1980s is common to all rules, or just to the narrow range that have been the subject of prior academic research.

4.2 Technical Trading Rules and Data

In this section, I discuss previous studies of technical trading rules and introduce a set of trading rules that are known to traders but which have received little or no attention in the academic literature.

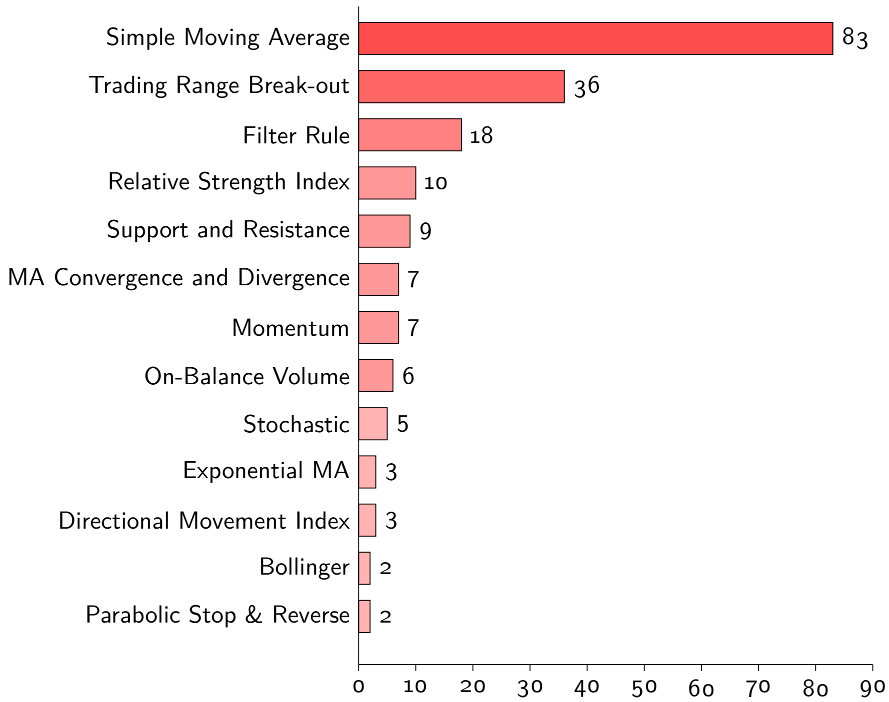
4.2.1 Technical Trading Rules in the Existing Literature

I used Google Scholar to search for papers on technical trading rule profitability published between 1992 and 2013.[5]. The 88 papers that I found considered a total of 32 different technical trading rules. Of these, 18 rules appeared in only one paper and these are listed in Table 4.1. The 13 trading rules that appeared in more than one paper are listed in Figure 4.1, along with the number of papers in which they appear. It is clear from Figure 4.1 that the literature on technical trading rule profitability has focused on a narrow range of rules. Simple Moving Average rules have appeared in 83 of the 88 papers that I considered. Trading Range Break rules appear in 36 papers, and Filter

[5]That is, papers that were published between the appearance of Brock et al. (1992) and the commencement of my research. A full list of the papers is presented in Appendix 4.7. Readers interested in the literature prior to 1992 are referred to the survey by Park and Irwin (2007)

rules appear in 18 papers. The next most popular rule (the Relative Strength Index) appears in only 10 papers, and the popularity of rules continues to decline after this. Additionally, Figure 4.2 is a histogram which displays the distribution of the number of different rules that appeared in each of the 88 papers surveyed. Most of the papers applied only one rule (32 papers) or two rules (36 papers) and only 3 papers considered more than 5 rules. To avoid misunderstanding, I stress that many authors consider a large number of different parameterisations of each rule. For example Sullivan et al. (1999) analyse 7,846 different parameterisations of the 5 trading rules that they consider. The paper that considers the largest number of rules is Park and Irwin (2010), who analyse the profitability of 14 different rules. As can be seen in Figure 4.2, however, this is exceptional.

FIGURE 4.1: Summary of Rules Applied in Previous Studies

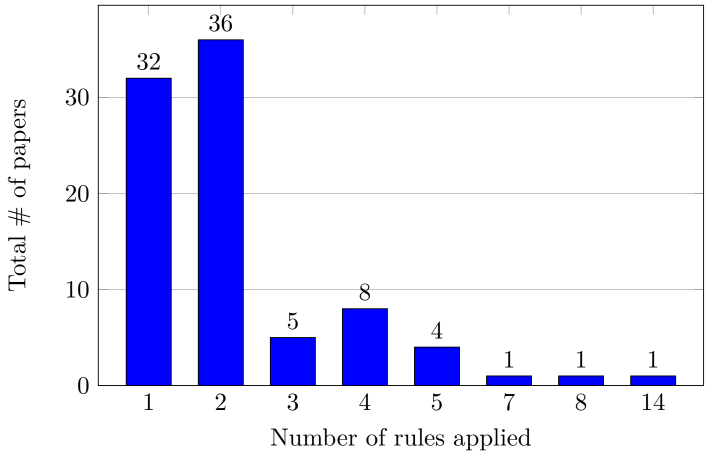


This figure summarize the trading rules applied from previous literature. Among them the most popular rules, Simple Moving Average rules have appeared in 83 of the 88 papers.

4.2.2 Technical Trading Rules Considered in this Chapter

A primary objective of my research was to extend the analysis of trading rule profitability beyond the narrow range of rules that have been considered in the academic literature, and to consider rules that are popular among practitioners. To this end, I

FIGURE 4.2: Number of Rules Applied per Paper



This figure is another summarize on the number of trading rules applied each paper.Most of the paper applied one or two rules for return predictability analysis.

TABLE 4.1: 18 Rules only applied once in the Literature since 1992

	Full Name	Abbreviation	This Chapter	Paper Applied
1	Adaptive MA	AMA	No	Ellis and Parbery (2005)
2	Directional Indicator	DRI	Yes	Lukac et al. (1988)
3	Directional Movement	DRM	Yes	Lukac et al. (1988)
4	Directional Parabolic	DRP	No	Lukac et al. (1988)
5	Ease of Movement	EMV	Yes	Batten and Ellis (1996)
6	MACD Histogram	MACDH	No	Metghalchi et al. (2012a)
7	Improved MA	IMA	No	Metghalchi et al. (2012b)
8	Linear Regession Slope	LRS	Yes	White (2000)
9	Long Short Channel	LSO	No	Lukac et al. (1988)
10	MII Price Channel	MII	No	Lukac et al. (1988)
11	Money Flow Index	MFI	Yes	Metghalchi et al. (2012a)
12	Momemtum Strategy in Price	MSP	Yes	Hsu and Kuan (2005)
13	Momemtum Strategy in Volume	MSP	No	Hsu and Kuan (2005)
14	Neural Networks	NN	No	Gencay (1998)
15	Price Volume	PV	No	Batten and Ellis (1996)
16	Reference Deviation	RD	No	Lukac et al. (1988)
17	Range Quotient	RQ	No	Lukac et al. (1988)
18	Weighted MA	WMA	Yes	Batten and Ellis (1996)

We searched trading rules ever applied to academic research since 1992.We find the number of rules previously used were 18 rules and "No" means the rule is no included in this study.

collected rules from popular websites for traders[6] , and from software packages written in Matlab(MATLAB (2014)) and R (R Core Team (2013)).[7] In total, I collected 54 different trading rules. I classified my rules into four groups: trend, momentum, volatility and volume.[8]. A list of the rules in each group is presented in Table 4.2.

[6] I recommend http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators and http://www.barchart.com/education/std_studies.php

[7] R TTR package of Ulrich (2013)and Technical Analysis Toolbox of the MATLAB (2014) are downloadable free from http://cran.r-project.org/web/packages/TTR/index.html and http://www.mathworks.com/matlabcentral/fileexchange/10573-technical-analysis-tool

[8] Bold fonts mean five classical rules on Sullivan et al. (1999)

Table 4.2: Technical Trading Rules Applied

	Trend	Momentum	Volume
1	Average directional index (ADX)	Aroon (ARN)	Ease of Movement (EMV)
2	Allegator (ALLE)	Center of Gravity(COG)	Force Index (FI)
3	**Channel Break Out (CBO)**	Chande Momentum Oscillator(CMO)	Money Flow Index (MFI)
4	Commodity Channel Index(CCI)	Coppock Curve(COP)	**On-Balance Volume (OBV)**
5	Double Exponential MA (DEMA)	Cyber Cycle Ocillator (CYC)	
6	Exponential MA (EMA)	Demarker (DMK)	
7	**Filter Rule (FTR)**	Detrend Price Oscillator(DPO)	**Volatility**
8	Moving Average Convergence/Divergence (MACD)	Entropy (ETRP)	Average True Range (ATR)
9	Moving Average Convergence/Divergence4 (MACD4)	Elder Ray Indicator (ERI)	Bollinger Bands (BB)
10	Pentuple EMA (PEMA)	KDJ Lines (KDJ)	Keltner Channel (KELT)
11	Quadruple EMA(QEMA)	Linear Regression Index (LRI)	
12	**Simple Moving Average (SMA)**	Laguerre RSI (LRSI)	
13	Smoothed SMA (SSMA)	Price Momentum Oscillator (PMO)	
14	SONAR (SNR)	Percentage Price Oscillator (PPO)	
15	**Support and Resistance(SAR)**	Range Expansion Index (REI)	
16	Triple EMA (TEMA)	Relative Strength Index (RSI)	
17	Triple Exponential Smoothing (TRIX)	Relative Vigor Index (RVI)	
18	True Relative Strength Index (TRSI)	Stochastic Oscillator (STO)	
19	True Strength Index (TSI)	Stochastic CCI (SCCI)	
20	Variance Ratio (VR)	Stochastic CGI (SCGI)	
21	Vortex Indicator (VI)	Stochastic RSI (SRSI)	
22	Wilder MA(WDMA)	Stochastic RVI (SRVI)	
23		True strength index (TSI)	
24		Ultimate Oscillator (ULTI)	
25		Williams %R (WPR)	

We collect 48 rules which are regarded as "Trend" which indicate bullish and bearish market, "Momentum" which is for finding selling and buying timing,"Volume" genrerate signals from volume information, not from price movements and lastly,"Volatility" indicator show the speed of market movements or expected price moving ranges.

Trend indicators give the direction of current market trend: up, down or sideways. The most popular trend indicators are Simple Moving Averages (SMA), which compare smoothed past prices to current market prices and recommend buying (selling) if the current price is higher (lower) than the SMA. In contrast, momentum indicators seek changes in current market momentum and recommend selling (buying) if the current price is in the overbought (oversold) zone. Momentum indicators inform the possibility of reversal in the current price by giving certain fixed selling and buying thresholds. One of the most popular indicators in this group is relative strength index (RSI). Like an oscillator, RSI ranges from 0 to 100%, and recommends selling a current position if the threshold exceeds 80% (overbought) and buying if below 20% (oversold).

In addition, volume indicators reveal reversals or continuity of movement of the market not only with the price but both of price and trading volumes, as volume acts as a complementary factor for measuring market sentiment. Similarly, volatility indicators show the density and the speed of the price movements, recommending stop loss or detection of price reversal based on the price volatility. Bollinger bands, a popular volatility indicator, indicate possible market reversal if prices hit the upper (lower) band of the confidence interval.

The rules that are listed in Table 4.2 are all implementations of these basic ideas. Space restrictions prevent us from providing a detailed description of each rule. However, I provide references for each rule in Thesis Appendix A, to which I refer readers interested in the details of each rule.

With 54 rules, I construct a universe of 28,631 parameterizations of trading rules which includes the 7,849 parameterizations of 5 rules of Sullivan et al. (1999). The detailed explanations of the parameterizations are discussed in this chapter Appendix4.6.

4.3 Research Methodology

This section is to explain the methodologies applied in this study. I firstly discuss how I measure trading performance and then describe multiple hypothesis tests.

4.3.1 Performance Measurement

The purpose of this subsection is to give a detailed explanation of how I calculated the returns generated by each rule based on the daily price change. I followed the methods and terminologies introduced in Sullivan et al. (1999) and replicated in Bajgrowicz and Scaillet (2012)[9]. My interest of performance measurement is outperformance of the trading profit over the benchmark or buy and hold (BH) strategy, which means holding the financial asset from the trading start date until the trading end date, without any selling trade, regardless of direction of the market. In addition to measuring mean excess return over the buy and hold strategy, Sullivan et al. (1999) also considered the Sharpe ratio of each trading rule. In this respect, Sullivan et al. (1999)'s approach is unusual, and its utility has been questioned. Bajgrowicz and Scaillet (2012) pointed out that "the Sharpe ratio does not take into account higher moments and recent studies have shown that incorporating skewness and kurtosis into the portfolio decision causes major changes in the optimal portfolio". In any case, the Sullivan et al. (1999) Sharpe ratio measurement are very similar to their findings for the mean excess return. For these reasons, I do not consider the Sharpe ratio in this chapter.

One of the criticisms (Hudson et al. (1996), Sullivan et al. (1999), Bajgrowicz and Scaillet (2012)) of the excess return measured by Brock et al. (1992) was that it included no transaction costs and stock borrowing costs. Hence, in this chapter I applied costs of 5, 10 and 20 basis points, when there was a buy or sell signal and zero cost when no action was taken. I also apply stock borrowing costs of 5, 10 and 20 basis points once short

[9] programming codes for the paper are available from `http://jfe.rochester.edu/data.htm`.

selling is occured.[10] The borrowing costs apply for every day that the position is held, whereas the transactions costs apply only on the day that the position is changed.

I consider l trading rules utilized over T time periods. For a given time period $t \in \{1, ..., T\}$, each rule $k \in \{1, ..., l\}$ generates a trading signal $S_{k,t-1}$ computed from closing prices up until period $t-1$. There are three signals, $S_{k,t-1} \in \{-1, 0, 1\}$ where 1 means buy (long) position, -1 is sell (short) position and 0 means neutral (no action) position. When a signal generates a long position, the investor buys the stock with principal and when a short position is generated, the investor borrows stock by paying the stock borrowing cost and selling into the market; and when a neutral signal is generated, the principal goes to the deposit market to earn a risk-free rate. For risk-free rate, I applied the same effective federal funds rate set used by Bajgrowicz and Scaillet (2012) which is sourced from Federal Reserve Economic Data (FRED)[11].

Let X_t be the closing price of the stock on day t. The daily net return of an investment in the stock, denoted y_t, is defined as

$$y_{t+1} = \frac{(X_{t+1} - X_t)}{X_t} \tag{4.1}$$

I follow Sullivan et al. (1999) and let T be the number of time periods for which data on returns are available. Since trading rules are functions of prices in previous time periods, I reserve the first R observations in the sample for use in calculating the trading rules for the first trading day in the simulation. Let n be the number of time periods over which I apply the trading rules. I then have $T = R + n - 1$. I set $R = 250$ to allow for the implementation of moving average rules of orders up to 250.

As in Sullivan et al. (1999), the following is the formula to calculate performance measurement of the mean return based aforementioned explanation.

$$f_{k,t+1} = (ln[1 + y_{t+1} * S_k(\chi_t, \beta_t)] - ln[1 + y_{t+1}S_0(\chi_t)]) - TC_t(S_k(\chi_t, \beta_t)), \quad k = 0 \ldots, l \tag{4.2}$$

where $\chi_t = [X_{t-1}]_{i=0}^{R}$, $t = R, ...T$, TC_t is the transaction costs which are written as a proportion of the portfolio value and β_k the vector of paramters of the k^{th} trading rule.

[10] refer Table 6 and Appendix H of Bajgrowicz and Scaillet (2012) for the discussion of transaction costs.

[11] https://research.stlouisfed.org/fred2/

4.3.2 Statistical Procedures

Numerous studies (Lovell (1983); Lo and MacKinlay (1990); Brock et al. (1992); White (2000); Qi and Wu (2006)) emphasized the risk of using traditional statistics (i.e.,standard t-statistics) for multiple hypothesis testing.

Standard methods can control the probability of a Type 1 error when applied to a single hypothesis, but control is lost if these methods are applied to multiple hypotheses, in the sense that the probability of rejecting at least one true null hypothesis can be much larger than the nominal significance level. For a collection of hypotheses, the Family-Wise Error Rate (FWER) of a testing procedure is defined as the probability that at least one true null hypothesis will be rejected.

A test that controls the FWER when all the null hypotheses are true is said to provide weak control of the FWER. Such a test may be used to identify cases in which the *best* trading rule considered is profitable. White (2000)'s Reality check (RC) and Hansen (2005)'s Superior Predictive Ability (SPA) test are two popular methods[12] that provide weak control of the FWER and have been applied widely in the technical trading rule literature (Sullivan et al. (1999); Hsu and Kuan (2005); Marshall et al. (2008); Metghalchi et al. (2008b); Park and Irwin (2010)). A test that controls the FWER for any combination of true and false null hypotheses is said to provide strong control of the FWER. Such a test may be used to identify sets of profitable trading rules. Romano and Wolf (2005) and Hsu et al. (2010) propose stepwise versions of the RC and SPA tests respectively, which provide strong control of the FWER. According to Dudoit et al. (2003), the strong and weak control concept is often overlooked in the multiple hypothesis testing literature.

The null hypotheses of interest are

$$H_0 : E(\bar{f}_k) \leqslant 0, \qquad k = 1, ..., l$$

where $\bar{f}_k = n^{-1} \sum_{t=R}^{T} f_{(k,t+1)}$ denotes the individual trading rule mean excess return over the benchmark, net of costs. n is the length of prediction periods ,n=T-R+1.

The Studentized StepM Method of Romano and Wolf (2005) requires the use of a bootstrap algorithm. We use the stationary bootstrap of Politis and Romano (1994). Let B be the number of bootstrap resamples and I set the B is 1000. The Studentized StepM algorithm is as follows.

[12] I provide details of these tests in this chapter Appendix 4.A.

1. Compute the standardized statistics $z_k = \frac{\sqrt{T}\bar{f}_k}{\hat{\sigma}_k}$ for $k = 1, ..., l$ where $\hat{\sigma}^2$ is the bootstrap estimator of the variance of $\bar{f}_k$. Sort $z_k, k = 1, ..., l$ into descending order and relabel them such that $z_1 \geqslant z_2 \geqslant ... \geqslant z_l$. Define $Z(1) = \{z_1, ..., z_l\}$.

2. For $b = 1, ..., B$, compute the bootstrapped excess returns $\bar{f_1}^{(b)}, ..., \bar{f_l}^{(b)}$ and compute the resampled standardized statistics $z_k^{(b)} = \frac{\sqrt{T}(\bar{f_k}^{(b)} - \bar{f}_k)}{\hat{\sigma}_k}$ for $k = 1, ..., l$. Construct $Z^{(b)}(1) = \{z_1^{(b)}, ..., z_l^{(b)}\}$ for $b = 1, ..., B$.

3. Set $i = 1$. Until the algorithm is complete, iterate the following steps:

   (a) For $b = 1, ..., B$, compute $z_{max}^{(b)} = max(Z^{(b)}(i))$. Let $\hat{F}(i)$ be the empirical distribution of $z_{max}^{(b)}, b = 1, ..., B$ and let $\hat{c}(i)$ be the $(1-\alpha)\%$ quantile of $\hat{F}(i)$.

   (b) Construct $Z(i+1)$ as the largest subset of $Z(i)$ for which $z \in Z(i) \implies z < \hat{c}(i)$. Construct $Z^{(b)}(i+1)$ to be the corresponding subset of $Z^{(b)}(i)$.

   (c) If $Z(i+1) = Z(i)$ then the algorithm is complete. Otherwise, set $i = i+1$ and return to step 3a.

4. When the algorithm is complete, the set $Z(1) - Z(i)$ contains statistics that correspond to the trading rules for which the null hypothesis is rejected.

Romano and Wolf (2005) Theorem 4.1 prove that this procedure is consistent and provides strong asymptotic control of the FWER at level α. Hsu et al. (2010) extend the Studentized StepM algorithm by incorporating elements of the SPA test of Hansen (2005). They name this the Step-SPA test. Specifically, the Step-SPA algorithm is the same as the Studentized StepM algorithm outlined above except that in Step 2, the equation $z_k^{(b)} = \frac{\sqrt{T}(\bar{f_k}^{(b)} - \bar{f}_k)}{\hat{\sigma}_k}$ is replaced by $z_k^{(b)} = \frac{\sqrt{T}(\bar{f_k}^{(b)} - \bar{f}_k + \hat{\mu}_k)}{\hat{\sigma}_k}$ where $\hat{\mu}_k = \bar{f}_k \mathbf{1}(\bar{f}_k \leqslant -\hat{\sigma}_k\sqrt{2lnlnT})$ and $\mathbf{1}(x) = 1$ if x is true. The rationale for this modification is to improve the power of the test by asymptotically removing rules with a negative expected net return from the estimation of the null distribution. For more details, I refer the reader to Hsu et al. (2010) and Hansen (2005).

4.4 Empirical Results

I computed the daily returns generated by the 28,631 different parameterisations of the 54 technical trading rules listed this chapter Appendix 4.6.

Table 4.3 presents the returns on the buy-and-hold benchmark strategy (Bench) for each of the 6 subperiods and the full sample. Also presented is the return on the best (Best) trading rules considered. Note that the best trading rule (Best) is more profitable than the benchmark (Bench) in all periods, but that the magnitude of the difference between the benchmark and best-rule returns differs substantially across sub-periods. In particular, note that this difference is very small in the 1987-1996 subperiod. Table 4.3 also presents the results of the White (2000)'s Reality Check bootstrap p-value (RC) and Hansen (2005)'s consistent SPA bootstrap p-values (SPA). At the 5% significance level, White's p-values indicate the statistical significance holds for the full period, Sub-periods 3 and 4 and Hansen's SPA p-values provide similar results. Thus, in spite of the wider range of rules applied, I found similar results to Sullivan et al. (1999) and Bajgrowicz and Scaillet (2012). It is interesting to observe from Table 4.3 that the predictability of the market index is only found in the 1939 to 1986 period both from five Sullivan et al. (1999) rules and my 54 Rules.

Table 4.3: Best Rule and Data Snooping Bias Tests *p*-values

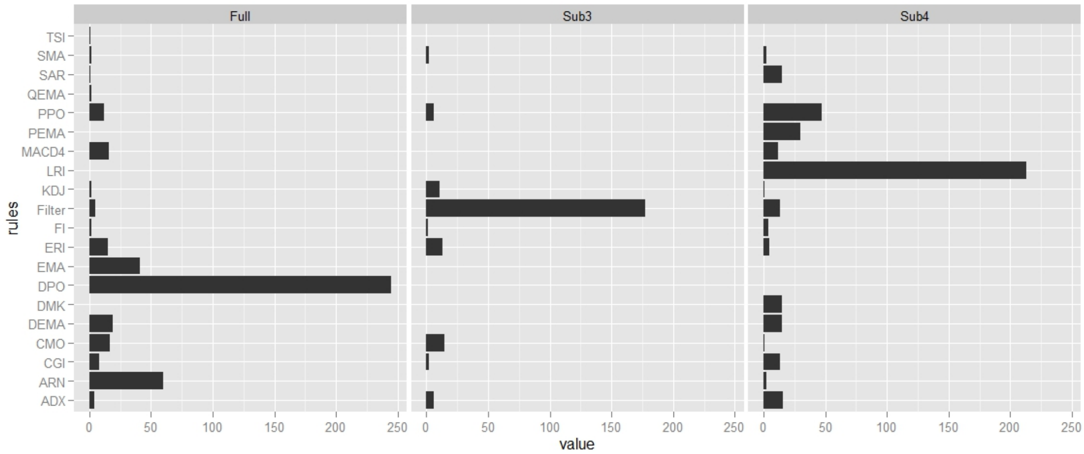
	Period		Return (%)		Empirical Tests Results			
	Start	End	Bench	Best	RC	SPA	Studentized StepM	Step-SPA
Full	1897	2013	4.63	15.10	0.0048	0.0027	401	452
Sub1	1897	1914	0.59	21.67	0.0672	0.0818	0	0
Sub2	1915	1938	1.83	20.05	0.2065	0.1946	0	0
Sub3	1939	1962	5.75	25.38	0.0000	0.0000	184	233
Sub4	1962	1986	4.48	24.15	0.0012	0.0000	380	404
Sub5	1987	1996	13.39	14.07	1.0000	1.0000	0	0
Sub6	1997	2013	4.78	13.41	0.8763	0.8486	0	0

This Table present the summary of four tests we applied for the full and 6 sub-periods. Bench is market benchmark annual mean yield and the Best means the best mean return from the best trading rule. RC and SPA denote White (2000)'s and Hansen (2005)'s nominal p-values, while "Studentized StepM" is stepwise RC version Romano and Wolf (2005) and "Step-SPA" is the single stepwise test of Hsu and Kuan (2005),respectively.

From the Studentized StepM and Step-SPA columns in Table 4.3, I found 401 and 452 parameterizations of rules were significant for full period and also more than 200 and 400 significant rules were identified for sub-period 3 (Sub3) and 4 (Sub4) from Step-SPA tests. The table also shows that the Step-SPA is more powerful to Studentized StepM throughout the sample periods. However, I found no regular decreasing or increasing pattern of number of rejections from the Table 4.3.

Figure 4.3 identifies which particular rules were found to be profitable in the full sample and sub-periods 3 and 4. For each rule that was found to be profitable, it indicates the number of parameterisations that were profitable. Rules that were not found to be profitable in any time period are excluded from the figure. For the full sample period, 17 rules were identified as containing parameterisations that exhibit statistically significant profits. Among them, three rules were classical rules (SMA, Filter, and SAR), and fourteen others were new generation rules. I regard the DPO rule as the overall best performer for the full period. For Sub-period 3, nine rules were significant and the Filter rule was the best performer, and for sub-period 4, the LRI rule was superior among 16

Figure 4.3: Significantly Outperforming Rules from Stepwise Tests



This figure is the counting of the significantly outperforming rules from step-wise test for full period and two sub-period which had significant outperforming rues.

significant rules. Table 4.4 provides some further perspective on the outperforming rules over full period and two sub-periods to identify the persistence of the 20 profitable rules. I found overall nine rules (ADX, CGI, CMO, ERI, FI, Filter, KDJ, PPO and SMA) are profitable for the full and sub-periods 3 and 4. (see Full∩Sub3 ∩ Sub4 and Full∩Sub3). I also found four rules (ARN, DEMA, MACD4 and SAR) were outperforming over the full period and sub-period 4 (see Full∩Sub4). However, I found some rules are only dominant over certain periods(e.g., DPO, EMA, QEMA for full period (See Full Only) and DMK, LRI and PEMA for sub-period 4 (See Sub4 Only). As such, I found some rules were dominant over three sample periods but some rules were superior in only single periods. In addition, I found SMA and alternatives of SMA (e.g., DEMA, EMA, QEAM and PEMA) were profitable rules.

Table 4.4: Further Tracking the Significant Rules

Period	Significant Rules
Full∩Sub3∩Sub4	ADX,CGI,CMO,ERI,FI,Filter,KDJ,PPO,SMA
Full∩Sub3	ADX,CGI,CMO,ERI,FI,Filter,KDJ,PPO,SMA
Full∩Sub4	ARN,DEMA,MACD4,SAR
Full Only	DPO,EMA,QEMA,TSI
Sub3 Only	N/A
Sub4 Only	DMK,LRI,PEMA

This Table further seek the continuously outperforming rules over full period and two sub-periods to identify the persistence of the 20 profitable rules.

Table 4.5 illustrates the changed profitability once I include a set of transaction costs. The third column named “TC05/SBC00” means only five basis points transaction cost (TC) but no application of stock borrowing cost (SBC). Similarly, “TC00/SBC05” and “TC05/SBC05” on 4th and 5th column are the scenario when I apply no TC but only five basis points of SBC and application of five basis point for both TC and SBC, respectively. From the table, I find no statistically significant profitability of any full and sub-periods. This illustrates, together with data snooping bias, the cost is another crucial factor to determine the possibility of the profitability. This is same finding of Bajgrowicz and Scaillet (2012) which only applied Sullivan et al. (1999)'s five rules.

TABLE 4.5: Data Snooping Bias Tests with Transaction Costs

	Period		TC05/SBC00		TC00/SBC05		TC05/SBC05	
	Start	End	RC	SPA	RC	SPA	RC	SPA
Full	1897	2013	0.5480	0.4510	0.9210	0.6260	0.9460	0.6490
Sub1	1897	1914	0.1434	0.2403	0.4071	0.3996	0.5712	0.5318
Sub2	1915	1938	0.4527	0.5496	0.8183	0.6896	0.8429	0.6980
Sub3	1939	1962	0.3904	0.3892	0.2119	0.0679	1.0000	0.9546
Sub4	1962	1986	0.2113	0.1588	0.4055	0.1826	0.9064	0.5414
Sub5	1987	1996	1.0000	1.0000	1.0000	0.9991	1.0000	1.0000
Sub6	1997	2013	0.9622	0.9596	0.9961	0.9852	0.9985	0.9900

This Table illustrates how the transaction costs impact the changes in profitability. "TC05/SBC00" means only five basis points transaction cost (TC) but no application of stock borrowing cost (SBC). Similarly, "TC00/SBC05" and "TC05/SBC05" are the scenario when no TC but only five basis points of SBC and application of five basis point for both TC and SBC, respectively.

In summary, despite the fact that I consider a much wider set of technical trading rules than has appeared in the prior literature, my results are remarkably similar to previous findings. When I consider transactions costs, I found no evidence that technical trading rules generate profits in excess of those generated by a buy-and-hold strategy. In the absence of transactions costs, I found clear evidence that some technical trading rules have been profitable at different times in the US market, but the evidence of profitability disappears in the second half of the 1980s. Timmermann and Granger (2004) have suggested that when it becomes widely known that a trading rule is profitable, the profitability will be traded away, rendering the rule ineffective. This may have been viewed as a plausible explanation for the decline of profitability in the prior literature, since it focussed on a narrow set of well-known trading rules. However, my analysis also considers many rules that are relatively new and less well-known. The fact that none of them appear to be profitable after the late 1980s suggests that the decline in profitability is due to market-wide phenomena, rather than traders learning individual rules.

It is of interest to compare my results with those of researchers who have investigated the presence of time-varying serial correlation in stock indices. Kim et al. (2011)[13] found evidence of time varying serial correlation in 110 years of DJIA returns. They found positive first-order autocorrelation around the 1940s and the 1970s but the magnitude

[13] see Figure 5 of (Kim et al., 2011, p.878) for details.

of the first-order autoregressive coefficent began to decline in the 1970s and reached zero around 2000. Similarly, Ito and Sugiyama (2009) found evidence of time varying autocorrelation in S&P500 returns. They found that the magnitude of the autocorrelation went into long-term decline starting in the second half of the 1980s. Gu and Finnerty (2002) compute serial correlation, variance ratio, and runs tests for the DJIA from 1896 to 1998 and find that evidence of serial correlation is strongest in the 1970s but disappeared by the mid-1980s. Lo (2004a) computes rolling first-order autocorrelation coefficients for the S&P Composite Index from 1871 to 2003 and find evidence that autocorrelation is time-varying and declined sharply in the mid-1980s. The fact that all of these authors found evidence of serial correlation in US stock returns, which disappeared some time around the 1980s, is interesting since it broadly coincides with my finding that all the technical trading rules that I considered ceased to be profitable around the same time. This supports the notion that the decline in trading rule profitability that occurred from the mid-1980s was due to market-wide phenomena, and not due to the profitability of individual rules being traded away.

4.5 Conclusions

Prior studies of the profitability of technical trading rules in the US equity market focus on a narrow range of well-known rules, and find that profitability over the long run has been time-varying, and has disappeared since the mid-1980s. In this chapter I analyzed 116 years of the DJIA with 54 different types of technical trading rule, 35 of which had never previously been examined in the academic literature, using a statistical methodology that provides strong control of the family-wise error rate (FWER). Despite using a wide range of rules, my findings are quite similar to those of the prior literature – technical trading rule profitability is time-varying and disappeared in the late 1980s. In particular, it is not the case that the new trading rules that I consider are profitable during time periods that the classical rules are not. A particular feature of my study is that I use statistical techniques which provide strong control of the FWER. This allows us to identify sets of profitable trading rules. Interestingly, this set includes both new and classical rules. The Simple Moving Average and the Filter Rule – perhaps the two best-known technical trading rules, are in the set of profitable trading rules for all the sub-periods that I considered.

When faced with a broad menu of technical trading rules, it is natural to ask: “which rules are profitable?” My results suggest that a better question to ask might be: “when are rules profitable?” The fact that I don’t find any new rules that are profitable when the classical rules are not, suggests that technical trading rule profitability is generally episodic. It is interesting that the periods in which I found evidence of profitability coincide with those in which other authors have found evidence of serial correlation in US index returns since this suggests that trading rules are simply exploiting this correlation when it exists, and are unable to generate profits when it doesn't. This is consistent with the Adaptive Market Hypothesis of Lo (2004a), and it raises questions about why markets would be efficient at some times and not others, and how these periods might be predicted. These are questions that I leave for future research.

Appendix 4.A Explanation on Single Step Tests

4.A.1 White's Reality Check

White (2000) advocates the Reality Check (hereafter RC) which tests whether a specific model has superior predictive power against benchmark model. To evaluate the relative performance of each of k technical trading rules against the benchmark, a performance measure can be expressed:

$$f_{k,t+1} = r_{k,t+1} - r_{0,t+1} \tag{4.3}$$

where where $k = 1, \ldots, M$ and $r_{k,t+1}$ and $r_{0,t+1}$ denote net returns of each trading rule period and the benchmark rule, respectively, at time t+1.

Let f_k $(k = 1, \ldots, M)$ denote a performance measure(my case is the returns) of t he kth rule relative to the benchmark and $\mu_k \equiv \mathrm{E}(f_k)$. The null hypothesis is that there does not exist a superior model (rule) in the collection of M models (rules):

$$H_0 : \max_{k=1,\ldots,M} \mu_k \leq 0 \tag{4.4}$$

The alternative hypothesis is that there exists an outperforming model. Rejecting Equation (2) implies that there exists at least one model (rule) that outperforms the benchmark.

RC takes the maximum average value of $f_{k,t}$ as a test statistic,$\bar{V}_n$.

$$\bar{V}_n = \max_{k=1,\ldots,M} \sqrt{n}\bar{f}_k \tag{4.5}$$

where$\bar{f}_k = \sum_{t=1}^{n} f_{k,t}/n$ with $f_{k,t}$ the t th observation of f_k.

To find a p-value, White (2000) suggested using the stationary bootstrap method of Politis and Romano (1994).

$$\bar{V}_n^*(b) = \max_{k=1,\ldots,M} \sqrt{n}\,\bar{f}_k^*(b) - \bar{f}_k,\ b = 1, \ldots, B. \tag{4.6}$$

Let $f_k^*(b)$ denote the bth bootstrapped sample of f_k and $\bar{f}_k^*(b)$=$\sum_{t=1}^{n} f_{k,t}^*(b)/n$ denote its sample average. I then obtain the empirical distribution of $\bar{V^*}_n$with the realizations.

Finally, White's reality check p-value is obtained by counting $\bar{V}_n^* > \bar{V}_n$ with the quantiles of the empirical distribution with B, the number of bootstrap simulations.

$$p_{RC} \equiv \sum_{b=1}^{B} \frac{\mathbf{I}(\bar{V}_n^* > \bar{V}_n)}{B} \tag{4.7}$$

4.A.2 Hansen's Superior Predictive Ability Test

The RC is a least favourable configuration (LFC) based test, so it derives critical values on the condition of μ_k=0. In empirical research however, under-performing technical trading rules are inevitably included in the tests. Therefore the RC of White (2000) tends to be conservative.

$$\mathbf{T}_{SPA} = \tilde{V}_{SPA} = \max(\max_{k=1,\ldots,M} \frac{\sqrt{n}\,\bar{f}_k}{\hat{\omega}_k}, 0), \tag{4.8}$$

where $\hat{\omega}_k^2$ is a consistent estimator of $\hat{\omega}_k^2 \equiv var(\sqrt{n}\,\bar{f}_k)$.

Secondly, Hansen (2005) suggested a threshold $(-\sqrt{2log\,log\,n})$ to extract models which performs worse than the threshold level from the estimation of the null distribution.

$$\hat{\mu_k^c} = \bar{f}_k \mathbf{I}[\sqrt{n}(\frac{\bar{f}_k}{\hat{\omega}_k}) \leq -\sqrt{2log\,log\,n}], \tag{4.9}$$

where $\mathbf{I}$ denotes the indicator function and the threshold ensures that $\hat{\mu_k^c}$ stays within certain range asymptotically.

The corresponding bootstrap statistics are computed as follows. For the kth rule, let $Z_k^*(b)$ denote the sample average of the bth bootstrapped sample of the centered returns.

$$Z_{k,t,b}^{C*} = f_{k,t}^*(b) - \bar{f}_k \mathbf{I}[\sqrt{n}(\frac{\bar{f}_k}{\hat{\omega}_k}) \geq -\sqrt{2log\,log\,n}] \tag{4.10}$$

The consistent p-values of $\tilde{V}_{SPA}$ are determined by the empirical distribution of $\tilde{V}_{SPA}^*$ whose realizations are

$$\mathbf{T}_{b,n}^{SPA*} = \tilde{V}_{SPA}^*(B) = \max(\max_{k=1,\ldots,M} \frac{\sqrt{n}\,\bar{Z}_k^{C*}(b)}{\hat{\omega}_k}, 0), b = 1, \ldots, B. \tag{4.11}$$

By counting $\bar{V}_{SPA}^* > \bar{V}_{SPA}$, p-value can be calculated as a quantile of number of bootstrap (B).

$$p_{SPA} \equiv \sum_{b=1}^{B} \frac{\mathbf{I}(\bar{V}_{SPA}^* > \bar{V}_{SPA})}{B} \tag{4.12}$$

Appendix 4.B Technical Trading Rule Paramatarizations

I define the following variables: X and Y are parameters of the particular trading rule. B is a band filter. The trading signal is acted upon when the price exceeds $1 + B$ times the trigger price. C is a prespecified number of days for which a position must be held, ignoring all other trading signals during that time. D is the number of days for which a trading signal must be maintained before it is acted upon. I refer the reader to Sullivan et al. (1999) for further discussion of the paramters. The number of different values used for each parameter for each rule are listed in Table 4.6.

Table 4.6: Technical Trading Rule Parametrization and Bibliography

	Name in Full	Abbrev.	X	Y	B	C	D	Total	Reference
1	Allegator	ALLE	56			336	336	728	Williams (1995)
2	Aroon Indicator	ARN	12			72	72	156	Chande (1995)
3	Average Directional Index	ADX	12			72	72	156	Wilder (1978)
4	Average True Range	ATR	54			324	324	702	Wilder (1978)
5	Bollinger Band	BOL	54			324	324	702	Bollinger (1992)
6	Commodity Channel Index	CCI	12			72	72	156	Lambert (1980)
7	Center of Gravity Oscillator	CGO	11			66	66	143	Ehlers (2004)
8	Chande Momentum Oscillator	CMO	55			330	330	715	Chande (1994)
9	Coppock Indicator	COPP	56			336	336	728	Coppock (1962)
10	Cyber Cycle Indicator	CYC	12			72	72	156	Ehlers (2004)
11	Double Exponential Moving Average	DEMA	45	225			270	540	Mulloy (1994a)
12	DeMark's Range Expansion Index	DREI	60			360	360	780	DeMark (1997)
13	Demark's Demarker	DEMK	12			72	72	156	DeMark (1997)
14	Detrend Price Oscillator	DPO	12			72	72	156	Achelis (2001)
15	Exponential Moving Average	EMA	45	225			270	540	Haurlan (1968)
16	Easy of Movement	EMV	24			144	144	312	Arms (1996)
17	Entropy	ENTP	12			72	72	156	Ehlers (2002a)
18	Elder Ray Indicator	ERI	12			72	72	156	Elder (1993)
19	Force Index	FI	12			72	72	156	Elder (1993)
20	Keltner Channel Indicator	KELT	55			330	330	715	Keltner (1960)
21	Laguerre Relative Strength Index	LRSI	44			264	264	572	Ehlers (2004)
22	Linear Regression Indicator	LRI	55			330	330	715	Chande (1992)
23	Moving Average Convergence & Divergence	MACD	56			336	336	728	Appel (1979)
24	MACD with 4 Parameters	MACD4	588					588	John (2010)
25	Money Flow Indicator	MFI	36			216	216	468	Quong (1989)
26	Pentuple EMA	PEMA	36	180			216	432	Eremee and Kositsin (2010)
27	Price Momentum Oscillator	PMO	216			54	54	324	Swenlin (1997)
28	Percentage Price Oscillator	PPO	252			54	54	360	Achelis (2001)
29	Quadruple EMA	QEMA	36	180			216	432	Lebeau (1991)
30	Rate of Change	ROC	45			270	270	585	Murphy (1998)
31	Relative Strength Index	RSI	44			264	264	572	Wilder (1978)
32	Relative Vigor Index	RVI	12			72	72	156	Ehlers (2002b)
33	Stochastic Cyber Cycle	SCC	12			72	72	156	Ehlers (2004)
34	Stochastic Center of Gravity	SCG	45			270	270	585	Ehlers (2004)
35	Stochastic KDJ	SKDJ	240			54	54	348	Scarborough (2008a)
36	SONAR Momentum Indicator	SONAR	12			72	72	156	Okamoto (1978)
37	Stochastic RSI	SRSI	36			216	216	468	Ehlers (2004)
38	Stochastic RVI	SRVI	12			72	72	156	Ehlers (2004)
39	Smoothed Moving Average	SSMA	36	180			216	432	MQL5 (2005)
40	Stochastic	STOC	56			336	336	728	Lane (1984)
41	Triple EMA	TEMA	36	40		216	140	432	Mulloy (1994b)
42	Triple Smoothed EMA	TRIX	108				648	756	Hutson (1984)
43	TRUE RVI	TRVI	12			72	72	156	Eremeev (2010)
44	Triple Strength Index	TSI	36			216	216	468	Blau (1991)
45	Ultimate	ULTI	56			336	336	728	Williams (1985)
46	Vertex Index	VI	18			108	108	234	Botes (2010)
47	Volatility Ratio	VR	98			84	84	266	Schwage (1997)
48	Wilder's Moving Average	WDMA	36	180		216	0	432	Wilder (1978)
49	William's Percent R	WPR	44			264	264	572	Williams (1967)
	STW(1999) Five Rules								
50	Filter	Filter	24		192	96	185	497	Alexander (1961)
51	Moving Average	SMA	120	960	480	480	9	2049	Gartley (1935)
52	Support& Resistance	SAR			100	800	320	1220	Wyckoff (1910)
53	Channel Breakouts	CBO				320	1720	2040	Donchian (1960)
54	On-Balance Volume Averages	OBV	15	105	960	480	480	2040	Granville (1963)

Appendix 4.C Summary of Existing studies with Technical Trading Rules since Brock et al. (1992)

TABLE 4.7: Existing studies with Technical Trading Rules since Brock et al. (1992)

Author(s)	Rule(s) applied	Periods	Region/Country/Indice	Error[14]
BLL (1992)	MA, TRB	1897 1986	DJIA	Type1
Corrado & Lee (1992)	Filter	1963 1989	DJIA & S&P100	Type1
Levich & Thomas (1993)	Filter,MA	1976 1990	GBP,CAD,DEM,JPY,CHF	Type1
Silber(1994)	MA	1976 1991	DEM,CHF,JPY,GBP,CAD, EuroDollar,S&P500	Type1
Bessembinder & Chan (1995)	MA, TRB	1975 1989	Japan,Hong Kong, Korea, Malaysia, Thailand and Taiwan	Type1
Battern & Ellis(1996)	SMA,WMA, TRB, Stochastic EOM, Price Volume	1987 1991	ASX AOI	Type1
Gencay(1996)	MA	1963 1988	DJIA	Type1
Hudson, Dempsey & Keasey (1996)	MA, TRB	1897 1987	UK FT 30	Type1
Kho(1996)	MA	1980 1991	GBP,DEM,CHF,JPY Futures	Type1
Lee & Mathur(1996)	MA	1988 1993	JPY/GBP,DEM/GBP,JPY/DEM,CHF/DEM,CHF/GBP,JPY/CHF	Type1
Raj & Thurston (1996)	MA & TRB	1989 1993	Hang Seng Index Futures	Type1
Mills (1997)	MA & TRB	1935 1994	UK FT30	Type1
Bessembinder & Chan (1998)	MA, TRB	1926 1991	DJIA	Type1
Gencay(1998)	MA, Neural Networks	1897 1988	DJIA	Type1
Ito (1999)	MA, TRB	1980 1996	Japan, Canada, Indonesia, Mexico, Taiwan & US	Type1
Ratner & Legal (1999)	MA	1982 1995	India, Korea,Malaysia,Philippines, Taiwan, Thailand,Argentina, Brazil, Chile and Mexico	Type1
LeBaron (1999)	MA	1979 1992	USD/DEM, USD/JPY	Type1
STW(1999)	Filter, CBO, TRB, MA, OBV	1897 1986	DJIA	Type1
Ahmed, Beck & Goldreyer(2000)	MA	1994 1999	Taiwan, Thailand & Philliphines Stocks	Type1
Coutts & Cheung(2000)	MA, TRB	1985 1997	Hong Kong HIS	Type1
Mailet & Michel (2000)	MA	1974 1996	USD/DEM, USD/FRF, USD/JPY,GBP/FRF, DEM/FRF,JPY/FRF	Type1
Parisi & Vasquez(2000)	MA, TRB	1987 1998	Chile Stock Market	Type1
White (2000)	MA, RSI, LRS, Momentum	1988 1994	US S&P 500	FWER(weak)
Taylor(2000)	MA	1971 1991	UK FTA, FTSE100, DJIA & SNP500	Type1
Fong & Ho (2001)	MA	1997 2000	DJ Internet Composite Internet Index	Type1
Gunasekarage & Power (2001)	MA	1990 2000	Bombay, Colombo, Dhaka and Karachi Stock Exchange	Type1
Lee, Pan & Liu (2001)	MA	1988 1995	AUD, HKD, KRW, MYR, NZD, PHP, SGD, TWD, THB	Type1
Kwon & Kish(2002)	MA	1962 1996	US NYSE	Type1
Lai, Balachandher & Nor(2002)	MA	1977 1999	Malaysian Stock	Type1
Tian, Wan & Guo (2002)	MA, TRB	1926 2000	US and China Equity Markets	Type1
Neely (2002)	MA	1985 1999	AUD,DEM,JPY, CHF	Type1
Day & Wong (2002)	MA,TRB	1962 1986	DJIA	Type1
Ready(2002)	MA	1897 2000	DJIA	Type1
Wong, Manzur and Chew(2003)	MA, RS	1974 1994	Singapore Stock Exchange	Type1
Fang & Xu (2003)	MA	1896 1996	DJIA	Type1
Olson (2004)	MA	1971 2000	18 currencies (Inc. AUD)	Type1

Table 4.7 – continued from previous page

Author(s)	Rules(s) applied	Period	Region/Country/Indice	Data Snoop
Sapp(2004)	MA	1975 1998	USD/DEM	Type1
Bokhari, Cai, Hidson & Keasey(2005)	MA, TRB (company size)	1987 2002	UK FTSE100, FTSE250, FTSE Small Cap	Type1
Fong & Yong (2005)	MA	1998 2002	AMEX inter@active Internet Index	Type1
Hsu & Kuan (2005)	5 STW(1999), 5 Technical Patterns, 2 momentum strategies	1989 2002	DJIA, SNP500,NASDAQ, RUSSELL2000	FWER(weak)
Marshall & Cahan(2005)	MA,TRB	1970 2002	New Zealand Stock (NZX)	Type1
Ellis & Parbery (2005)	Adaptive MA	1980 2002	ASX, DJIA, S&P 500	Type1
Cai et al (2005)	MA,TRB	1969 2003	US,CHINA,UK,HK,Japan Stock Markets	Type1
Fieield et al (2005)	Filter,MA	1991 2000	11 European Stock Market	Type1
Ming & Hwa (2006)	MA, TRB	1988 2003	China, Thailand, Taiwan, Malaysia, Singapore, Hong Kong,Korea and Indonesia Stock Markets	Type1
Qi & Wu (2006)	4 STW(1999)	1973 1998	G7 FX	FWER(weak)
Hawtrey & Nguyen (2006)	Filters	1984 2003	AUD/USD, AUD/GBP, AUD/JPY,AUD/CHF	Type1
Balsara, Chen and Zheng(2007)	MA, TRB, Bollinger band	1990 2005	China Stock Markets	Type1
Hatgioannides & Mesomeris(2007)	MA,TRB	1988 2002	MSCI Latin (Mexico, Brasil, Argentina, Chile) , Aisian (Philippines, Taiwan, Thailand, Indonesia)	Type1
Lento, Gradojevic & Wright (2007)	MA, Filter, Bollinger	1995 2004	DJIA, Canada TSX, USD/CAD	Type1
Loh(2007)	MA, Stochastic	1990 2005	Australia, Hong Kong, Japan, Singapore and Korea Stock markets	Type1
Metghalchi, Glasure, Garza & Chen (2007)	MA	1990 2006	Austrian Stock Market	Type1
Shik & Chong (2007)	MA,RSI	1983 2002	6 develpoed currencies	Type1
McKenzie(2007)	MA,TRB	1986 2003	17 EM and USA Currincies	Type1
Chong & Ng (2008)	MA, MACD,RSI	1935 1994	UK FTSE Index	Type1
Fifield, Power & Knipe(2008)	MA, Filter	1989 2003	US, UK, Japan, Argentina,Chile, Hong Kong, India, Indonesia, Korea, Malaysia, Mexico, Philleppines,South Africa, Sri Lanka, Taiwan, Thailand, Turkey and Zimbabwe Stock Markets	Type1
Marshall, Cahan & Cahan(2008)	STW(1999)	1984 2005	15 US Commodities	FWER(weak)
Marshall, Cahan & Cahan(2008)	STW(1999)	2002 2003	5Min AMEX	FWER(weak)
Metghalchi, Garza-Gomez, Glasure & Chang (2008)	MA	1988 2004	Mexico Stock Market	FWER(weak)
Metghalchi, Chang & Marcucci (2008)	MA	1986 20004	Sweden Stock Market	FWER(weak)
Pukthuanthong-Le, Thomas III (2008)	Momentun, MA	1975 2006	6 develpoed currencies	Type1
Schulmeister(2008)	MA	1973 1999	EUR/USD	Type1
Lento(2008)	MA	1950 2008	SNP500	Type1
Chen, Huang & Lai(2009)	STW(1999)	1975 2006	Hong Kong, Indonesia, Korea, Malaysia, Singapore, Taiwan, Thailand, Japan Stock Markets	FWER(weak)
Lento (2009)	MA, TRB, and Filters	1987 2005	Australia, India, Indonesia, Korea, Japan, Hong Kong, Singapore, Taiwan Stock Markets	Type1

Table 4.7 – continued from previous page

Author(s)	Rules(s) applied	Period	Region/Country/Indice	Data Snoop
Zhu & Zhou(2009)	Momentun Trading	2001 2008	24 MCSI developed & 26 MSCI Ems	Type1
Schulmeister(2009)	MA,Momemtun, RSI	1983 2007	S&P 500 spot and futures	Type1
Coutts(2010)	MA & TRB	1997 2008	Hang Seng Index	Type1
Park & Irwin (2010)	14 rules (MA,EMV,MACD, RSI, DRI, Filter, Parabolic, DMI)	1985 2004	US Futures	FWER(weak)
Hsu, Hsu & Kuan (2010)	MA, Filters	1998 2003	US ETF, MSCI Emerging, MCSI Brazil, MCSI Malaysia, MSCI Mexico	FWER(strong)
Szalmary, Shen & Sharma (2010)	MA	1992 2007	US 28 Commodity Futures	Type1
Cialenco & Protopapadakis (2011)	Filters, MA	1986 2009	14 countries currencies	Type1
Mitra(2011)	MA	1998 2008	Indian Stock Martket	Type1
Bajgrowicz & Scaillet(2012)	STW(1999)	1897~ 2011	US DJIA	FDR
Chiang,Ke & Wang(2012)	MA,DMI,MACD,RSI	1998 2008	Taiwan Stock Index Futures	Type1
Metghalchi, Marcucci & Chang(2012)	SMA,IMA	1990 2006	16 European Countries Stock Markets	FWER(weak)
Metghalchi, Chang & Gomez(2012)	SMA,RSI,PSAR,DMS,OBV,Stochastic,Histogram,MFI	1990 2010	Taiwan Stock Index Futures	FWER(weak)
Pavlov & Hurn (2012)	SMA,EMA	1973~2008	Australian Stock Market	Type1
Rosillo, Fuente & Brugos(2012)	MACD,RSI,momentum, Stochastic	1986 2009	Spain Stock Market	Type1
Shintani et al (2012)	MA	2004 2006	TOPIX, USD/JPY	Type1
Shynkevich(2012a)	4 STW(1999)	1995 2010	US technology and small cap	FWER(strong)
Yamamoto(2012)	4 STW(1999)	2006 2007	Nikkei 225	FWER(weak)
Wang et al (2012)	MA, Stochastic	2005 2006	Taiwan Stock Exchange Daily & Intraday	Type1
Yu et al.(2013)	MA,TBR	1991 2008	SE Asia Stock Markets	Type1
Rosillo et al (2013)	RSI,MACD,Momentum,Stochastic	1986 2009	Spain Stock Market	Type1
Neely et al(2013)	Filter,SMA,Momentum,Channel (Momentum)	1976 2012	21 Currencies	Type1
Ulku & Prodan (2013)	MA & MACD	2001 2012	44 International Stock Indexes	Type1
Narayan et al (2013)	MA, TRB	1986 2011	4 commodities	Type1

Appendix 4.D URL links for Existing studies with Technical Trading Rules since Brock et al. (1992)

TABLE 4.8: URL links for Existing studies with Technical Trading Rules

Author(s)	**URL Links**
BLL (1992)	http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1992.tb04681.x/abstract
Corrado & Lee (1992)	http://onlinelibrary.wiley.com/doi/10.1111/j.1475-6803.1992.tb00119.x/abstract
Levich & Thomas (1993)	http://www.sciencedirect.com/science/article/pii/0261560693900349
Silber(1994)	http://www.iijournals.com/doi/abs/10.3905/jod.1994.407887?journalCode=jod#sthash.6WUydOpg.dpbs
Bessembinder & Chan (1995)	http://www.sciencedirect.com/science/article/pii/0927538X95000023
Battern & Ellis(1996)	http://link.springer.com/article/10.1007/BF01739683#page-1
Gencay(1996)	http://www.sfu.ca/ rgencay/jarticles/jfor-technical.pdf
Hudson, Dempsey & Keasey (1996)	http://www.sciencedirect.com/science/article/pii/0378426695000437
Kho(1996)	http://www.sciencedirect.com/science/article/pii/0304405X95008618
Lee & Mathur(1996)	http://www.sciencedirect.com/science/article/pii/0378426695000372
Raj & Thurston (1996)	http://www.tandfonline.com/doi/abs/10.1080/758525512
Mills (1997)	http://web.ist.utl.pt/ adriano.simoes/tese/referencias/Papers%20-%20Adriano/Technical%20Analysis.pdf
Bessembinder & Chan (1998)	http://www.jstor.org/stable/3666289
Gencay(1998)	http://onlinelibrary.wiley.com/doi/10.1002/(SICI)1099-131X(1998090)17:5/6%3C401::AID-FOR704%3E3.0.CO;2-C/pdf
Ito (1999)	http://www.sciencedirect.com/science/article/pii/S0927538X99000086
Ratner & Legal (1999)	http://www.sciencedirect.com/science/article/pii/S0378426699000424
LeBaron (1999)	http://www.sciencedirect.com/science/article/pii/S0022199698000610
STW(1999)	http://onlinelibrary.wiley.com/doi/10.1111/0022-1082.00163/abstract
Ahmed, Beck & Goldreyer(2000)	http://www.emeraldinsight.com/journals.htm?articleid=865695&show=abstract
Coutts & Cheung(2000)	http://www.tandfonline.com/doi/abs/10.1080/096031000437935#.UzzjHvmSx8E
Mailet & Michel (2000)	http://www.tandfonline.com/doi/pdf/10.1080/13518470050020842
Parisi & Vasquez(2000)	http://www.sciencedirect.com/science/article/pii/S1566014100000066
White (2000)	http://onlinelibrary.wiley.com/doi/10.1111/1468-0262.00152/abstract
Taylor(2000)	http://www.tandfonline.com/doi/pdf/10.1080/135184700336955
Fong & Ho (2001)	http://onlinelibrary.wiley.com/doi/10.1111/1468-2443.00029/pdf
Gunasekarage & Power (2001)	http://www.sciencedirect.com/science/article/pii/S1566014100000170
Lee, Pan & Liu (2001)	http://www.sciencedirect.com/science/article/pii/S1042443100000500
Kwon & Kish(2002)	http://www.tandfonline.com/doi/abs/10.1080/09603100010016139#.Uzzms_mSx8E
Lai, Balachandher & Nor(2002)	http://www.jstor.org/stable/40473346?seq=1#page_scan_tab_contents
Tian, Wan & Guo (2002)	http://link.springer.com/article/10.1023/A:1024181515265#page-1

Table 4.8 – continued from previous page

Author(s)	URL Links
Neely (2002)	http://www.sciencedirect.com/science/article/pii/S0022199601001635
Day & Wong (2002)	http://www.sciencedirect.com/science/article/pii/S092753980200004X
Ready(2002)	http://www.jstor.org/stable/3666314
Wong, Manzur and Chew(2003)	http://www.tandfonline.com/doi/abs/10.1080/0960310022000020906#.Uz4tLPmSx8E
Fang & Xu (2003)	http://www.sciencedirect.com/science/article/pii/S0169207002000134?np=y
Olson (2004)	http://www.sciencedirect.com/science/article/pii/S0378426602003990
Sapp(2004)	http://www.sciencedirect.com/science/article/pii/S0378426602004107
Bokhari, Cai, Hidson & Keasey(2005)	http://www.sciencedirect.com/science/article/pii/S0165176504002204
Fong & Yong (2005)	http://www.sciencedirect.com/science/article/pii/S0927539804000209
Hsu & Kuan (2005)	http://jfec.oxfordjournals.org/content/3/4/606.short
Marshall & Cahan(2005)	http://www.tandfonline.com/doi/abs/10.1080/09603100500386008#.Uz4ys_mSx8E
Ellis & Parbery (2005)	http://www.sciencedirect.com/science/article/pii/S0275531905000310
Cai et al (2005)	http://link.springer.com/article/10.1007%2Fs10690-006-9012-y#page-1
Fieield et al (2005)	http://www.tandfonline.com/doi/abs/10.1080/1351847042000304099?journalCode=rejf20#.VbbqIooViUk
Ming & Hwa (2006)	http://www.sciencedirect.com/science/article/pii/S1049007805001788
Qi & Wu (2006)	http://www.jstor.org/stable/4123046
Hawtrey & Nguyen (2006)	http://onlinelibrary.wiley.com/doi/10.1111/j.1759-3441.2006.tb00400.x/abstract
Balsara, Chen and Zheng(2007)	http://www.jstor.org/stable/40473435?seq=1#page_scan_tab_contents
Hatgioannides & Mesomeris(2007)	http://www.sciencedirect.com/science/article/pii/S0261560607000629
Lento, Gradojevic & Wright (2007)	http://www.tandfonline.com/doi/pdf/10.1080/17446540701206576
Loh(2007)	http://www.tandfonline.com/doi/abs/10.1080/09603100600749352#.Uz4srfmSx8E
Metghalchi, Glasure, Garza & Chen (2007)	http://www.cluteonline.com/journals/index.php/IBER/article/view/3405
Shik & Chong (2007)	http://www.tandfonline.com/doi/abs/10.1080/17446540600771084
McKenzie(2007)	http://www.jstor.org/stable/27750558?seq=1#page_scan_tab_contents
Chong & Ng (2008)	http://www.tandfonline.com/doi/abs/10.1080/13504850600993598#.Uzzju_mSx8E
Fifield, Power & Knipe(2008)	http://www.tandfonline.com/doi/abs/10.1080/09603100701720302
Marshall, Cahan & Cahan(2008)	http://www.sciencedirect.com/science/article/pii/S0927539807000588
Marshall, Cahan & Cahan(2008)	http://www.sciencedirect.com/science/article/pii/S0927539807000588
Metghalchi, Garza-Gomez, Glasure & Chang (2008)	http://www.journals.cluteonline.com/index.php/JABR/article/view/1372
Metghalchi, Chang & Marcucci (2008)	http://www.sciencedirect.com/science/article/pii/S1057521907000257
Pukthuanthong-Le, Thomas III (2008)	http://www.jstor.org/discover/10.2307/40390214?uid=3737536&uid=2&uid=4&sid=21103804489657

Table 4.8 – continued from previous page

Author(s)	URL Links
Schulmeister(2008)	http://www.tandfonline.com/doi/pdf/10.1080/09603100701335416
Lento(2008)	http://www.cluteinstitute.com/ojs/index.php/JBER/article/view/2460
Chen, Huang & Lai(2009)	http://www.sciencedirect.com/science/article/pii/S1049007809000682
Lento (2009)	http://www.tandfonline.com/doi/abs/10.1080/17446540802260886#.Uz4z7fmSx8E
Zhu & Zhou(2009)	http://www.sciencedirect.com/science/article/pii/S0304405X09000361
Schulmeister(2009)	http://www.sciencedirect.com/science/article/pii/S1058330008000372
Coutts(2010)	http://www.tandfonline.com/doi/abs/10.1080/09603107.2010.524613
Park & Irwin (2010)	http://onlinelibrary.wiley.com/doi/10.1002/fut.20435/abstract
Hsu, Hsu & Kuan (2010)	http://www.sciencedirect.com/science/article/pii/S0927539810000022
Szalmary, Shen & Sharma (2010)	http://www.sciencedirect.com/science/article/pii/S037842660900199X
Cialenco & Protopapadakis (2011)	http://www.sciencedirect.com/science/article/pii/S1042443110000661
Mitra(2011)	http://www.tandfonline.com/doi/abs/10.1080/14697680903493581
Bajgrowicz & Scaillet(2012)	http://www.sciencedirect.com/science/article/pii/S0304405X1200116X
Chiang,Ke & Wang(2012)	http://www.tandfonline.com/doi/abs/10.1080/09603107.2011.631893
Metghalchi, Marcucci & Chang(2012)	http://www.tandfonline.com/doi/abs/10.1080/00036846.2010.543084#.Uz4GuPmSx8E
Metghalchi, Chang & Gomez(2012)	http://www.ccsenet.org/journal/index.php/ijef/article/download/13675/9437?
Pavlov & Hurn (2012)	http://www.sciencedirect.com/science/article/pii/S0378426611002123
Rosillo, Fuente & Brugos(2012)	http://www.tandfonline.com/doi/abs/10.1080/00036846.2011.631894
Shintani et al (2012)	http://www.sciencedirect.com/science/article/pii/S0304407612000292
Shynkevich(2012a)	http://www.sciencedirect.com/science/article/pii/S0378426611002123
Yamamoto(2012)	http://www.sciencedirect.com/science/article/pii/S0378426612001756
Wang et al (2012)	http://www.sciencedirect.com/science/article/pii/S1059056011001365
Yu et al.(2013)	http://www.sciencedirect.com/science/article/pii/S1059056012000767
Rosillo et al (2013)	http://www.tandfonline.com/doi/abs/10.1080/00036846.2011.631894
Neely et al(2013)	http://www.sciencedirect.com/science/article/pii/S0378426613002549
Ulku & Prodan (2013)	http://www.sciencedirect.com/science/article/pii/S1057521913001269
Narayan et al (2013)	http://www.sciencedirect.com/science/article/pii/S0378426613002793

Chapter 5

A Cross-Country Study of Technical Trading Rule Profitability

5.1 Introduction

The question of whether technical trading rules generate profits above those available from a buy-and-hold strategy is still open, despite the large volume of empirical research published on the subject. Research on the US equity market suggests that trading rules used to be profitable, but that profitability disappeared some time in the second half of the 1980s[1]. On the other hand, several studies of have suggested that technical trading rules are still able to generate profits in emerging markets[2]. However, as Marshall et al. (2010) pointed out, there are inconsistencies in studies' results with respect to predictablility for particular countries. For example, Bessembinder and Chan (1995) found the Malaysian market was profitable but Ratner and Leal (1999) did not. Bessembinder and Chan (1995) found Japan's market was not profitable, but Ito (1999) reported the opposite result.

In my opinion, the literature on cross-country analysis of trading rule profitability suffers from a number of shortcomings, which might explain the lack of consistent results, and certainly cast doubt on the robustness of many of the results that have been reported. Firstly, it has focussed largely on a narrow range of Latin American or Asian countries. Secondly, as discussed in Chapter 4, it has also focussed on a narrow range of technical

[1] See, for example, Sullivan et al. (1999); Hsu and Kuan (2005); Schulmeister (2009); Hsu et al. (2010); Shynkevich (2012); Bajgrowicz and Scaillet (2012).

[2] Bessembinder and Chan (1995); Ito (1999); Ratner and Leal (1999); Metghalchi et al. (2012a); Yu et al. (2013); Ulku and Prodan (2013)

trading rules. Consequently, in cases for which no evidence is found of profitable trading rules, it might be the case that the rules which were profitable and/or the markets that they are profitable in, were simply not included in the study. Thirdly, there are inconsistencies in the sample period used, the treatment of transactions costs and the measurement of returns. Most importantly, much of the existing literature has failed to control the family-wise error rate (FWER) of the hypotheses that they test. That is to say, most of the reported research in the field consists of conducting a test of the hypothesis of no net profit over a buy-and-hold strategy for each of many different trading rules in multiple markets, such that the probability of rejecting at least one true null hypothesis is uncontrolled, and may be much greater than the probability of rejecting a true null hypothesis in any of the individual tests. This method of testing multiple hypotheses is referred to as data-snooping. Its consequence is that many of the reported findings of trading rule profitability may be spurious. It is sometimes claimed that data-snooping distortions may be avoided by doing out-of-sample testing[3], but this is not the case. Data-snooping may only be avoided by using testing procedures that explicitly control the FWER, or some other error criterion that is relevant for multiple hypothesis tests. Cross-country studies that have controlled the FWER[4] have generally failed to find evidence of trading rule profitability.

It should be emphasized that the FWER controls the probability of rejecting a *single* false null hypothesis. In a study that involves a large number of hypotheses, this is a stringent criterion and, as a consequence, the test may lack power to reject null hypotheses that are false. In cases in which the rejection of more than one true null hypothesis is tolerable, power improvements may be achievable by controlling a more general definition of the error rate than the FWER. One simple generalization of the FWER which achieves this is the k-FWER. This is defined as the probability of rejecting no more than k true null hypotheses where k is a natural number. Obviously, the FWER is the special case of the k-FWER for which $k = 1$. An alternative error criterion which allows for the rejection of more than one false null hypothesis is the False Discovery Proportion (FDP). The FDP is defined as the proportion of the rejected hypotheses that are false. A multiple hypothesis testing procedure should ensure that $P(FDP > \gamma) \leqslant \alpha$ where γ and α are user-chosen parameters.

The objective of this chapter is to provide a comprehensive cross-country study of technical trading rules that uses a consistent methodology and adopts error criteria that are suitable for the task at hand. It extends the literature in two main ways. Firstly, it is the most comprehensive single cross-country study of technical trading rule profitablity

[3]For example, Allen and Karjalainen (1999), Olson (2004), Schulmeister (2008), Fang et al. (2014), name a few.

[4]e.g. Marshall et al. (2010) and Chen et al. (2009).

in equity markets to date, covering 28,631 different parameterizations of 54 different technical trading rules in 39 countries. Secondly, to the best of my knowledge[5], this is the first study of the cross-sectional pattern of trading rule profitability to adopt the k-FWER and FDP as error criteria. Consequently, in contrast to much of the prior literature, my results are not the outcome of data-snooping. Furthermore, my methodology has much greater power to discover profitable trading rules than the methodologies used by Marshall et al. (2010) and Chen et al. (2009).

The remainder of this chapter is structured as follows. Section 2 contains a review of the literature on the profitability of technical trading rules. Section 3 lists the markets I studied and presents details of the data and trading rules. Section 4 provides an outline of the research methodologies applied in this study. In Section 5 I discuss the empirical results of the study; Section 6 further explains the statistical tests for serial correlation and martingale difference hypothesis, and conclusions are presented in Section 7.

5.2 Previous Studies

This section provides a summary of the prior literature on technical trading rule profitability in emerging markets. The Appendix 5.A contains a list in tabular form of prior publications, the markets, periods and trading rules they considered, and the statistical methodology they used.

Bessembinder and Chan (1995) conducted the earliest cross-sectional study of technical trading rule profitability in equity markets in the literature. Their study considers six Asian countries over 1975-1989. Following the well-cited US study of Brock et al. (1992) they employed two rules (Moving Average Rules and Trading Range Break-Out Rules), and found evidence of profitability in Malaysia, Thailand and Taiwan, but mixed results for more mature countries like Korea, Hong Kong and Japan. With the same two technical trading rules, Ito (1999) studied the profitability of six Pacific basin equity markets (Japan, Indonesia, Taiwan, USA, Canada and Mexico) from 1980 to 1996, and found the rules were profitable for all countries (except the USA) even after transaction costs. The same negative finding for the USA was confirmed by Tian et al. (2002), who simultaneously determined that the Brock et al. (1992) rules were successful in the Shanghai and Shenzhen markets. Similarly, Chang et al. (2004) employed the two Brock et al. (1992) rules to examine Asian markets (including the four SEA tiger cub stock markets) from 1992 to 2000. Like Bessembinder and Chan (1995) and Ito (1999) , they concluded that technical trading strategies are more effective in emerging stock

[5] I conducted a Google Scholar search for papers that have cited Romano and Wolf (2007) or Hsu et al. (2014) on 25th November 2015.

markets. Lai and Lau (2006) examined the power of the two Brock et al. (1992) rules for nine Asian countries (Malaysia, Singapore, Hong Kong, Taiwan, Japan, Korea, China, Indonesia and Thailand) from 1988 to 2003 and found strong support for moving average (MA) rules, except in Japan. In a comparison of four Latin American (Argentina, Brazil, Chile and Mexico) and four Asian (Indonesia, Philippines, Taiwan, Thailand) countries' markets using Morgan Stanley Capital Index (MSCI) prices, Hatgioannides and Mesomeris (2007) found significant predictability of the Brock et al. (1992) rules and showed Asian markets are more favourable, even after accounting for transaction costs. Additionally, Yu et al. (2013) examined daily data from five South-East Asian stock markets (Indonesia, Malaysia, Philippines, Thailand and Singapore) from 1991 to 2008 using two Brock et al. (1992) rules. They measured strong performance of the rules for emerging countries (Malaysia, Thailand, Indonesia and Philippines), but for Singapore only the Trading Range Break-Out rule showed predictive ability before accounting for transaction costs, and profitability for Thailand was minimal.

Ratner and Leal (1999) tested the predictive power of Moving Average rules in 10 Asian (India, Korea, Malaysia, Philippines, Taiwan and Thailand) and Latin American (Argentina, Brazil, Chile and Mexico) countries from 1982 to 1995, and concluded that the rules supported the existence of profitability in Taiwan, Thailand and Mexico, but not in the other emerging markets. Gunasekarage and Power (2001) tested the same rules in four South Asian countries (Bangladesh, India, Pakistan and Sri Lanka) from 1990 to 2000 and found they generated profits in these markets. Fifield et al. (2008) also tested the predictive power of these rules in three Latin American (Argentina, Chile and Mexico), nine Asian (Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand), three other emerging countries (South Africa, Zimbabwe and Turkey) and three more developed countries (USA, UK and Japan). The study was to compare the performance of the profitability between developed and emerging markets. Most emerging markets had high profitability (the exceptions were Argentina, Hong Kong and Turkey) and among the developed countries Japan showed profitability for Moving Average rules. They found evidence of profit using filter rules in Finland, Italy, Hungary, Turkey and Greece, and using Moving Average rules in Greece, Hungary, Portugal and Turkey. Chen et al. (2009) examined the predictability of the five technical trading rules considered by Sullivan et al. (1999) in eight Asian countries (Hong Kong, Indonesia, South Korea, Malaysia, Singapore, Taiwan, Thailand and Japan) from 1975 to 2006, concluding that evidence of profits was negligible after inclusion of the transaction costs, when the family-wise error rate was controlled using the Reality Check of White (2000). Finally, Ulku and Prodan (2013) investigated the cross-sectional variation of technical trading rule performance among the stock indexes of 44 countries for 2001-2012; they found the Austrian, Brazilian, Egyptian, Greek, Indian, Indonesian, Mexican, Romanian, Russian and Taiwanese markets were predictable with Moving Average rules, and Turkey, Bulgaria, Egypt and Saudi Arabia predictable with Moving Average Convergence and Divergence rules.

Overall, it is difficult to draw firm conclusions from the existing literature on the profitability of technical trading rules. Previous studies (exceptions being Ulku and Prodan (2013) and Marshall and Cahan (2005)) have focused on small groups of Latin and Asian countries and only a few technical trading rules. Consequently, there may exist particular rules in certain countries that are profitable but which have simply been missed by the literature. On the other hand, few cross-country studies have implemented formal multiple hypothesis testing strategies, so many of the apparent findings of trading rule profitability could be due to data-snooping. Indeed, two studies which do implement multiple hypothesis testing strategies (Marshall et al. (2010) and Chen et al. (2009)) find no evidence of trading rule profitability. Nonetheless, Marshall et al. (2010) and Chen et al. (2009) both use approaches which control the family-wise error rate, which is a stringent criterion to apply in this context. Consequently, despite the validity of their statistical techniques, their methodologies are also prone to miss profitable trading rules.

5.3 Markets and Rules

The objective of my research was to conduct a cross-country study of the profitability of technical trading rules that is comprehensive in the sense that it considers a large number of technical trading rules applied over a wide range of countries. MSCI maintains a series of regional and global indexes that cover developed, emerging and frontier markets. Based on the countries listed in the MSCI Global Equity Indexes[6], we selected 39 countries with full length data for 1998 to 2013 (with the exceptions of Singapore and Tunisia, whose data start from August 1999 and September 1999 respectively).

We intentionally include the countries which do not allow short-selling[7] as the purpose of our study is to test whether technical trading rules actually generate superior profit over benchmark. If we only test the profitability from long position only then we only test partial ability of the technical trading rules.Furthermore, Taylor (2014) suggests that technical trading rules are more profitable when short selling is allowed and this is why we want to test both of the long and short position trading. We also assume, in spite of the short selling ban, if stock futures market is allowed, the market offers the tool for synthetic short selling position for the investor.

[6] https://www.msci.com/market-cap-weighted-indexes

[7] see Appendix C for the list of countries

The data were downloaded from Bloomberg. My goal was to include as many countries as possible, but due to widespread unavailability of data during my target period I was left with 18 countries from developed markets and 21 countries from emerging and frontier markets. Table 5.1 shows the countries and index names. Important historical events within the research periods are the Asian financial crisis (1997-1998), the Russian and Brazil turmoil (1998), the bursting of the US IT bubble (2001), the US sub-prime crisis and subsequent global financial crisis (2007-2008), and the first Greek bailout (2010).

TABLE 5.1: Full names of Data Series

Developed Markets		Emerging Markets	
Country	**Index Name**	**Country**	**Index Name**
Australia	S&P/ASX 200	Argentina	Buenos Aires SE Merval Index
Austria	Vienna SE Austrian Traded	Brazil	Ibovespa Brasil Sao Paulo SE Index
Belgium	Belgium 20 Index	China	Shanghai Composite Index
Canada	S&P TSX Composite Index	Greece	Athens SE General Index
Denmark	OMX Copengagen 20 Index	Hungary	Budapest Stock Exchange
France	CAC 40 Index	India	National SE CNX Index
Germany	Deutsche Boerse AG	Indonesia	Jakarta SE Composite Index
Hong Kong	Hong Kong Hang Seng Index	Korea	Korea SE Index
Ireland	Irish SE Overall Index	Malaysia	FTSE Bursa Malaysia KLCI
Israel	Tel Aviv 100 Index	Mexico	Mexican SE Bolsa IPC Index
Japan	Nikkei 225	Pakistan	Karachi SE KSE100 Index
Netherland	Amsterdam SE Index	Peru	Bolsa de Valores de Lima General Sector
Norway	Oslo SE Benchmark Index	Philippines	Philippines SE PSE Index
Portugal	Portugal SE 20 Index	Poland	Polish modified capitalization-weighted 20
Singapore	Straits Times Index	Romania	Bucharest SE Trading Index
Switzerland	Switzerland Market Index	Russia	Moscow capitalization-weighted index(MICEX)
UK	FTSE 100 Index	Sri Lanka	Sri Lanka Colombo SE all share Index
USA	Russel 3000 Index	Taiwan	Taiwan SE Weighted Index
		Thailand	SE of Thailand Index
		Tunisia	Tunisia SE Index
		Turkey	Borsa Istanbul 100 Index

This table introduce full names of the individual country's stock indices I applied.

I applied to these market indexes the 28,631 parameterizations of the 54 technical trading rules that were used in Chapter 4. These include classical trading rules such as moving averages, filter rules, and trading range break rules; and also include many other classes of technical trading rule that have not received prior attention in the academic literature. I refer the reader to Table 4.6 in Chapter 4 for a list of the rules, the parameterizations, and references to the literature.

I measured the performance of each trading rule in the same way as I did in Chapter 4. To reiterate, I considered $l = 28,631$ trading rules utilized over T time periods. For a given time period $t \in \{1, ..., T\}$, each rule $i \in \{1, ..., l\}$ generates a trading signal $S_{i,t-1}$ computed from closing prices up until period $t-1$. There are three signals, $S_{i,t-1} \in \{-1, 0, 1\}$ where 1 means buy (long) position, -1 is sell (short) position and 0 means neutral (no action) position. When a signal generates a long position, the investor buys the stock with principal and when a short position is generated, the investor borrows stock by paying the stock borrowing cost and selling into the market. When a neutral signal is generated, the principal goes to the deposit market to earn a risk-free rate. For the risk-free rates for each country, I applied overnight rates (or equivalent) downloaded from Thomson Reuters Datastream or each country's central bank, and I provide a summary table with URLs in this chapter Appendix 5.B.

Let X_t be the closing price of the stock on day t. The daily net return of an investment in the stock, denoted y_t, is defined as

$$y_{t+1} = \frac{(X_{t+1} - X_t)}{X_t} \tag{5.1}$$

Since trading rules are functions of prices in previous time periods, I reserve the first R observations in the sample for use in calculating the trading rules for the first trading day in the simulation. Let n be the number of time periods over which I apply the trading rules. I then have $T = R + n - 1$. I set $R = 250$ to allow for the implementation of moving average rules of orders up to 250.

I measure the net return of trading rule i in period $t + 1$ as

$$f_{i,t+1} = (ln[1+y_{t+1}*S_i(\chi_t, \beta_t)] - ln[1+y_{t+1}S_0(\chi_t)]) - TC_t(S_i(\chi_t, \beta_t)), \quad i = 0\ldots, l \tag{5.2}$$

where $\chi_t = [X_{t-1}]_{i=0}^{R}$, $t = R, ...T$, TC_t is the transaction costs which are written as a proportion of the portfolio value and β_i the vector of parameters of the i^{th} trading rule.

The average return of trading rule i over the entire period is as following;

$$\bar{f}_i = n^{-1} \sum_{t=R}^{T} f_{(i,t+1)} \tag{5.3}$$

The hypotheses of interest are then

$$H_0 : E(\bar{f}_i) \leqslant 0, \qquad i = 1, ..., l$$

5.4 Generalized Error Rates and the False Discovery Proportion

The standard approach to hypothesis testing controls the probability of rejecting a true null hypothesis. Consequently, it is suitable for testing a single hypothesis only. For cases in which multiple hypotheses need to be tested – as is the case when the profitability of many trading rules is being assessed – the application of standard hypothesis tests to each rule is inappropriate since the family-wise error rate (FWER) (that is the probability of rejecting at least one true null hypothesis) may be much larger than the probability of a Type 1 error nominated for each individual hypothesis. The last couple of decades have seen the development of a number of approaches to multiple hypothesis testing that provide (asymptotic) control of the family-wise error rate. Two popular approaches are the Reality Check (RC) of White (2000) and the Superior Predictive Ability (SPA) test of Hansen (2005). Marshall et al. (2010) applied the RC to a cross-country analysis of technical trading rule profitability and Chen et al. (2009) applied both the RC and the SPA. In contrast to many studies that used standard hypothesis testing techniques, they found no evidence of trading rule profitability. Nonetheless, it must be conceded the FWER is a stringent criterion to control. In many applications that require multiple hypotheses to be tested, one might be prepared to tolerate more than one true null hypothesis being rejected, particularly if allowing for this results in greater power to reject hypotheses that are false. In this paper, I am testing the profitability of 28,631 different parameterizations of 54 technical trading rules in 39 different markets, so I am prepared to tolerate the false rejection of more than one true null hypotheses in order to increase the power to reject hypotheses that are false. Accordingly, I considered the following two generalized error criteria.

The k-FWER The k-family-wise error rate is the probability of rejecting at least k true null hypotheses, where k is an integer. Note that if $k = 1$, then this is the FWER.

The False Discovery Proportion (FDP) The FDP is the proportion of rejections of the null hypothesis for which the null hypothesis is true. More precisely, let R denote the number of hypotheses that are rejected and let F denote the number of rejected hypotheses that are false. Then

$$FDP = \begin{cases} \frac{F}{R}, & \text{if } R > 0, \\ 0, & \text{if } R = 0. \end{cases} \tag{5.4}$$

Note that the False Discovery Rate (FDR) of Benjamini and Hochberg (1995) is the expected value of the FDP. A test that controls the FDP is designed such that $P(FDP > \gamma) \leqslant \alpha$ where γ and α are parameters chosen by the researcher.

I use the method of Romano and Wolf (2007) and the extension due to Hsu et al. (2014) to control the k-FWER and the FDP. These methods are described below. In this analysis, I set k=3, $\gamma = 0.1$ and $\alpha = 0.05$[8].

The Romano and Wolf (2007) algorithm to control the k-FWER is as follows:

Let $T_{n,i} = \frac{\sqrt{n}\bar{f}_i}{\hat{\sigma}_i}$ for $i = \{1, \ldots, l\}$, where $\hat{\sigma}_i^2$ is the stationary bootrap variance estimator of Politis and Romano (1994).

1. Arrange $T_{n,i}$ in descending order.

2. Let $A_1 = \{1, ..., l\}$. Let $\hat{c}_{n,A1}(1-\alpha, k)$ be the stationary bootstrap estimate of the α-quantile of the distribution of the k^{th} largest value of $\{T_{n,1}, ..., T_{n,l}\}$. For $i = 1, ..., l$ reject any hypothesis H_i for which $\max\left(T_{n,i} : i \in A_1\right) \geq \hat{c}_{n,A1}(1-\alpha, k)$. If no hypotheses are rejected, stop the algorithm. Otherwise, move on to Step 3.

3. Let R_2 be the set of indices of the rejected models from the previous step and let A_2 denote set of indices of the non-rejected hypotheses. If number of rejections is less than k, then stop. Otherwise, let

$$\hat{d}_{n,A_2}(1-\alpha, k) = \max_{I \subset R_2, |I| = k-1} \{\hat{c}_{n,K}(1-\alpha, k) : K = A_2 \cup I\} \tag{5.5}$$

   For $i \in A_2$ reject the null if $T_{n,i} \geq \hat{d}_{n,A_2}(1-\alpha, k)$. If there are no rejections, stop the algorithm.[9]

4. Let R_j denote the set of indices for the hypotheses rejected up to previous step and let A_j denote the indices for those hypotheses not rejected. The new critical value for this stage is calculated as follows;

$$\hat{d}_{n,A_j}(1-\alpha, k) = \max_{I \subset R_j, |I| = k-1} \{\hat{c}_{n,K}(1-\alpha, k) : K = A_j \cup I\} \tag{5.6}$$

   For $i \in A_j$, reject any H_i satisfying $T_{n,i} \geq \hat{d}_{n,A_j}(1-\alpha, k)$. If there are no rejections, stop the algorithm.

5. If there are further rejections, Let $j = j + 1$ and repeat the Step 4 until there are no additional rejections.

[8]We applied Romano and Wolf (2007) and Hsu et al. (2014) and they applied parameter input value of k=3, gamma=0.1 and alpha=0.05 which we used.

[9]Note that the number of K is greater than A2 because K=$A_2 \cup I$ and if $k = 3$, then $I = k - 1 = 2$.

Note that in steps 3 and 4, the critical values are computed using all the non-rejected trading rules and $k-1$ of the rejected trading rules. The k-FWER controls the probability of rejecting k true null hypotheses. Since it is not known *which* k of the rejected hypotheses might be true, the algorithm computes the critical values for every possible combination of $k-1$ rejected hypotheses and takes the maximum of these. Consequently, for the j^{th} iteration of the algorithm, $N_j = \binom{|R_j|}{k-1}$ quantiles must be computed. If $|R_j|$ is a large number, the computational burden may be quite high. Romano and Wolf (2005) therefore introduce an operative method that reduces this computation burden, while at the same time maintaining the key properties of original algorithm. With the method, the user chooses a feasible maximum number of iterations N_{max}. In this chapter, I set N_{max}=50. Let M be the largest integer for which $\binom{M}{k-1} \leq N_{max}$. Instead of calculating the maximum critical value from the non-rejected rules and all possible combinations of $k-1$ rules from the $|R_j|$ rejected rules, the operative method is to calculate the maximum critical value from the rejected rules and all possible combinations of $k-1$ rules from the M least significant rejected rules. Thus, the operative method computes the critical value at Step j is

$$\hat{d}_{n,A_j}(1-\alpha,k) = \max_{I \subset \{r_{max\{1,|R-j|-M+1\}},\ldots,r_{|R_j|}\},|I|=k-1} \{\hat{c}_{n,K}(1-\alpha,k) : K = A_j \cup I\} \quad (5.7)$$

where $\{r_1, r_2,\ldots,r_{|R_j|}\}$ is the appropriate permutation of associated hypotheses indices based on the order of test statistic. i.e., $\{T_{n,r_1} \geq T_{n,r_2} \geq \ldots \geq T_{n,r_{|R_j|}}\}$. Romano and Wolf (2007) (Theorem 3.4) prove that this algorithm provides asymptotic control of the k-FWER.

Hsu et al. (2014) extend the k-FWER algorithm of Romano and Wolf (2007) by incorporating elements of the SPA test of Hansen (2005) and the Step-SPA of Hsu et al. (2010). They name this the Step-SPA(k) test. The Step-SPA(k) algorithm is the same as the k-FWER algorithm outlined above except that $\hat{c}_{n,K}(1-\alpha,k)$ is replaced with $\hat{q}_{n,K}(1-\alpha,k)$ where.

$$\hat{q}_{n,K}(1-\alpha,k) = max(\tilde{q}_{n,K}(1-\alpha,k),0)$$

and $\tilde{q}_{n,K}(1-\alpha,k)$ is α-th quantile of $max(z_i^{(b)})$.

where b is $1,\ldots,B.B$ is the number of bootstrap resamples and I set the B is 1000, $z_i^{(b)} = \frac{\sqrt{n}(\bar{f}_i^{(b)} - \bar{f}_i + \hat{\mu}_i)}{\hat{\sigma}_i}$ where $\hat{\mu}_i = \bar{f}_i \mathbf{1}(\bar{f}_i \leqslant -\hat{\sigma}_i\sqrt{2lnlnn})$ and $\mathbf{1}(x) = 1$ if x is true.

Hsu et al. (2014) prove (Theorem 1) that their procedure provides asymptotic control of the k-FWER and (Theorem 2) that it is more powerful than the procedure of Romano and Wolf (2007) using any of the definitions of power considered by Romano and Wolf (2005).

Romano and Wolf (2007) explain how the above algorithms can be extended to control the False Discovery Proportion (FDP). The approach is to apply a test procedure that controls the k-FWER for increasing value of k. Specifically:

1. Set $j = 1, k_j = 1$. The procedure is designed to control $P(FDP > \gamma) \leqslant \alpha$, so the values of γ and α must be chosen at this point. In this chapter, I choose $\gamma = 0.1$ and $\alpha = 0.05$.
2. Apply a test that controls the k_j-FWER and let N_j denote the number of hypotheses rejected.
3. If $N_j < k_j/\gamma - 1$, stop and reject hypotheses. Otherwise, set $j = j + 1$ and $k_j = k_{j-1} + 1$ and return to Step 2.

Romano and Wolf (2007) (Theorem 4.1) prove that this procedure provides asymptotic control of the FDP.

5.5 Empirical Results

Table 5.2 presents the gross returns from the most profitable technical trading rule (Best) and the benchmark buy-and-hold strategy (Bench) for each market. Note that for each market the best rule generates a return that is well in excess of the benchmark. The mean returns of the best rules range from a low of 10.6% for Australia to a high of 26.3% for Portugal, and those of emerging markets range from 21.0 of Korea to 57.8% for Sri Lanka. Additionally, the highest net returns are 29.6% for Portugal (developed market) and 52.5% for Greece (emerging market). The lowest performing countries are Australia and Korea respectively. On average, the net return of emerging markets is about 10% higher than for advanced markets.

The pVal column of Table 5.2 contains the nominal p-value results from applying the standard t-test of Diebold and Mariano (1995) to the best trading rule only, thereby ignoring the effects of data snooping. Taken at face value, these statistics might be interpreted as indicating that, at the 5% significance level, technical trading rules generate profits in 12 of 18 developed markets and 15 of 21 emerging markets. However, Table 5.3 which contains the results of tests which provide weak and strong control of the FWER, the k-FWER and the FDP, paints a different picture, which illustrates the dangers of data-snooping in applications such as this.

In Table 5.3, the RC column contains the p-values from the White (2000) RC test and the SPA column indicates the p values from the Hansen (2005) SPA test. Based on these two tests, which weakly control the FWER, I found evidence that profitable trading rules exist for seven countries: Portugal (developed group) and Greece, Malaysia, Peru, Philippines, Sri Lanka and Tunisia (emerging countries). The changes from Tables 2 to 3 are from 12 to 1 developed countries and 15 to 8 emerging countries. These sharp drops in the number of countries with predictability in their markets mean traditional statistical tests seriously overestimate the predictability of technical trading rules. Moreover, they suggest the findings in Table 5.2 are largely due to data snooping rather than genuine profitability of trading rules.

The columns of Table 5.3 that are headed SRC_1[10] and SPA_1 contain the number of trading rules for which the Studentized StepM test of Romano and Wolf (2005) and the extension due to Hsu et al. (2010) respectively. These tests provide strong control of the FWER. Note however that they do not reveal evidence of trading rule profitability for countries in which no evidence was found by the RC and SPA tests. The columns that

[10]The SRC_1 is step wise version of the RC test of White (2000) or "Studentized StepM test" of the Romano and Wolf (2005), while SRC_3 is generalized version of the SRC_1 of Romano and Wolf (2007), respectively.

TABLE 5.2: Technical trading profitability with traditional statistical tests

	Developed	Bench(%)	Best(%)	pVal	Emerging	Bench(%)	Best(%)	pVal
1	**Australia**	**4.60**	**10.57**	**0.1511**	**Argentina**	**17.14**	**44.34**	**0.0135**
2	**Austria**	**5.42**	**25.82**	**0.0104**	**Brazil**	**13.72**	**26.9634**	**0.1018**
3	**Belgium**	**-1.21**	**19.42**	**0.0084**	**China**	**2.96**	**29.58**	**0.0025**
4	**Canada**	**5.0**	**17.06**	**0.0519**	**Greece**	**-5.74**	**46.72**	**0.0002**
5	**Denmark**	**6.73**	**18.26**	**0.0751**	**Hungary**	**6.69**	**23.47**	**0.0543**
6	**France**	**0.01**	**22.16**	**0.0040**	**India**	**13.10**	**27.77**	**0.0443**
7	**Germany**	**4.26**	**22.37**	**0.0116**	**Indonesia**	**15.36**	**49.31**	**0.0042**
8	**Hong Kong**	**5.29**	**20.83**	**0.0842**	**Korea**	**10.50**	**21.0**	**0.1453**
9	**Ireland**	**-1.20**	**17.73**	**0.0225**	**Malaysia**	**10.07**	**23.89**	**0.0002**
10	**Israel**	**9.33**	**20.90**	**0.0591**	**Mexico**	**16.01**	**29.09**	**0.0652**
11	**Japan**	**1.26**	**19.08**	**0.0139**	**Pakistan**	**21.59**	**35.56**	**0.0043**
12	**Netherland**	**-1.95**	**17.27**	**0.0117**	**Peru**	**16.50**	**55.17**	**0.0013**
13	**Norway**	**10.50**	**21.92**	**0.0958**	**Philippines**	**7.07**	**45.09**	**0.0002**
14	**Portugal**	**-3.35**	**26.27**	**0.0002**	**Poland**	**4.13**	**21.57**	**0.0343**
15	**Singapore**	**2.72**	**18.01**	**0.0266**	**Romania**	**20.67**	**47.97**	**0.0124**
16	**Switzerland**	**0.90**	**17.88**	**0.0073**	**Russia**	**23.65**	**39.19**	**0.1245**
17	**UK**	**0.84**	**18.24**	**0.0104**	**Sri Lanka**	**13.87**	**35.87**	**0.0002**
18	**USA**	**3.42**	**15.60**	**0.0177**	**Taiwan**	**1.24**	**26.37**	**0.0080**
19					**Thailand**	**8.06**	**37.82**	**0.0002**
20					**Tunisia**	**9.39**	**24.81**	**0.0002**
21					**Turkey**	**21.54**	**39.79886**	**0.1152**

This Table present the summary of four tests we applied for the full periods. Bench is market benchmark annual mean yield and the Best means the best mean return from the best trading rule. RC and SPA denote White (2000)'s and Hansen (2005)'s nominal p-values, while "Studentized StepM" is stepwise RC version Romano and Wolf (2005) and "Step-SPA" is the single stepwise test of Hsu and Kuan (2005),respectively.

TABLE 5.3: Profitability of Technical Trading with Mean Return : Mean Excess Return with costs

	Country Name	Costs	*RC*	*SPA*	SRC_1	SRC_3	SRC_{FDP}	SPA_1	SPA_3	SPA_{FDP}
Developed Market										
1	Australia	No TC	0.9528	0.8922	0	0	0	0	0	0
2	Austria	No TC	0.4254	0.4570	0	0	0	0	0	0
3	Belgium	No TC	0.2797	0.4053	0	0	0	0	0	0
4	Canada	No TC	0.8307	0.8716	0	0	0	0	0	0
5	Denmark	No TC	0.8423	0.8331	0	0		0	0	0
6	France	No TC	0.2684	0.2568	0	0	0	0	0	0
7	Germany	No TC	0.6079	0.5508	0	0	0	0	0	0
8	Hong Kong	No TC	0.7834	0.6861	0	0	0	0	0	0
9	Ireland	No TC	0.4669	0.6310	0	0	0	0	0	0
10	Israel	No TC	0.7584	0.7175	0	0	0	0	0	0
11	Japan	No TC	0.5835	0.6195	0	0	0	0	0	0
12	Netherland	No TC	0.4676	0.4863	0	0	0	0	0	0
13	Norway	No TC	0.8711	0.9044	0	0	0	0	0	0
14	Portugal	No TC	0.0162	0.0095	1	7	7	1	7	7
		TC_5	0.0531	0.0495	0	0	0	0	0	0
15	Singapore	No TC	0.6016	0.6836	0	0	0	0	0	0
16	Switzerland	No TC	0.4880	0.4698	0	0	0	0	0	0
17	UK	No TC	0.3540	0.3074	0	0	0	0	0	0
18	USA	No TC	0.7381	0.5968	0	0	0	0	0	0
Emerging Market										
	Country Name	Costs	*RC*	*SPA*	SRC_1	SRC_3	SRC_{FDP}	SPA_1	SPA_3	SPA_{FDP}
1	Argentina	No TC	0.6237	0.5620	0	0	0	0	0	0
2	Brazil	No TC	0.9335	0.9292	0	0	0	0	0	0
3	China	No TC	0.2140	0.1843	0	0	0	0	0	0
4	Greece	No TC	0.0031	0.0015	6	17	17	6	17	17
		TC_5	0.0542	0.0467	0	0	0	0	0	0
5	Hungary	No TC	0.7388	0.8242	0	0	0	0	0	0
6	India	No TC	0.8214	0.7644	0	0	0	0	0	0
7	Indonesia	No TC	0.1759	0.1800	0	0	0	0	0	0
8	Korea	No TC	0.9650	0.9745	0	0	0	0	0	0
9	Malaysia	No TC	0.0386	0.0094	2	4	4	3	6	6
		TC_5	0.1595	0.0745	0	0	0	0	0	0
10	Mexico	No TC	0.8421	0.8310	0	0	0	0	0	0
11	Pakistan	No TC	0.2977	0.1558	0	0	0	0	0	0
12	Peru	NO TC	0.0447	0.0228	4	13	13	7	17	17
		TC_5	0.0955	0.0565	0	0	0	0	0	0
13	Philippines	No TC	0.0840	0.0859	0	6	0	0	0	0
		TC_5	0.1536	0.1723	0	0	0	0	0	0
14	Poland	No TC	0.7112	0.6920	0	0	0	0	0	0
15	Romania	No TC	0.4060	0.3574	0	0	0	0	0	0
16	Russia	No TC	0.9444	0.9204	0	0	0	0	0	0
17	Sri Lanka	No Cost	0.0059	0.0002	67	85	113	85	106	135
		TC_5	0.0142	0.0014	31	46	56	51	67	81
		TC_10	0.0269	0.0047	2	5	5	2	16	16
		TC_20	0.3266	0.1894	0	0	0	0	0	0
18	Taiwan	No TC	0.2643	0.3413	0	0	0	0	0	0
19	Thailand	No TC	0.1318	0.0956	0	0	0	0	0	0
20	Tunisia	No TC	0.0338	0.0148	1	3	3	6	7	7
		TC_5	0.3131	0.2265	0	0	0	0	0	0
21	Turkey	No TC	0.9009	0.8626	0	0	0	0	0	0

The SRC_1 is step wise version of the RC test of White(2000) or “Studentized StepM” test of Romano and Wolf (2005) and SRC_3 is generalized version of the SRC_1 of Romano and Wolf (2007) , respectively. If k=3, SRC_k is identical to SRC_3 and by allowing 3 more false rejections, SRC_k test achieves the asymptotic control of the FWER(k) and also an improvement of the SRC_1. Read SRC_{FDP} as False Discovery Portion based on the SRC_k. Same logic goes to SPA tests results. SPA_1 is the single stepwise test of Hsu and Kuan (2005) and SPA_3 is generalized version SPA test of Hsu et al. (2010) and SPA_{FDP} is False Discovery Portion calculating using SPA_3, respectively.

are headed SRC_3 and SPA_3 contain the number of trading rules rejected by the tests due to Romano and Wolf (2007) and the extension due to Hsu et al. (2014) respectively, configured to provide strong control over the 3-FWER. Note that allowing for 3 true null hypotheses to be rejected (with a probability of 5%) can greatly increase the power of the tests to find profitable rules over the standard case in which at most one true null hypothesis is rejected with a probability of 5%. For example, changing from $k = 1$ to $k = 3$ increases the number of profitable rules found for Portugal from 1 to 7. For Greece it increases from 6 to 17, and for Sri Lanka it increases from 71 to 96 for the SRC_3 statistics, and from 98 to 127 for the SPA_3 statistics. For this reason, I regard the use of generalized error rates as a useful methodology for the empirical analysis of the profitability of technical trading rules. In my application, control of the FDP to be less than $\gamma = 0.1$ with a probability of 0.05 only increases the number of profitable rules found for Sri Lanka over the number found by controlling the 3-FWER. Nonetheless, for the other countries, control of the FDP leads to the finding of as many profitable rules as control of the 3-FWER, so I consider FDP control to be a useful methodology for the analysis of trading rule profitability.

Many empirical studies address the impact of transaction costs on profitability (e.g. Fama and Blume (1966), Bessembinder and Chan (1995), Kho (1996), Bajgrowicz and Scaillet (2012) and Shynkevich (2012),Hsu and Taylor (2014)). In my analysis, in addition to the zero transaction cost case, I consider once-only transaction costs of five and ten basis points, and per-period stock borrowing costs of five and ten basis points. With an inclusion of a five basis point transaction cost (TC_5), the evidence of return predictive ability for Greece, Pakistan, Peru, Philippines and Tunisia vanished as showed in Table 5.3. Furthermore, after applying an additional five basis points to the stock borrowing cost (TC_5, SBC_5) when short-selling, there is no evidence that Malaysia is profitable with my technical trading rules. The evidence of profitability for Sri Lanka vanished after the application of five and 10 basis points to the (TC_{10}, SBC_5). This shows the importance of the application of the transaction costs on technical trading rule studies.

In summary, I found evidence that some trading rules are profitable for 6 of the 21 emerging markets that I considered: Greece, Malaysia, Peru, Philippines, Sri Lanka and Tunisia[11]; and 1 of 18 developed markets: Portugal. However, the evidence of profitability exists for only a small proportion of the rules. Furthermore, when non-zero transactions costs are applied, the evidence disappears.

[11]Sri Lanka is the country where short selling is not allowed (see Appendix 5.C for the list of short selling ban countries). However, our intention for the research is to test the forecasting ability of technical trading rules for both long and short so we assumed short selling is allowed for this country. We include performance when short selling is not allowed (see Appendix 5.D). We find short selling gives better performance but still these country have the return profitability from technical trading rules and this implies short selling restriction is not the key reason for the predictability.

My next objective was to determine which of the 54 candidate rules was the best-performing rule across every country. Table 5.4 summarizes the significantly out-performing rules for each country and the rules rejected based on the SPA_{FDP}. The most consistently profitable rules are Moving Averages, Filter Rules and KDJ Rules, each of which was found to be profitable in all countries for which profitable rules exist.

TABLE 5.4: Analysis of the Number of Rejected Rules

Country	Rejected Rules and their number of Rejections								
Portugal	KDJ	Filter	MA	CBO					
	8	4	1	7					
Greece	ERI	FI	KDJ	Filter	MA				
	3	2	4	1	7				
Malaysia	ERI	FI	KDJ	Filter	MA				
	1	3	1	2	1				
Peru	KDJ	Filter	MA						
	3	3	10						
Philipines	Filter	MA							
	3	2							
Sri Lanka	ADX	ARN	CMO	ERI	FI	SNR	KDJ	Filter	MA
	16	14	3	1	1	6	5	116	1
Tunisia	FI	KDJ	MA						
	3	1	5						

This table presents the significantly out-performing technical trading rules of each country, and this is based on the SPA_{FDP}.

5.6 Statistical Tests for serial correlation and the martingale difference hypothesis

In the previous chapter, it was noted that the periods of profitability in the DJIA roughly coincided with the periods in which other researchers had found evidence of serial correlation in the DJIA, which raises the question of whether a similar result exists in a cross-country analysis of trading rule profitability. If stock returns are not martingale difference sequences, then they are predictable and so it is possible that a well-designed trading rule will be profitable. I have found evidence that some technical trading rules are profitable in some countries. A rejection of the martingale difference hypothesis for those countries would reinforce these results. A rejection for the other countries would also be interesting since it would suggest that it is possible in principle to design profitable trading rules for those countries, even though I found no direct evidence that any of the rules I considered are profitable. The distinction between serial correlation and the martingale difference property is an interesting one in this context since it is possible that stock returns could be serially uncorrelated but not a martingale difference sequence. In such a case, rules designed to exploit serial correlation would not work, even though profitable rules might potentially be designed. I conduct two different tests of serial correlation and two different tests of the martingale difference hypothesis. These are briefly described below.

5.6.1 Automatic Portmanteau Q (AQ) Test

The classical autocorrelation test of Box and Pierce (1970) is based on the following statistic.

$$Q_p = T \sum_{i=1}^{p} \hat{\rho}^2(i), \tag{5.8}$$

where $\hat{\rho}(i)$ is the sample estimate of $\rho(i)$, ith order autocorrelation and the T is the sample size and p is lag for autocorrelation. Lobato et al. (2001) proposed the following modified version of this statistic.

$$Q_p^* = T \sum_{i=1}^{p} \tilde{\rho}^2(i), \tag{5.9}$$

where $\tilde{\rho}^2(i) = \hat{\gamma}^2(i)/\hat{\tau}(i)$, $\hat{\gamma}(i)$ is the sample autocovariance of y_t, and $\hat{\tau}(i)$ is the sample autocovariance of y_t^2. Escanciano and Lobato (2009a) propose an automatic test where the optimal value of p is determined by a fully data-dependent procedure.

$$AQ = Q_{\tilde{p}}^*, \tag{5.10}$$

where $\tilde{p}$ is the optimal lag selected based on the combination of the Akaike information criterion(AIC) and Bayesian information criterion(BIC). The test statistic asymptotically follows the χ_1^2 distribution.

5.6.2 Wild Automatic Variance Ratio (WAVR) Test

The variance ratio, VR is the ratio of two different variances: the variance of the k-period return and the variance of the one day return.

$$V(k) = \frac{var(y_t - y_{t-k})/k}{var(y_t - y_{t-1})} = 1 + 2\sum_{i=1}^{k-1} \frac{(k-i)}{k}\rho_i \tag{5.11}$$

where ρ_i is the ith lag autocorrelation coefficient of x_t, $x_t = y_t - y_{t-1}$ and $1 \leq k \leq t$.

If a stock price has no serial correlation, then the variance of the k-period return is equal to k times the variance of the one period return. The equation shows as long as x_t is not serially correlated (ρ_i=0, V(k)=1). The null hypothesis is VR=1 for all k-period which corresponds to there being no serial correlation. Alternatively, VR(k) greater than 1 imply positive serial correlations while values less than 1 imply negative serial correlations.

The Automatic VR (AVR) test of Chow and Denning (1993) extends the VR test by automatically choosing the optimal size of the lags by a data dependent procedure with quadratic spectral kernal, using Andrews (1991)'s procedure for estimating the optimal bandwidth of a quadratic spectral kernel estimator of the variance at frequency zero. Kim (2006) proposes that the distribution of this statistic be estimated using the wild bootstrap, resulting in the Wild Automatic Variance Ratio (WAVR) Test.

5.6.3 Generalized Spectral Test (GST)

The generalized spectral test (henceforth denoted as GST) of Escanciano and Velasco (2006) is a test of the martingale difference hypothesis (MDH) and is robust to conditional higher moments of unknown form especially conditional heteroskedasticity. Unlike their time-domain counterparts such as the VR tests, the frequency domain GST incorporates information on the serial dependence from all lags, and hence there is no need to choose any lag-order parameter. Let

$$\hat{H}(\lambda, x) = \hat{\gamma}_0(x)\lambda + 2\sum_{j=1}^{n-1}(1-\frac{j}{n})^{\frac{1}{2}}\hat{\gamma}_j(x)\frac{sinj\pi\lambda}{j\pi}, \tag{5.12}$$

and

$$S_n(\lambda, x) = (\frac{n}{2})^{\frac{1}{2}}\{\hat{H}(\lambda, x) - \hat{H}_0(\lambda, x)\} = \sum_{j=1}^{n-1}(n-j)^{\frac{1}{2}}\hat{\gamma}_j(x)\frac{\sqrt{2}sinj\pi\lambda}{j\pi}, \tag{5.13}$$

The test statistic is then the Cramér-von Mises norm.

$$D_n^2 = \int_{\mathbb{R}}\int_0^1 |S_n(\lambda, x)|^2 W(dx)d\lambda = \sum_{j=1}^{n-1}(n-j)\frac{1}{(j\pi)^2}\int_{\mathbb{R}}|\hat{\gamma}(x)|^2 W(dx) \tag{5.14}$$

Escanciano and Velasco (2006) propose that critical values be computed using a wild bootstrap.

5.6.4 Phillips and Jin Test (PJ)

Phillips and Jin (2014) introduce new tests based on the generalized versions of the Kolomrov-Smirnov and Cramér-von Mises tests of Park and Whang (2005)[12]. The martingale null is formulated as weak drift in the null model.

$$X_t = \mu + \theta X_{t-1} + u_t, \qquad with \quad \theta = 1 \tag{5.15}$$

The test statistics are self-normalized quantities formed as follows

$$\begin{aligned} gKS_n^* &= \sup_{a\in\mathbb{R}} |\Gamma_n^*(x)|, and \\ gCvM_n^* &= \frac{1}{n}\sum_{t=1}^{n}\Gamma_n^*(X_{t-1})^2 \end{aligned} \tag{5.16}$$

where

$$\Gamma_n^* = \frac{\frac{1}{n}\sum_{t=1}^{n}(\Delta X_t - \overline{\Delta X_t})\mathbf{1}(X_{t-1} \leq x)}{(\frac{1}{n}\sum_{t=1}^{n}\hat{u}_t^2)^{1/2}}, \tag{5.17}$$

and $\overline{\Delta X_t}$=$\frac{1}{n}\sum_{t=1}^{n}(\Delta X_t)$. Critical values are computed using Monte Carlo methods.

5.6.5 Test Results

Table 5.5 summarises the four statistical test results. Note that there is evidence of serial correlation in the returns series of far more countries than I found profitable trading rules for. This raises the possibility that profitable trading rules, other than those considered in the previous section, may exist.

I find evidence of serial correlation for all the markets for which I found profitable trading rules in the previous section, except for Malaysia. Kim and Shamsuddin (2008, pp.527-530) found similar results from VR tests of Malaysia and interpreted the phenomenon as due to outliers that occurred in the Asian crisis. I confirmed this interpretation by dropping the maximum and minimum returns from the dataset and recomputing the AVR and AQ statistics for Malaysia. The statistics are presented in Table 5.6. Note that after the removal of these two observations, the null hypothesis is rejected by both tests.

[12] Park and Whang (2005) and Escanciano and Lobato (2009b) are recent development of the tests based on the Kolomrov-Smirnov and Cramér-von Mises tests but I only report the most recent PJ test here.

TABLE 5.5: Four Statistical Tests Results for DM and EM countries

Developed Markets						Emerging Markets					
Tests	AQ	AVR	GST	PJ		Tests	AQ	AVR	GST	PJ	
Pval/Stat	Pval	Pval	Pval	KS	CvM	Pval/Stat	Pval	Pval	Pval	KS	CvM
Australia	0.2025	0.2233	0.8333	0.6841	0.7538	Argentina	0.0288	0.0100	0.0567	0.8061	0.7100
Austria	0.0283	0.1600	0.0900	0.8032	0.8116	Brazil	0.7575	0.6967	0.5967	0.3084	0.5543
Belgium	0.0054	0.1167	0.0000	0.8332	0.6463	China	0.6059	0.5700	0.7400	0.8336	0.8572
Canada	0.9009	0.9233	0.3900	0.4815	0.6069	Greece	0.0000	0.0000	0.0000	0.9391	0.9139
Denmark	0.1169	0.3233	0.4133	0.9943	0.9962	Hungary	0.0504	0.3600	0.2867	0.0996	0.4487
France	0.4911	0.6933	0.1233	0.3612	0.3149	India	0.0259	0.1700	0.0000	0.5681	0.8207
Germany	0.9672	0.9200	0.6100	0.9297	0.8641	Indonesia	0.0000	0.0000	0.0700	0.9328	0.8558
Hong Kong	0.6940	0.6833	0.5167	0.4319	0.6544	Korea	0.0179	0.0567	0.0533	0.3190	0.7146
Ireland	0.0382	0.1000	0.0300	0.8807	0.8141	Malaysia	0.6948	0.3700	0.7000	0.9973	0.9987
Israel	0.0166	0.0367	0.1100	0.5826	0.7892	Mexico	0.0000	0.0000	0.0400	0.9677	0.9100
Japan	0.2232	0.1633	0.3867	0.6889	0.5795	Pakistan	0.0000	0.0000	0.0000	0.2626	0.6240
Netherland	0.9626	0.8833	0.3067	0.6555	0.5775	Peru	0.0000	0.0000	0.0000	0.2605	0.6199
Norway	0.5012	0.4467	0.2733	0.0000	0.0000	Philippines	0.0000	0.0000	0.0466	0.9215	0.9570
Portugal	0.0002	0.0033	0.0000	0.9522	0.8185	Poland	0.0022	0.0267	0.2433	0.2988	0.5683
Singapore	0.3071	0.2400	0.7300	0.0000	0.0000	Romania	0.0231	0.0067	0.0100	0.5452	0.7793
Switzerland	0.2619	0.6167	0.3867	0.7349	0.5310	Russia	0.0000	0.0833	0.0167	0.2589	0.4490
UK	0.2210	0.0633	0.1700	0.3631	0.2302	Sri Lanka	0.0000	0.0000	0.0000	0.8486	0.6244
USA	0.0154	0.0033	0.0833	0.7661	0.7227	Taiwan	0.0012	0.0000	0.0533	0.4894	0.3869
						Thailand	0.0245	0.0067	0.1500	0.9737	0.9971
						Tunisia	0.0000	0.0000	0.0000	0.4218	0.5868
						Turkey	0.9534	0.8533	0.8100	0.8575	0.9462

This table summarises the four statistical test results. "AQ" is Automatic Portmanteau Q test of Box and Pierce (1970), "AVR"is Automatic Variance Ratio (AVR) Test of Kim (2006), "GST" denotes the generalized spectral test of Escanciano and Velasco (2006), "PJ" is Phillips and Jin Test Phillips and Jin (2014)and "KS" stands for generalizations of the Kolomrov-Smirnov test and "CvM" means the Cramér-von Mises goodness-of-fit test,respectively.

5.7 Conclusion

This chapter reports the results of a comprehensive analysis of the profitability of technical trading rules that considers 28,631 different parameterizations of 54 different classes of technical trading rule in 39 different countries. I found evidence that trading rules are profitable in 7 of those countries, 6 of which are emerging markets. This confirms the proposition that emerging markets tend to be less efficient than developed markets. The trading rules that were most often succesful were Moving Average Rules, Filter Rules, and KDJ Rules. I also found evidence of serial correlation in the returns of all markets for which I found evidence of profitability, which suggests that this may be the structure that successful trading rules exploit, rather than necessarily any type of higher-order dependence. It should be stressed that while my evidence of profitability is *statistically*

TABLE 5.6: Changes in Inferences Before/After Removing Few Outliers

	Before	After1	After2
AVR	0.4010	0.0210	0.0090
AQ	0.6949	0.0060	0.0000

This table show changes in p-values before/after the removal of outlier.

significant, it is *economically* insignificant in the sense that the inclusion of small trading costs eliminates the evidence of profitability.

To my knowledge, this is the first study of technical trading rule profitability to use the k-FWER and FDP as criteria for finding profitable trading rules. My research provides a useful illustration of the importance of choosing an appropriate error criterion when testing the profitability of multiple trading rules. Had I followed most of the prior literature and conducted tests that control the Type 1 error of an individual test, then I would have "found evidence" of profitability in 27 of the 39 markets that I considered. Clearly data snooping is an important issue in this type of study. On the other hand, if I had only conducted tests that control the family-wise error rate, I would have discovered far fewer profitable trading rules.

Appendix 5.A Previous Studies on Emerging Markets

TABLE 5.7: Summary on Previous Studies on Emerging Markets

Author	**Rule(s) Applied**	**Periods**	**Countries/Region/Indices**	**Statistical Methodology**
BLL (1992)	MA, TRB	1897-1986	DJIA	Traditional
Corrado & Lee (1992)	Filter	1963-1989	DJIA & S&P100	Traditional
Bessembinder & Chan (1995)	MA, TRB	1975 1989	Japan,Hong Kong, Korea, Malaysia, Thailand and Taiwan	Traditional
Battern & Ellis(1996)	SMA,WMA, TRB, Stochastic, Ease of Movement(EMV), Price Volume	1987-1991	ASX AOI	Traditional
Gencay(1996)	MA	1963-1988	DJIA	Traditional
Hudson, Dempsey & Keasey (1996)	MA, TRB	1897 1987	UK FT 30	Traditional
Mills (1997)	MA & TRB	1935-1994	UK FT30	Traditional
Bessembinder & Chan (1998)	MA, TRB	1926 1991	DJIA	Traditional
Gencay(1998)	MA, Neural Networks	1897 1988	DJIA	Traditional
Ito (1999)	MA, TRB	1980-1996	USA, Japan, Canada, Indonesia, Mexico & Taiwan	Traditional
Ratner & Legal (1999)	MA	1982-1995	India, Korea,Malaysia,Philippines, Taiwan, Thailand,Argentina, Brazil, Chile and Mexico	Traditional
STW(1999)	Filter, CBO, TRB, MA, OBV	1897-1986	DJIA	Traditional
Ahmed, Beck & Goldreyer(2000)	MA	1994-1999	Taiwan, Thailand & Philliphines	Traditional
Coutts & Cheung(2000)	MA, TRB	1985-1997	Hong Kong Hang Seng	Traditional
Parisi & Vasquez(2000)	MA, TRB	1987-1998	Chile Stock Market	Traditional
Taylor(2000)	MA	1971-1991	UK FTA, FTSE100, DJIA & SNP500	Traditional
Fong & Ho (2001)	MA	1997-2000	DJ Internet Composite Internet Index	Traditional
Gunasekarage & Power (2001)	MA	1990-2000	Bombay, Colombo, Dhaka and Karachi	Traditional
Kwon & Kish(2002)	MA	1962-1996	US NYSE	Traditional
Lai, Balachandher & Nor(2002)	MA	1977 1999	Malaysia	Traditional

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Table 5.7 – *Continued from previous page*

Author	**Rule(s) Applied**	**Periods**	**Countries/Region/Indices**	**Statistical Methodology**
Tian, Wan & Guo (2002)	MA, TRB	1926-2000	US and China	Traditional
Day & Wong (2002)	MA,TRB	1962-1986	DJIA	Traditional
Ready(2002)	MA	1897-2000	DJIA	Traditional
Wong, Manzur and Chew(2003)	MA, RS	1974-1994	Singapore	Traditional
Fang & Xu (2003)	MA	1896 1996	DJIA	Traditional
Bokhari, Cai, Hidson & Keasey(2005)	MA, TRB (company size)	1987-2002	UK FTSE100, FTSE250, FTSE Small Cap	Traditional
Fong & Yong (2005)	MA	1998 2002	AMEX inter@active Internet Index	Traditional
Hsu & Kuan (2005)	Filter, CBO, TRB, MA, OBV, 5 Technical Patterns, 2 momentum strategies	1989-2002	DJIA, SNP500,NASDAQ, RUSSELL2000	RC SPA
Marshall & Cahan(2005)	MA,TRB	1970-2002	New Zealand	Traditional
Ellis & Parbery (2005)	Adaptive MA	1980 2002	ASX, DJIA, S&P 500	Traditional
Fieield et al (2005)	Filter,MA	1991-2000	11 European Stock Markets	Traditional
Balsara, Chen and Zheng(2007)	MA, TRB, Bollinger band	1990 2005	China	Traditional
Hatgioannides & Mesomeris(2007)	MA, TRB	1988-2002	MSCI Latin (Mexico, Brasil, Argentina, Chile) , Aisian (Philippines, Taiwan, Thailand, Indonesia)	Traditional
Lento, Gradojevic & Wright (2007)	MA, Filter, Bollinger	1995 2004	DJIA, Canada TSX, NASDAQ,USD/CAD	Traditional
Loh(2007)	MA, Stochastic	1990-2005	Australia, Hong Kong, Japan, Korea and Singapore	Traditional
Metghalchi, Glasure, Garza & Chen (2007)	MA	1990 2006	Austria	Traditional
Chong & Ng (2008)	MA, MACD,RSI	1935-1994	UK FTSE Index	Traditional
Fifield, Power & Knipe(2008)	MA, Filter	1989-2003	US, UK, Japan, Argentina,Chile, Hong Kong, India, Indonesia,	Traditional

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Table 5.7 – *Continued from previous page*

Author	**Rule(s) Applied**	**Periods**	**Countries/Region/Indices**	**Statistical Methodology**
			Korea, Malaysia, Mexico, Philippines,South Africa, Sri Lanka, Taiwan, Thailand, Turkey and Zimbabwe	
Metghalchi, Garza-Gomez, Glasure & Chang (2008)	MA	1988-2004	Mexico	SPA
Metghalchi, Chang & Marcucci (2008)	MA	1986 2004	Sweden	RC
Lento(2008)	MA	1950-2008	SNP500	Traditional
Chen, Huang & Lai(2009)	Filter, CBO, TRB, MA, OBV	1975-2006	Hong Kong, Indonesia, Korea, Malaysia, Singapore, Taiwan, Thailand, Japan	RC, SPA
Lento (2009)	MA, TRB, and Filters	1987-2005	Australia, India, Indonesia, Korea, Japan, Hong Kong, Singapore, Taiwan	Traditional
Schulmeister(2009)	MA,Momemtun, RSI	1983 2007	S&P 500 spot and futures	Traditional
Coutts(2010)	MA & TRB	1997-2008	Hang Seng Index	Traditional
Mitra(2011)	MA	1998-2008	India	Traditional
Bajgrowicz & Scaillet(2012)	Filter, CBO, TRB, MA, OBV	1897-2011	US DJIA	FDR
Metghalchi, Marcucci & Chang(2012)	SMA,IMA	1990-2006	16 European Countries Stock Markets	RC
Shynkevich(2012)	Filter, CBO, TRB, MA	1995-2010	US technology and small cap	SPA, SSPA, Sub
Yamamoto(2012)	Filter, CBO, TRB, MA	2006-2007	Nikkei 225	RC, SPA
Yu et al.(2013)	MA,TRB	1991-2008	SE Asia Stock Markets	Traditional
Ulku & Prodan (2013)	MA & MACD	2001-2012	44 International Stock Indexes	Traditional
Fang et al (2014)	MA, TRB	1987-2011	DJI & SNP500	Traditional
Taylor(2014)	MA, TRB	1928-2012	DJIA	Traditional
Heng & Niblock(2014)	EMA, MACD	2007-2012	Tiger Club Stock Index(Indonesia, Malaysia, Philippines and Thailand.)	Traditional
Neely et al (2014)	MA, Momentum,OBV	1950-2011	US Equity	Traditional

On 5th column (Statistical Methodology) summarize which statistical tests were applied and;

1. **"Traditional"** includes t-test type test, out-of-sample test or bootstrap test applied in Brock et al. (1992)).
2. **"RC"** is Reality Check of White (2000), **"SPA"** is Superior Predictive Ability of Hansen (2005) and **"SSPA"** is stepwise SPA of Hsu et al. (2010).
3. **"Sub"** means sub-period analysis and **FDR** means False Discovery Rate.

Appendix 5.B Summary of Deposit Rates

Country	Name of the rate	URL/Datastream
Australia	Overnight Rate	Datastream
Austria	Euro Overnight Rate	Datastream
Belgium	Euro Overnight Rate	Datastream
Canada	Overnight Rate	Datastream
Denmark	Overnight Rate	Datastream
France	Euro Overnight Rate	Datastream
Germany	Euro Overnight Rate	Datastream
Hong Kong	Overnight Rate	Datastream
Ireland	Euro Overnight Rate	Datastream
Israel	Overnight Deposit	Datastream
Japan	Overnight Deposit	Datastream
Netherland	Euro Overnight Rate	Datastream
Norway	Overnight Deposit	Datastream
Portugal	Overnight Deposit	Datastream
Singapore	Overnight Deposit	Datastream
Switzerland	Overnight Deposit	Datastream
UK	Overnight Deposit	Datastream
USA	Overnight Deposit	Datastream
Argentina	30 Days Deposit	Datastream
Brazil	Target Rate	http://www.bcb.gov.br/?INTEREST
China	1 Day Deposit	Datastream
Greece	Overnight Deposit	Datastream
Hungary	Base Rate	https://www.mnb.hu/en/Jegybanki_alapkamat_alakulasa?datefrom=02%2F12%2F1999&datetill=02%2F12%2F2015&order=0 =02%2F12%2F1999&datetill=02%2F12%2F2015&order=0
India	Repo Rate	http://dbie.rbi.org.in/DBIE/dbie.rbi?site=home
Indonesia	BI rate	http://www.bi.go.id/en/statistik/seki/terkini/moneter/Contents/Default.aspx
Korea	Base rate	http://ecos.bok.or.kr/flex/EasySearch_e.jsp
Malaysia	Interbank deposit rates	http://www.bnm.gov.my/index.php?ch=statistic&pg=stats_convinterbkrates&eId=box1
Mexico	Interbank Interest Rate	http://www.banxico.org.mx/SieInternet/consultarDirectorioInternetAction.do?accion =consultarCuadro&idCuadro=CF111&sector=18&locale=en
Pakistan	Overnight Repo Rate	http://www.sbp.org.pk/ecodata/index2.asp#monetary
Peru	Reference Rate	http://www.bcrp.gob.pe/monetary-policy/inflation-reports.html
Philippines	Interbank Call Loan	http://www.bsp.gov.ph/statistics/statistics_online.asp
Poland	Deposit Rate	http://www.nbp.pl/homen.aspx?f=/en/statystyka/instrumenty/instrumenty.html
Romania	Reference Rate	http://www.bnro.ro/Baza-de-date-interactiva-604.aspx
Russia	Deposit Rate	http://www.cbr.ru/eng/hd_base/Default.aspx?Prtid=deposit_base
Sri Lanka	Standing Deposit Facility Rate	http://www.cbsl.gov.lk/htm/english/_cei/pr/p_2.asp?date=&Mode=2&Page=1
Taiwan	Discount Rate	http://www.cbc.gov.tw/lp.asp?CtNode=695&CtUnit=303&BaseDSD=32&mp=2
Thailand	Key Interest Rate	https://www.bot.or.th/English/Statistics/Pages/default.aspx
Tunisia	Money Market Average	http://www.bct.gov.tn/bct/siteprod/stat_index.jsp?la=AN
Turkey	One-week repo rate	http://www.tcmb.gov.tr/wps/wcm/connect/tcmb%20tr/tcmb%20tr/bottom%20menu/egitim-akademik/terimler%20sozlugu /sozluk/b/bir%20hafta%20vadeli%20repo%20faiz%20orani%20(one-week%20repo%20rate)

Appendix 5.C List of Short Selling Ban Countries and Stock Futures Markets

Table 5.8: List of Short Selling Ban Countries and Stock Futures Markets

Developed Markets			
Country	Period when legal	Period when illegal	Futures Market
Australia	Pre-Sep.,2008; Nov.,- present	Sep.,2008 Nov.,2008	1983
Austria	Since inception	None	1992
Belgium	Since inception	None	1993
Canada	Since inception	None	1984
Denmark	Since inception	None	1989
France	Since inception	None	1988
Germany	Since inception	None	1990
Hong Kong	Since 1994	Before 1994	1986
Ireland	Pre-September 19, 2008	Sep.,2008– present	MSCI
Israel	Since inception	None	1995
Japan	Since inception	None	1988
Netherlands	Since inception	None	1988
Norway	Since 1992	None	1992
Portugal	Since inception	None	1996
Singapore	Since inception	NOne	2000
Switzerland	Since inception	None	1990
UK	Since inception	None	1984
USA	Since inception	None	1982
Emerging Markets			
Country	Period when legal	Period when illegal	Futures Market
Argentina	Since 1999	Before 1999	2011
Brazil	Since inception	None	1986
China	None	Always	2010
Greece	Pre-Oct.,2008;June,2009-present	Oct.,2008– May,2009	1999
Hungary	Since 1996	Before 1996	1995
India	Since Dec.,2007	Before Dec.,2007	2000
Indonesia	Pre-Oct.,2008; May,2009–present	Oct.,2008–Apr.,2009	2001
Korea	Sep.,1996–Sep.,2008;Jun.2009 present	Before 1996; Oct.,2008-May2009	1996
Malaysia	Pre-1997; Jan.,2007–present	Sep.,1997–Dec.2006	1995
Mexico	Since inception	None	1998
Pakistan	Since inception	None	2012
Peru	None	Always	MSCI
Philippines	Since 1998	Before 1998	MSCI
Poland	Since 2000	Before 2000	1998
Romania	None	Always	2007
Russia	Pre-Sep.,2008;Jun.,2009-present	Sep.,2008 June,2009	1997
Sri Lanka	None	Always	MSCI
Taiwan	Pre-Oct.,2008; Nov.,2008-present	Oct.,2008–Nov.,2008	1998
Thailand	Since January 2001	Before January 2001	2004
Tunisia	None	Always	MSCI
Turkey	Since inception	None	1997

List of short selling ban are based on Jain et al. (2013), Beber and Pagano (2013). For futurers market, we form the list from Gulen and Mayhew (2000) and reminders are collected from each country's futures market web-homepages. "MSCI" on the Futures Market column are the countries with no futures market but countries for MSCI stock index.

Appendix 5.D Comparison of without and with Short Selling Ban

TABLE 5.9: Comparison Table for without and with Short Selling Ban

	Without Short Selling Ban				With Short Selling Ban			
	RC	SPA	SPA_3	SPA_FDP	RC	SPA	SPA_3	SPA_FDP
China	0.2864	0.2415	0	0	0.2140	0.1843	0	0
Ireland	0.3899	0.5261	0	0	0.8145	0.7701	0	0
Malaysia	**0.0062**	**0.0021**	**6**	**6**	**0.0386**	**0.0094**	**1**	**1**
Malaysia_0_5	**0.0491**	**0.0344**	**1**	**1**	0.1595	0.0745	0	0
Peru	**0.0221**	**0.0100**	**16**	**16**	**0.0547**	**0.0228**	**17**	**17**
Peru_5	0.0955	0.0565	0	0	0.1474	0.0681	0	0
Philippines	**0.0047**	**0.0060**	**6**	**6**	0.0840	0.0859	0	0
Romania	0.4060	0.3574	0	0	0.3919	0.3149	0	0
Sri Lanka	**0.0012**	**0.0002**	**127**	**155**	**0.0032**	**0.0002**	**130**	**157**
Sri Lanka_0_5	**0.0055**	**0.0002**	**103**	**142**	**0.0123**	**0.0013**	**59**	**76**
Sri Lanka_5_5	**0.0396**	**0.0016**	**20**	**20**	**0.0266**	**0.0028**	**22**	**22**
Tunisia	**0.0048**	**0.0021**	**8**	**8**	**0.0253**	**0.0096**	**7**	**7**
Tunisia_0_5	0.1795	0.1461	0	0	0.0131	0.2265	0	0

Chapter 6

Conclusion

6.1 Summary and Main Findings

This thesis includes of three papers which examine the profitability of technical trading rules in Australia, the USA, and a cross-section of 39 countries. It makes a number of distinct contributions to the literature.

Firstly, Chapter 3 is the first comprehensive analysis of technical trading rule profitability in the Australian financial markets. While prior studies have examined Australian markets, they have typically considered only a small number of rules. Chapter 3 is the first study to consider a large number of parametrizations of popular trading rules for the Australian markets and to achieve weak control of the family-wise error rate. Chapter 4 introduces a number of newer technical trading rules that are well-known amongst practitioners, but have not been considered in the prior academic literature. It also considers many trading rules that have received very little attention in the prior literature. By using statistical techniques that provide strong control of the family-wise error rate, it identifies sets of trading rules which are profitable, and is the first study of which we are aware which does so. Chapter 5 reports a cross-sectional study of technical trading rule profitability. To my knowledge, this is the first such study that has been designed to control generalized family-wise error rates and the false discovery proportion.

Overall, I am able to draw a number of conclusions about technical trading rule profitability. Firstly, and most importantly, we do find evidence that technical trading rules are able to generate profits in excess of those available from a buy-and-hold strategy. However, these profits are not available at all times, in all markets, or from all rules. I confirm the finding of Sullivan et al. (1999) that evidence of profitable trading rules disappears in the USA in the second half of the 1980s and I extend this finding to a much wider range of technical trading rules than they considered. Timmermann and Granger (2004) suggested that trading rules cease to be profitable once evidence of their profitability is published since market participants will adopt the trading rules found to be profitable and trade away the market anomaly that they exploit. My results do not support this proposition since we found no evidence of profitability for any technical trading rule after the mid-1980s, including many rules that were not well-known at the time and many which had received no prior attention in the academic literature. This suggests that the elimination of profitability was caused by market-wide changes that affected all rules. I note in Chapter 4 that the time periods in which we find evidence of trading rule profitability in the US market broadly coincide with periods for which other authors have found evidence that US stock indices are serially correlated. This suggests that the US market is periodically inefficient, as suggested by the Adaptive Market Hypothesis of Lo (2004b), and that when they work, technical trading rules are exploiting serial correlation. This proposition is supported by my cross-country study of technical trading profitability, in which we find evidence of serial correlation in the stock indices of all markets for which we find evidence of trading rule profitability. Chapters 4 and 5 employ tests that provide strong control of the (generalized) family-wise error rate and so allow us to identify which rules generate statistically significant profits. I found a considerable amount of instability in the identity of the profitable rules over time and across countries. Nonetheless, we note that filter rules and moving average rules (both well-known classical trading rules) are often in the set of profitable rules. In particular, I do not find evidence that new rules tend to be profitable and old rules tend to be unprofitable. Finally, it is important to stress that my evidence of trading rule profitability disappears when we include reasonable trading costs in my evaluation method. Consequently, while I find *statistically* significant evidence of trading rule profitability, the profits found are *economically* insignificant.

I am also in a position to draw methodological conclusions. There exists tens of thousands of different parametrizations of technical trading rules, and financial theory provides little guidance of which are likely to be profitable, so studies of technical trading rule profitability must necessarily consider large numbers of rules. As such, when studying technical trading rule profitability, it is important that an error criterion that is appropriate for multiple hypothesis tests is adopted and that a statistical testing methodology that provides control of that criterion is used. In each of chapters 3, 4 and 5, I have computed results using traditional hypothesis testing procedures, in addition to tests which provide control of well-defined error rates. My results indicate that data-snooping can result in many false discoveries. Since most of the studies in the prior literature have not controlled an appropriate error rate, we conclude that (unfortunately) much of the evidence that they present should be disregarded.

6.2 Directions for Future Research

A major finding of this thesis is that technical trading rule profitability is something which occurs at certain times in certain places - apparently due to serial correlation in stock returns appearing and disappearing. An investigation of the precise nature of this time-varying serial correlation could provide some criteria useful for designing and choosing technical trading rules. The question of why serial correlation appears and disappears is also pertinent. The existing literature has investigated the relationship between autocorrelation and trading volumes (Campbell et al. (1993); McKenzie and Faff (2003); Getmansky et al. (2004)) and between autocorrelation and volatility (LeBaron (1992); Bandi and Perron (2008); Kinnunen (2014)), but firm conclusions are yet to emerge from this literature.

My research also illustrates the importance of multiple hypothesis testing techniques for investigating trading rule profitability. Standard hypothesis testing procedures may be highly misleading due to data-snooping. On the other hand, the family-wise error rate is a very stringent criterion to control when many thousands of hypotheses are being tested, which reduces the power of a test to detect profitable trading rules. I recommend that future researchers use the generalized family-wise error rate and/or false discovery proportion that we employed in Chapter 5. These are sensible error criteria, in the context of a large number of hypotheses, which provide greater power to discover profitable rules. However, the introduction of these techniques occurred quite recently and scope exists for their further development.

Appendix A

Explanation on Technical Trading Rules Applied on this Thesis

A contribution of this thesis is that it introduces many technical trading rules that are known by practicioners, but have not previously appeared in the the academic literature. This appendix provides a description of each rule. Throughout the explanations, **n** is period parameter. For example, if n=10, then SMA(n) means moving average for 10 days period. In addition, for time series data, Close(t) means closing price of today and accordingly Close(t-1) indicates yesterday's closing price. In addition to the following explanations, these websites which provides many technical trading rules.

- http://stockcharts.com/school/doku.php?id=chart_school
- https://mahifx.com/indicators/
- http://www.binarytribune.com/forex-trading-indicators
- http://www.metastock.com/Customer/Resources/TAAZ/?c=3&p=6
- http://www.barchart.com/education/std_studies.php
- https://www.instaforex.com/forex_indicators.php?p=2
- http://www.mesasoftware.com/papers/
- https://www.linnsoft.com/indicators-list

A.1 Alligator(ALLE)

Williams (1995) introduced the Alligator indicator, a moving average-based trading system in 1995. It consists of three lines that represent the jaw, the teeth and the lips of the alligator, and was created to help the trader confirm the presence of a trend and its direction, using smoothed moving average (SMMA)[1]. The indicator utilizes the convergence and divergence of three Smoothed Moving Averages (SMMAs) to generate trade decisions. The benefit of the indicator is to identity start and end of the market trend so the indicator will perform poorly when market is in range.

- The Alligator's Jaw (Line1) is a 13-period Smoothed Moving Average and the slowest indicator;
- The Alligator's Teeth (Line2) is an 8-period Smoothed Moving Average
- The Alligator's Lips (Line3) is a 5-period Smoothed Moving Average and the fastest indicator
    - MEDIAN PRICE = (HIGH + LOW) / 2
    - Alligator's Jaw = SMMA (MEDIAN PRICE, 13, 8)
    - Alligator's Teeth = SMMA (MEDIAN PRICE, 8, 5)
    - Alligator's Lip = SMMA (MEDIAN PRICE, 5, 3)

Among three indicators, Jaw is the the slowest moving indicator and Lips is the fastest moving indicator.

Like the idea of moving average cross-over, a trading signal is in the order of "Jaw"," Teeth" and "Lip". Buying when Lip>Teeth>Jaw ; short term moving average is greater than long term means price start moving upside recently and this suggest for the buying action. (Alligator wakes up and opens mouth for eating in order of lip, teeth and jaw.) • Selling when Jaw>Teeth>Lip ; If long term average price is higher than the medium and short term average, this is a phenomenon of sluggish market and suggest selling action.(If jaw is higher than lip, this means the alligator is full so he will not eat anymore and close his mouth for sleeping .) • No action, otherwise

- Strategy
    - ⋆ Like the idea of moving average cross-over, a trading signal is in the order of "Jaw"," Teeth" and "Lip".

[1]See section 34 of Appendix for detailed explanation of SMMA

- ⋆ Buy when Lip>Teeth>Jaw ; short term moving average is greater than long term means price start moving upside recently and this suggest for the buying action. (Alligator wakes up and opens mouth for eating in order of lip, teeth and jaw.)
- ⋆ Sell when Jaw>Teeth>Lip ; If long term average price is higher than the medium and short term average, this is a phenomenon of sluggish market and suggest selling action.(If jaw is higher than lip, this means the alligator is full so he will not eat anymore and close his mouth for sleeping .).
- ⋆ Otherwise, no action is required.

A.2 Aroon Indicator(ARN)

The Aroon indicator developed by attempts to identify starting trends. The name Aroon means "dawn's early light" in Sanskrit and the aim of Chande (1995) is to find an early changes in trend. The indicator consists of two lines, "Aroon Up" and "Aroon Down" to show market direction, which measures the number of days of highest/lowest since the last n period. For example, a 25-day (n=25) "Aroon Up (Down)" measures the number of days since a 25 day high (low). The Aroon is oscillate between 100 and 0. If today's price is a new high (low), then "Aroon Up (Down)" will be 100. If there is no new record of high(low), then it decreased (1 / n) x 100 by each sequent day and at 25th day, the Aroon beacome 0. Following is sample calculation of 25 days Aroon.

- Aroon Up =
$$\frac{25 - \#\text{of days since } 25 \text{ Day High}}{25} \times 100$$
- Aroon Down =
$$\frac{25 - \#\text{of days since } 25 \text{ Day Low}}{25} \times 100$$
- Aroon = Aroon Up-Aroon Down

- Strategy
  - ⋆ Up (Down) trends are indicated when the Aroon Up(Down) is between 70 and 100.
  - ⋆ Aroon Up(Down) below 50 indicates weakening of current trend.
  - ⋆ Buy when Aroon Up(Down) is above 70 while the Aroon Down(Up) is below 30.

  - ⋆ Sell when Aroon Down(Up) is above 70 while the Aroon Up(Down) is below 30.
  - ⋆ Otherwise, no action is required.

A.3 Average Directional Movement Index(ADX)

The ADX indicator of Wilder (1978) is moving average of directional movement index (DX) and it indicate the strength of the trend, but not the direction of the trend (ie,up trend or down).The index values range from 0 to 100 and bigger number means strong in trend. Additional two indicators, Plus Directional Indicator (+DI) and Minus Directional Indicator (-DI) are complement to ADX indicator to generate the trend strength.

- ADX =

$$\frac{\text{Current Close - 5 (or x) days Lowest Low}}{\text{(5 (or x) days Highest High - 5 (or x) days Lowest Low)}} \times 100$$

- DX =

$$\frac{\text{(Close - Low)}}{\text{(High - 5 Low)}}$$

- +DI = 3 (or n) days Moving Average of K lines.
- $-$DI = 3*D $-$ 2*K and the value of J can go beyond [0, 100].

- Strategy
  - ⋆ Buy when +DI>-DI and ADX>25
  - ⋆ Sell when +DI<-DI and ADX>25

A.4 Average True Range(ATR)

Introduced by Wilder (1978), the Average True Range (ATR) is an indicator to measure volatility. Higher level of ATR means trending and lower ATR indicates a consolidation in price.

- Total Range(TR)

  - Method 1: Current High - Current Low
  - Method 2: |Current High - Previous Close|
  - Method 3: |Current Low - Previous Close|
  - TR= Max[Method1, Method2, Method3]

- ATR(1) = Average[Method1, Method2, Method3]
- ATR(t) = [ATR(t-1)*(n-1)+ TR(t)]/14

- Strategy
  - ⋆ Buy when Price> ATR
  - ⋆ Sell when Price<ATR

A.5 Bollinger Band(BOLL)

Developed by Bollinger (1992), Bollinger Bands consist of three bands that can be overlayed over a normal price chart or an indicator. The first, the middle band is a simple moving average and the default period (n) is 20.

- Bollinger Band
  - Middle Band = 20-day simple moving average (SMA)
  - Upper Band = 20-day SMA + (20-day standard deviation of price × 2)
  - Lower Band = 20-day SMA - (20-day standard deviation of price × 2)

- Strategy
  - ⋆ Buy if the price moves below the lower band,
  - ⋆ Sell if the price moves above the upper band.

A.6 Commodity Channel Index(CCI)

Commodity Channel Index (CCI) of Lambert (1980) is to identify a new trend or warn of extreme conditions. CCI measures the current price level relative to an average price level over a given period of time and indicate the weakening of a trend. CCI is relatively high when prices are far above their average. CCI is relatively low when prices are far below their average.

- Price=(High + Low + Close)/3
- Mean Deviation(MD)= Gap between SMA and each day Price =

$$\frac{\sum_{i=1}^{n}(\text{SMA(n)} - \text{Price(i)})}{\text{n}}$$

- CCI =

$$\frac{\text{Price - SMA}}{0.015\text{*MD}}$$

- Strategy
  - ⋆ A CCI reading above +100 can indicate that an asset has been overbought, and a reading below -100 can indicate that an asset has been oversold.
  - ⋆ Buy when CCI turns up from below -100.
  - ⋆ Sell if the CCI turns down from above 100.

A.7 Center of Gravity Oscillator(CGO)

The Center of Gravity is an oscillator developed by Ehlers (2004) . In Physics, the Center of Gravity (CG) means its balance point and CG oscillator seek the CG of prices over the window of observation to identify the turning points of the price.

- Price = (High+Low)/2
- x= 0, . . . , n-1
- CGO(t) =

$$\frac{\sum_{i=0}^{n}((x_i + 1) \times \text{Price}_i}{\sum_{i=0}^{n} \text{Price}_i}$$

- Trigger=CGO(t-1)

- Strategy
  - ⋆ The crossing of CGO and Trigger lines serves as the indicator's major trading signal.
  - ⋆ Sell when CGO line crosses the Trigger to the downside.
  - ⋆ Buy if the CGO line crosses over the Trigger line.

A.8 Chande Momentum Oscillator(CMO)

The Chande (1994) is momentum indicator to seek the overbought and oversold levels by using sum of up movement (S_u) and down movement(S_d) over n periods.

- CMO =

$$\frac{\text{Sum of all positive changes in price}(S_u)\text{ - Absolute sum of all negative changes in price}(S_d)}{\text{Sum of all positive changes in price}(S_u) + \text{Absolute sum off all negative changes in price}(S_d)} \times 1$$

- positive change = Close(t)-Close(t-1) > 0
- negative changes = Close(t)-Close(t-1) < 0

- Strategy
  - ⋆ The CMO oscillates between 100 and -100,
  - ⋆ Sell when the CMO is above 50 (overbought)
  - ⋆ Buy when the CMO is below -50 (oversold).

A.9 Coppock Indicator(COPP)

Coppock (1962) is long term indicator and is to identify the commencement of bull markets. It is weighted moving average(WMA) of the differences between two Rate of Changes (ROC).

- Coppock = WMA(10) of (ROC(14)+ROC(11))
- WMA(10) = 10 day Weighted moving average

- ROC(14) = 14 day Rate-of-Change (see section 31)
- ROC(11) = 11 day Rate-of-Change

- Strategy
  - ⋆ The key aspect of the COPP is the zero line.
  - ⋆ Sell when the COPP is moving below the zero line
  - ⋆ Buy when the COPP is moving above the zero line

A.10 Cyber Cycle Indicator (CYC)

Cyber Cycle Indicator developed by Ehlers (2004) is an responsive trend following system and it generate entry and exit signal.

- Price = (High+Low)/2
- alpha = 0.05
- Smooth(t) = (Price(t) + 2*Price(t-1) + 2*Price(t-2) + Price(t-3))/6;
- CYC = (1–0.5*alpha)*(1–0.5*alpha)*(Smooth(t) –2*Smooth(t-1)+Smooth(t-2))+2*(1–alpha)*Cycle(t-1)-(1-alpha)*(1-alpha)*Cycle(t-2);
- Trigger(t)=2*Itrend(t) - ITrend(t-2);

- Strategy
  - ⋆ The crossing of CYC and Trigger lines serves as the indicator's major trading signal.
  - ⋆ Sell when CYC line crosses the Trigger to the downside.
  - ⋆ Buy if the CYC line crosses over the Trigger line.

A.11 Double Exponential Moving Average(DEMA)

The Mulloy (1994a) is a calculation based on both a single exponential moving average (EMA) and a double EMA. Double exponential moving average (DEMA) is a measure of a security's trending average price that gives the most weight to recent price data to give more faster signal than simple moving average, which is good for short term investor.

- EMA1= EMA(n,Close)
- EMA2= EMA(n,EMA1)
- DEMA = 2*EMA1 - EMA2

- Strategy
  - ⋆ Sell when Price is below DEMA.
  - ⋆ Buy when Price is above DEMA.

A.12 DeMark's Range Expansion Index (DREI)

The DeMark (1997) is a momentum oscillator to measure relative velocity and magnitude of directional price movements. The REI shows overbought/oversold price conditions by measuring the relation based on the comparison of the recent price changes and the overall price changes for the period. DREI use two type of summations, SUM1 and SUM2.

- $$\text{SUM1} = \sum_{j=1}^{n} \text{k(j)m(j)s(j)}$$
  - SUM1 = $\sum_{j=1}^{n}$ k(j)m(j)s(j)
  - k(j)= 0, if High(j-2)<Close(j-7) && High(j-2)<Close(j-8) && High(j)<High(j-5)&& High(j)<High(j-6)
  - k(j)= 1, otherwise
  - m(j)= 0, if Low(j-2)>Close(j-7) && Low(j-2)>Close(j-8) && Low(j)>Low(j-5)&& Low(j)>Low(j-6)

  - m(j)= 1, otherwise
  - s(j)= 0, High(j-2)- High(j-2) + Low(j)-Low(j-2)

- $$\text{SUM2} = \sum_{j=1}^{n} \text{(High(j)-High(j-2)+Low(j) -Low(j-2))}$$

- DREI = 100 × SUM1/SUM2;

- Strategy
  - ⋆ REI changes on a scale from -100 to +100
  - ⋆ Sell if REI is greater than 60 (overbought)
  - ⋆ Buy if REI is below -60 (oversold).

A.13 DeMark's DeMarker(DMark)

This indicator was introduced by DeMark (1997) as a tool to identify emerging buying and selling opportunities. It demonstrates the price depletion phases which usually correspond with the price highs and bottoms. The DeMarker indicator proved to be efficient at identifying trend break-downs as well as spotting intra-day entry and exit points.

- If high(t) > high(t-1) , then DeMax(t) = high(t)-high(t-1), otherwise DeMax(t) = 0
- If low(t) < low(t-1), then DeMin(t) = low(t-1)-low(t), otherwise DeMin(t) = 0
- DMark(t) = SMA(DeMax,N)/(SMA(DeMax,N)+SMA(DeMin,N))

- Strategy
  - ⋆ DeMarker changes on a scale from 0 to 1
  - ⋆ Sell if DeMarker is greater than 0.7 (overbought)
  - ⋆ Buy if DeMarker is below 0.3 (oversold).

A.14 Detrended Price Oscillator(DPO)

The DPO of Achelis (2001) is an indicator designed to remove trend element of price and identifies cycles by comparing a price to a simple moving average(SMA).

- DPO = Price(n/2 + 1)- SMA(n)
- default of n is 20 or 30 periods.

- Strategy
  - ⋆ Decision making is based on a horizontal 0 line.
  - ⋆ Sell when DPO hits zero line from below or even crosses above zero for a while and then turns back below zero. (overbought)
  - ⋆ Buy when DPO hits zero from above zero for a while and then goes up above zero(oversold).

A.15 Exponential Moving Average(EMA)

Haurlan (1968) is alternative type of SMA and it weight more on current price movement.

- Sample calculatrion for 10 days EMA
- EMA = Close(t) - EMA(t-1) × Multiplier + EMA(t-1))
  - Multiplier=(2/(n + 1)) = (2 / (10 + 1)) = 0.1818.

- Strategy
  - ⋆ Sam as Moving Averaage Crossover
  - ⋆ Sell if short term EMA < long term EMA.
  - ⋆ Buy if short term EMA> long term EMA.

A.16 Easy of Movement(EMV)

EMV, developed by Arms (1996) use both of price and volume data to identify the relationship between volume and price changes and is particularly useful for assessing the strength of a trend.

- Distance Moved = ((High(t) + Low(t))/2 - (High(t-1) + Low(t-1))/2)
- Box Ratio = ((Volume/10,000)/((High - Low)/8))
- EMV(1) = ((High(t) + Low(t))/2 - (High(t-1) + L(t-1))/2) / ((Volume/100,000,000)/(High(t) - Low(t))
- EMV(n) = SMA(EMV(1),n), which is n period SMA of EMV(1)

- Strategy
  - ⋆ Buy when EMV crosses to above zero,from below.
  - ⋆ Sell when EMV crosses to below zero,from above.

A.17 Entropy(ETPY)

Entropy rule of Ehlers (2002a) is indicator that demonstrates the power of price changes entropy. In Physics, the entropy is the measure of the disorder of the system and higher entropy means less predictive ability. The entropy is calculated using the Maximum Entropy Method, which minimising a smoothness of entropy and this is to enhance the predictive power when maker is in disorder.

For more understanding the concept of entropy and maximum entropy method,following links provide some more explanations. `http://mathworld.wolfram.com/Entropy.html` `http://mathworld.wolfram.com/MaximumEntropyMethod.html`

- SUM1 =
$$\sum_{t=1}^{n} log(P(t)/P(t-1)$$
- SUM2 = SUM1*SUM1
- AVG =SUM1/n

- MAX= $\sqrt{SUM2}$
- P= AVG/MAX
- ETPY=P*log(1+MAX) +(1-P)*log(1-MAX)

- Strategy
  - ⋆ The key aspect of the COPP is the zero line.
  - ⋆ Buy when the ETPY is below zero
  - ⋆ Sell when the ETPY is above zero

A.18 Elder Ray Indicator (ERI)

ERI of Elder (1993) measures the amount of buying and selling pressure in the market. This indicator consists of two separate indicators known as "bull power" and "bear power". These figures allow a trader to determine the position of the price relative to a certain exponential moving average (EMA).

- Bull Power = Daily High - n period EMA Bear Power = Daily Low - n period EMA

Using exponential moving average(EMA), Elder Ray Indicator (ERI), developed by Dr.Alxander Elder un check the buy and selling pressure in the market. developed

- Market Concensus (MC) = 13 (or n) day EMA
- Bull power = Daily High -MC
- Bear power = Daily Low- MC

- Strategy
  - ⋆ Sell if Bull Power is above zero (or Today's Low <MC)
  - ⋆ Buy if Bear Power is below zero(or Today's high>MC).

A.19 Force Index(FI)

Using both of price and volume data, the Force Index of Elder (1993) is to identify the possible of turning points. FI collects the market sentiment information by calculating the average level of the daily price changes and market volume to measure the buying and selling pressure.

- Force Index(1)= (Close(t)-Close(t-1)) × Volume(t)
- Force Index(n)= n period EMA of Force Index(1)

- Strategy
  - ⋆ sell if the Force index is above zero.
  - ⋆ buy if the Force index is below zero .

A.20 Keltner Channel Indicator(KELT)

Keltner Channels (Keltner, 1960) are volatility-based envelopes set above and below an exponential moving average. Instead of using the standard deviation, Keltner Channels use the Average True Range (ATR) to set channel distance. The channels are typically set two Average True Range values above and below the 20-day EMA

- Middle Line: 20-day exponential moving average
- Upper Channel Line: 20-day EMA + (2 x ATR(10))
- Lower Channel Line: 20-day EMA - (2 x ATR(10))

- Strategy
  - ⋆ sell when price turns down at or above the upper band. Close your position if price turns up near the lower band or crosses to above the moving average.
  - ⋆ buy when prices turn up at or below the lower band. Close your position if price turns down near the upper band or crosses to below the moving average.

A.21 Laguerre Relative Strength Index(LRSI)

The Laguerre Relative Strength Index of Ehlers (2004) is to upgrade RSI[2] by applying Laguerre filter. LRSI uses a 4-Element Laguerre filter to provide a "time warp" such that the low frequency components are delayed much more than the high frequency components. This enables much smoother filters to be created using shorter amounts of data.

- gamma=0.5;
- CU= Closes up
- CD= Closes down
-
- L0(t)=((1-gamma)*Close(t)) + (gamma*L0(t-1));
- L1(t)=(-gamma*L0(t)) + L0(t-1) + (gamma*L1(t-1));
- L2(t)=(-gamma*L1(t)) + L1(t-1) + (gamma*L2(t-1));
- L3(t)=(-gamma*L2(t)) + L2(t-1) + (gamma*L3(t-1));
- If(L0>=L1), CU=L0-L1, CD=L1-L0
- If(L1>=L2), CU=CU+L1-L2, CD=CD+L2-L1
- If(L2>=L3), CU=CU+L2-L3, CD=CD+L3-L2
- LRSI= CU/(CU + CD)

- Strategy
  - ⋆ Buy when LRSI crosses upwards above 0.15.
  - ⋆ Sell when LRSI crosses down below 0.85.

[2]see section 32

A.22 Linear Regression Indicator (LRI)

Using least squares slope as a fair value, the LSI of Chande (1992) identify trend and generates trend following signals similar to a moving average. If current price line moves below (over) the LRI line, this indicates price is cheaper (expensive) compare to fair value so signal to buy(sell) the stock.

- i=1:length(Close)
- x=Close(i:n)
- $Y = \beta_0 + \beta_1 x$ and get
- $\hat{\beta}_1 = \frac{\overline{xy} - \bar{x}\bar{y}}{\overline{x^2} - (\bar{x})^2}$
- LSMA=SMA(Y_t, n)
- LRS=$\hat{\beta}_1$/LSMA

- Strategy
  - ⋆ sell if the price line cross down LRI.(Death Cross)
  - ⋆ buy if the price line cross over LRI.(Golden Cross) .

A.23 Moving Average Convergence & Divergence(MACD)

MACD is one of the simplest and popular indicators developed by Appel (1979) Using two moving averages, the indicator calculate trend-following characteristics by subtracting the longer moving average from the shorter moving average.

The MACD is calculated by subtracting the 26-day exponential moving average (EMA) from the 12-day EMA. A nine-day EMA of the MACD, called the "signal line", is then plotted on top of the MACD, functioning as a trigger for buy and sell signals.

- MACD Line: (12 period EMA - 26 period EMA)
- Signal Line: (9 period EMA of MACD Line)
- MACD Histogram: MACD Line – Signal
- EMA = Exponential Moving Average.

- Strategy
  - ⋆ sell when MACD Line moves below 0.
  - ⋆ buy when MACD Line moves above 0.

The MACD generates a bullish signal when it moves above its own nine-day EMA, and it sends a sell sign when it moves below its nine-day EMA.

A.24 MACD with 4 Parameters (MACD4)

MACD4 add one more parameter MACD and it's firstly introduced as PhD thesis of John (2010).

Sample application is macd4(Close, params = c(12, 26, 1, 9)), where params are

- ⋆ First parameter - the "fast" average parameter
- ⋆ Second parameter - the "slow" average parameter
- ⋆ Third parameter - the new parameter, indicating a 'fast' averaging of the MACD line instead of the typical choice of the MACD line itself
- ⋆ Fourth parameter - the 'slow' averaging for the MACD signal line

- Strategy
  - ⋆ sell when MACD Line moves below 0.
  - ⋆ buy when MACD Line moves above 0.

A.25 Money Flow Index(MFI)

Quong (1989) is an oscillator to measures the strength of money flow in both of price and volume, it calculate the buying and selling pressure. As MFI both pirce and volume, it is also known as volume-weighted RSI. The example below is based on a 14-period MFI.

- Price = (High + Low + Close)/3
- Raw Money Flow = Typical Price x Volume

- Money Flow Ratio = (14-period Positive Money Flow)/(14-period Negative Money Flow)
- Money Flow Index = 100 - 100/(1 + Money Flow Ratio)

- Strategy
  - ⋆ The key aspect of the MFI is the zero line.
  - ⋆ Sell when the MFI is over 80
  - ⋆ Buy when the MFI is below 20

A.26 Pentuple EMA (PEMA)

PEMA of Eremee and Kositsin (2010) is Pentuple Exponential Moving Average. It is combinations of QEMA, Quadruple EMA (see Section 30) and TEMA, Triple EMA (see Section 41) .

- PEMA = QEMA(Close,n) + TEMA(Close - QEMA,n)

- Strategy
  - ⋆ Sell when the Close is moving below the PEMA line
  - ⋆ Buy when the Close is moving above the PEMA line

A.27 Price Momentum Oscillator (PMO)

Swenlin (1997) is to seek the up and down strength using the two times averaging of market price movement and give overbought or oversold signl.

- Smoothing Multiplier = (2 / Time period)
- Custom Smoothing Function = Close - Smoothing Function(previous day) * Smoothing Multiplier + Smoothing Function(previous day)
- PMO Line = 20-period Custom Smoothing of (10 * 35-period Custom Smoothing of (((Today's Price/Yesterday's Price) * 100) - 100))

- PMO Signal Line = 10-period EMA of the PMO Line

- Strategy
  - ⋆ Sell when the PMO is moving below the PMO Signal line
  - ⋆ Buy when the PMO is moving above the PMO Signal line

A.28 Percentage Price Oscillator(PPO)

The PPO of Achelis (2001) is a momentum oscillator that measures the difference between short and long term moving averages as a percentage of the larger moving average. Standard PPO is based on the 12-day Exponential Moving Average (EMA) and the 26-day EMA, but these parameters can be changed according to investor or trader preferences. A 9-day EMA of PPO is plotted as a signal line to identify upturns and downturns in the indicator.

- PPO =
$$\frac{\text{12 day EMA - 26 day EMA}}{\text{26 day EMA}} \times 100$$
  - Signal Line = 9 day EMA of PPO.
  - PPO Histogram = PPO - Signal Line

- Strategy
  - ⋆ Sell when the PPO Histogram is negative value
  - ⋆ Buy when the PPO Histogram is positive value

A.29 Quadruple EMA (QEMA)

Lebeau (1991) is combination of DEMA(see section A.11)and TEMA(see section A.41) and this indicator is to give more weight on current market movement while removing noises of price movement.

- QEMA = TEMA + DEMA(Close - TEMA)

- Strategy
  - ⋆ Buy when the shorter term QEMA crosses above the longer term QEMA (golden cross).
  - ⋆ Sell when the shorter term QEMA crosses below the longer term QEMA (dead cross).

A.30 Rate of Change (ROC)

ROC of Murphy (1998) measure the price change of current price with the price n periods ago. The ROC indicator can be used to confirm price moves or detect divergences; it can also be used as a guide for determining overbought and oversold conditions.

If momentum (>0) and periods with negative momentum (<0).

- ROC =

$$\frac{\text{(Close today- Close n periods ago)}}{\text{Close n periods ago}} \times 100$$

- Strategy
  - ⋆ Buy when ROC crosses to below the -10% level and then rises.
  - ⋆ Sell when ROC crosses to above the 10 % then falls back.

A.31 Relative Strength Index (RSI)

the RSI of Wilder (1978) is a momentum oscillator to measure the velocity and magnitude of directional price movements.

- RSI =

$$\frac{100}{1+\text{RS}}$$

- RS =
$$\frac{\text{Average Gain}}{\text{Average Loss}}$$
- First Average Gain =
$$\frac{\text{Sum of Gains over the last 14 periods}}{14}$$
- First Average Loss =
$$\frac{\text{Sum of Losses over the last 14 periods}}{14}$$

  The second, and subsequent calculations are based on prior averages and the current gain/ loss.

- Average Gain = [(previous Average Gain) * 13 + current Gain] / 14
- Average Gain =
$$\frac{\text{previous Average Gain*13 + current Gain}}{14}$$
- Average Loss =
$$\frac{\text{previous Average Loss*13 + current Loss}}{14}$$

- Strategy
  - ⋆ Sell when the RSI rises above 70
  - ⋆ Buy when the RSI falls below 30.

A.32 Relative Vigor Index (RVI)

Developed by Ehlers (2002b), RVI compares power of the today's market open compare to yesterday's close (Close-Open) relative to its price range(High-Low). Accordlingly the higher(lower) the RVI climbs, the stronger is the current price increase(decrease);

- RVI(1) =
$$\frac{\text{Close-Open}}{\text{High-Low}}$$

- RVI(n) = n-period SMA of RVI(1)
- signal = 4-period SMA of RVI(1)

- Strategy
  - ⋆ Sell when RVI crossing the signal line from above,
  - ⋆ Buy when RVI crossing the signal line from below.

A.33 Stochastic Cyber Cycle (SCYC)

Ehlers (2004) 's Stochastic Cyber Cycle is a combination of standard Stochastic oscillator (see section A.40) with its values calculated not based on price series but on Cyber Cycle (see section A.10) indicator values.

- SCYC =

$$\frac{\text{CYC(n) - CYC Lowest Low(n)}}{\text{CYC Highest High(n) - CYC Lowest Low(n)}}$$

- Strategy
  - ⋆ Same as RSI, SCYC values are between 0 and 100.
  - ⋆ Buy when SCYC is below 20
  - ⋆ Sell when SCYC os over 80 level.

A.34 Stochastic Center of Gravity(SCGO)

Ehlers (2004) 's Stochastic Center of Gravity is a combination of standard Stochastic oscillator (see section A.40) with its values calculated not based on price series but on Center of Gravity (see section A.7) indicator values.

- SCGO =

$$\frac{\text{CGO(n) - CGO Lowest Low(n)}}{\text{CGO Highest High(n) - CGO Lowest Low(n)}}$$

- Strategy
  - ⋆ SCGO values are between 0 and 100.
  - ⋆ Buy when SCGO is below 20
  - ⋆ Sell when SCGO os over 80 level.

A.35 Stochastic KDJ (KDJ)

Scarborough (2008b) [3] upgrades stochastic oscillator [4] by adding one more extra line called J line. The role for J line is to double confirm the trading signal of the stochastic indicator.

- %K line =

$$\frac{\text{Current Close - 5 (or x) days Lowest Low}}{\text{(5 (or x) days Highest High - 5 (or x) days Lowest Low)}} \times 100$$

- %D line = 3 (or n) days Moving Average of K lines.
- %J line = 3*D - 2*K

The trading strategy of the stochastic oscillator is simple. To sell when the two lines (K, D) reached 80% or higher level and to buy when two line reached 20% or below level. KDJ strategy is to buy when stochastic signals buy and J line lies below zero and sell when stochastic signals sell and J line lies over 100 level.

- Strategy
  - ⋆ the value of J can go beyond [0, 100].
  - ⋆ Sell when J goes above 100 when K and D are above 80 area.
  - ⋆ Buy when J goes under 0 when K and D are in below 20.

A.36 SONAR Momentum Indicator(SNR)

SONAR momentum chart of Okamoto (1978) was develpoed by Japanese Technical Analyst Okamoto when he was work for Nomura Securities. This is one of the popular Japan and Korea and the aim for SONAR momentum indicator is to seek the momentum of price cycle via slope.

- SNR =

$$\frac{\text{Close- n previous day's Close}}{\text{n previous day's Close}}$$

[3] I have been spent more than one year to find the direct reference of KDJ indicator but we finally fail to find the source of the journal/book. However, our finding are outcome from out best effort and introduction of the indicator via web-source is another way of practitioner's publication

[4] see section 36

- (n) = number of periods used in the calculation

- Strategy
  - ⋆ Buy when SNR is above 0 and crossover of SNR>SMA(SNR,n)
  - ⋆ Sell when SNR is below 0 and crossover SNR<SMA(SNR,n)

A.37 Stochastic RSI(SRSI)

SRSI of Ehlers (2004) is a combination of Stochastic indicator (see section A.40) and RSI(see section A.31). Instead of Close price, StochasticRSI apply RSI values to Stochastic Indicator formulae to seek the market is overbought or oversold.

- SRSI =
$$\frac{\text{RSI(n) - RSI Lowest Low(n)}}{\text{RSI Highest High(n) - RSI Lowest Low(n)}}$$

- Strategy
  - ⋆ SRSI values are between 0 and 100.
  - ⋆ Buy when SRSI is below 20
  - ⋆ Sell when SRCI os over 80 level.

A.38 Stochastic RVI(SRVI)

Ehlers (2004) 's Stochastic RVI is a combination of standard Stochastic oscillator (see section A.40) with its values calculated not based on price series but on RVI (see section A.32) indicator values.

- SRVI =
$$\frac{\text{RVI(n) - RVI Lowest Low(n)}}{\text{RVI Highest High(n) - RVI Lowest Low(n)}}$$

- Strategy
  - ⋆ SRVI values are between 0 and 100.
  - ⋆ Buy when SRVI is below 20
  - ⋆ Sell when SRVI os over 80 level.

A.39 Smoothed Moving Average(SMMA)

Mahi (2004)[5] Moving averages smooth past price data to form trend following indicators. The SMMA gives recent prices an equal weighting to historic prices. The calculation takes all available data series into account rather than referring to a fixed period. This is achieved by subtracting the prior periods SMMA from the current periods price. Adding this result to yesterday's Smoothed Moving Average gives today's Moving Average.

- The first value
  - SUM1=SUM (CLOSE, N)
  - SMMA1 = SUM1/ N
- The second and subsequent moving average
- SMMA (i) = (SUM1 - SMMA1+CLOSE (i))/ N
  - SUM1 is the total sum of closing prices for N periods
  - SMMA1 is the smoothed moving average of the first bar;
  - CLOSE is the current closing price;
  - N is the smoothing period.

- Strategy
  - ⋆ Buy when the shorter term SMMA crosses above the longer term SMMA (golden cross).
  - ⋆ Sell when the shorter term SMMA average crosses below the longer term SMMA (dead cross).

A.40 Stochastic(STO)

Lane (1984) developed stochastic indicators to measure the relationship between closing price and its price range over a n period. The default value of n is 14. The indicator measured the %K line and the %D line to identify the level of the close relative to the high-low range.

[5]Despite our best effort to find the author for this indicator for longer than one year, I have not received any confirmation of the answer from trader's website which contains this indicator. Instead, we use MahiFX as a interim author because the institution provides the best explanation for the indicator, among others.

- Fast Stochastic
  - %K = (Current Close - Lowest Low)/(Highest High - Lowest Low) * 100
  - %D = 3-day SMA of %K
- Slow Stochastic
  - Slow %K = Fast %K smoothed with a 3-period SMA (i.e. %D above)
  - Slow %D = 3-period SMA of Slow %K

- Strategy
  - ⋆ The Stochastic Oscillator is bound between 0 and 100.
  - ⋆ sell when stochastic index is over 80.
  - ⋆ buy when stochastic index is below 20.

A.41 Triple EMA (TEMA)

Mulloy (1994b) consist of triple EMAs (Single EMA, Double EMA and Triple EMA) to lessen the possibility of the false signals commonly encountered in the SMA cross-over, while weighting more on recent market movement. Popular parameters for TEMA are 10 EMA (fast), 25 EMA (medium) and 50 EMA (slow).

- EMA1= EMA(n,Close)
- EMA2= EMA(n,EMA1)
- EMA3= EMA(n,EMA2)
- TEMA=(3*EMA1)-(3*EMA2)+ EMA3

- Strategy
  - ⋆ Buy when the fast TEMA (n=10) crosses over the medium TEMA (n=25), and then through the slow TEMA (n=50), enter in the direction of the fast EMA.
  - ⋆ Sell when the fast TEMA touches the medium TEMA or Exit when the fast TEMA crosses over the medium TEMA.

A.42 Triple Smoothed EMA(TRIX)

Developed by Hutson (1984), the TRIX indicator calculates the rate of change of a triple exponential moving average.

- M=EMA(n)(EMA(n)(EMA(n,Close)))
- TRIX =

$$\frac{M_t - M_{t-1}}{M} * 100$$

- Strategy
  - ⋆ Buy/sell signals are generated when the TRIX crosses above/below zero.
  - ⋆ Sell when TRIX cross down over zero line.
  - ⋆ Buy when TRIX cross up over zero line.

A.43 TRUE RVI(TRVI)

True RVI of Eremeev (2010) is adding volume information into RVI (see section A.32) to confirm the price movement.

- TRVI(1) =

$$\frac{\text{(Close-Open)}}{\text{High-Low}} \times \text{Volume}$$

- TRVI(n) = n-period SMA of TRVI(1)
- signal = 4-period SMA of TRVI(1)

- Strategy
  - ⋆ Sell when TRVI crossing the signal line from above,
  - ⋆ Buy when TRVI crossing the signal line from below.

A.44 True Strength Index(TSI)

TSI of Blau (1991) double smoothing the price to capture more filtered and stable data series with less noises.

- PC = Today's Close - Yesterday's Close
- First EMA = 25-period EMA of PC
- Second EMA = 13-period EMA of First EMA
- ABS PC = |Today's Close - Yesterday's Close|
- First Absolute EMA = 25-period EMA of ABS
- Second Absolute EMA = 13-period EMA of First Absolute EMA
- TSI = 100 x (Second EMA/Second Absolute EMA)

- Strategy
  - ⋆ TSI ranges -100 to +100.
  - ⋆ Sell when the TSI is above +25
  - ⋆ Buy when the TSI is below -25

A.45 Ultimate(ULTI)

the Ultimate Oscillator of Williams (1985) is a momentum oscillator designed to capture momentum across three different time frames.

This example is based on the default settings (7,14,28).

- Ultimate =

$$\frac{(4 \text{ x Average7})+(2 \text{ x Average14})+\text{Average28}}{(4+2+1)} * 100$$

  - BP = Close - Minimum(Low or Prior Close)
  - TR =Maximum(High or Prior Close) - Minimum(Low or Prior Close)
    - ∗ Average 7 =

$$\frac{(7 \text{ period BP Sum})}{(7 \text{ period TR Sum})}$$

  * Average 14 =
$$\frac{(14 \text{ period BP Sum})}{(14 \text{ period TR Sum})}$$
  * Average 28 =
$$\frac{(28 \text{ period BP Sum})}{(28 \text{ period TR Sum})}$$

- Strategy
  - ⋆ The Ulitmate Oscillator is bound between 0 and 100.
  - ⋆ sell when Ulitmate is over 70.
  - ⋆ buy when Ulitmate is below 30.

A.46 Vortex Index(VI)

Developed by Botes (2010),the Vortex Indicator consists of two oscillators that capture positive and negative trend movement. This version of the Vortex Indicator plots the difference between the VI+ and VI- lines as a histogram that oscillates around the zero line.[6]

- Positive and negative trend movement
  - +VM = Current High less Prior Low (absolute value)
  - -VM = Current Low less Prior High (absolute value)
  - +VM14 = 14-period Sum of +VM
  - -VM14 = 14-period Sum of -VM
- True Range (TR) is the greatest of:
  - Current High less current Low
  - Current High less previous Close (absolute value)
  - Current Low less previous Close (absolute value)
  - TR14 = 14-period Sum of TR
- Normalize the positive and negative trend movements:
  - +VI14 = +VM14/TR14

[6] We sourced relevant functions from http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:vortex_indicator

  - −VI14 = -VM14/TR14

- Strategy
  - ⋆ sell when +VI< -VI
  - ⋆ buy when +VI> -VI.

A.47 Volatility Ratio(VR)

Volatility Ratio (VR) of Schwage (1997) is to identify current price ranges and possibility of the range breakouts. The indicator is calculated based on a current true price range and a previous true price range.

- Current True Range (CTR) = max(today's (high-low), (today's high - yesterday's close),(today's low - yesterday's close))
- Previous True Range (PTR) over n days = HIGH (=highest price over n days) - LOW (the lowest price over n days)
- Volatility Ratio(VR) = CTR/PTR(n)
- n=14 by default

If value of volatility ratio is greater than 0.5 it means the start of breakout (reversal) and if VR is greater than 2.0, it is regarded as wide movement and suggests the high change of reversal. VR generate trading signal together with Aroon(ARN) indicator.

- Strategy
  - ⋆ Sell if ARN(t)=1 & VR(t)> 0.5);
  - ⋆ Buy if ARN(t)=-1 & VR(t)> 0.5);

A.48 Wilder's Moving Average(WDMA)

Wilder (1978) uses a variation of the standard Exponential Moving Average formula, which has a significant impact when choosing suitable time periods for his indicators.

- EMA = price today*K + EMA yesterday*(1-K)
  where N = the number of periods,
  K = 2 / (N+1)
- Wilder MA = price today * K + EMA yesterday (1-K)
  where K =1/N

- Strategy
  - ⋆ Buy when the shorter term moving average crosses above the longer term moving average (golden cross).
  - ⋆ Sell when the shorter term moving average crosses below the longer term moving average (dead cross).

A.49 William's Percent R(WPR)

Williams (1967)'s WPR is a momentum indicator measuring overbought and oversold levels, similar to a stochastic oscillator. WPR compares a stock's close to the high-low range over a certain period of time, usually 14 days. It is used to determine market entry and exit points. The Williams %R produces values from 0 to -100, a reading over 80 usually indicates a stock is oversold, while readings below 20 suggests a stock is overbought. The indicator chart typically has lines drawn at both the -20 and -80 values as warning signals.

- W%R =

$$\frac{\text{Highest High-Close}}{\text{Highest High -Lowest Low}} \times -100$$

where Lowest Low is lowest low for the look-back period and Highest High is highest high for the look-back period %R is multiplied by -100 correct the inversion and move the decimal.

- Strategy
  - ⋆ Values between -80 and -100 are interpreted as a strong oversold condition, or selling signal,
  - ⋆ and between -20 and 0.0, as a strong overbought condition, or buying signal.

- Strategy

  same as moving average strategy

A.50 Additional Five STW Rules

I recommend the summary prepared by Sullivan et al. (1999, pp.1654–1657) for detailed explanations for following five classical rules.

- **Filter Rules (Filter)**
- **Simple Moving Averages(SMA)**
- **Support and Resistence(SAR)**
- **Channel Brealouts(CBO)**
- **On-Balance Volume(OBV)**

Appendix B

Main Programming Codes Used for This Thesis

B.1 Sample Technical Trading Rules with C++

The following websites are home of technical trading rules codes for this thesis.

- https://cran.r-project.org/web/packages/TTR/TTR.pdf
- http://www.mathworks.com/matlabcentral/fileexchange/10573-technical-analysis-tool
- http://au.mathworks.com/matlabcentral/fileexchange/33430-technical-indicators
- http://www.davenewberg.com/Trading/EhlersCodes.html

Following is a sample code of moving average rules that I modified from the following original source of Bajgrowicz and Scaillet (2012).

http://jfe.rochester.edu/data.htm

```
#include <iostream>
#include <cstdlib>
#include <cmath>
#include <direct.h>
#include <string>
#include <fstream>
#include <iostream>
#include <sstream>
#include <algorithm>
```

```
#include <vector>

using namespace std;

//=================================================================================
//* declare functions */

double FindHigh(double Prices[], long t_begin, long t_end) ;
double FindLow(double Prices[], long t_begin, long t_end);
double FindHigh2(double Prices[], long t_begin, long t_end, int e);
double FindLow2(double Prices[], long t_begin, long t_end, int e);

int MovingAverage1(int oldS, long t, long * t_holding_period, int nslow, int
    nfast, int c, double b, double * Prices);
int MovingAverage2(long t, int nslow, int nfast, int d, double * Prices);

//=================================================================================
/* declare variables */

  int S;
  int e;
  long t;
  long t_holding_period;
  long t_extrema;
  int i, j, k, l;
  stringstream ss;

  double DJ;
  double OBVI;
  long count=0;


//=================================================================================
int main() {

    const int nb_strats=8095; //ALL
    long count=0;
    //int nb_strats=7846;  //check !!!!!!!!!
   long R =1;
   long TT=5000;  // check the length of the data !!!!!!!
   long T=TT-1;
   long N = T-R +1;
   double DJ[TT];
   double OBVI[TT];
```

```
   //const string boulot_path_="E:";
   //int SSS[nb_strats][N];
    //const string period_="4"; //check !!!!!!!!!!

//===========================================================================================
/* Assign more memory to avoid stack over-flow */

int** SSS = new int * [39000]; // check !!!!!!!!! manual input numbers of strategies

for (i=0; i <nb_strats; ++i) // for loop...
{
SSS[i] = new int[39000]; // check !!!! manual inpout number larger than TT
if (SSS[i] == NULL) { cout<<" Watch, Error !!!!"; }
}

//===========================================================================================
/* Open file data*/

   cout << "Loading data..." << endl;
   string string_DJ="E:\\Global Preparations\\MarketData\\EM2\\DATA02.txt"; //check!!!!!!!!
   ifstream InputFile_DJ;
   InputFile_DJ.open(string_DJ.c_str());
   string s_DJ;

   string s_SS;
   for(t=0; t<TT; t++) {
         getline(InputFile_DJ, s_DJ);
         DJ[t]=atof(s_DJ.c_str());
         cout<< " DJ["<<t << "]: "<< DJ[t]<< "         s_DJ: "<< s_DJ<< "\n";
   }
   InputFile_DJ.close();

cout << nb_strats << endl;
cout << N << endl;
cout << DJ[100] << endl;
cout << OBVI[100] << endl;

/* Open file Volume data*/

   cout << "Loading Volume Data..." << endl;
   string string_OBVI="E:\\Global Preparations\\MarketData\\EM2\\VOL02.txt"; //check!!!!!!!!
```

```
   ifstream InputFile_OBVI;
   InputFile_OBVI.open(string_OBVI.c_str());
   string s_OBVI;

   string s_SS2;
   for(t=0; t<TT; t++) {
         getline(InputFile_OBVI, s_OBVI);
         OBVI[t]=atof(s_OBVI.c_str());
         cout<< " OBVI["<<t << "]: "<< OBVI[t]<< "         s_OBVI: "<< s_OBVI<<
    "\n";
   }
   InputFile_OBVI.close();

cout << nb_strats << endl;
cout << N << endl;
cout << DJ[100] << endl;
cout << OBVI[100] << endl;



//==============================================================================================

//Moving Averages:
const int ma_nn=16;
const int ma_n[]={1, 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200,
    250};
//percentage band:
const int ma_nb=9;
const double ma_b[]={0, 0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05}; //0
    for no filter
//time delay:
const int ma_nd=4;
const int ma_d[]={2, 3, 4, 5};
//constant holding period:
const int ma_nc=4;
const int ma_c[]={5, 10, 25, 50};
//for the 9 additional rules:
const int ma_nnf=3;
const int ma_nf[]={1, 2, 5};
const int ma_nns=3;
const int ma_ns[]={50, 150, 200};




cout << "So far So Good ~~~~~~~~~~~~~~~~~~~~ !!!! " <<endl;
```

```
//==============================================================================================

      //Moving average 1:
      //9 additional rules:
      for(i=0; i<ma_nns; i++) {
         for(j=0; j<ma_nnf; j++) {
            int c=10;
            double b=0.01;
            S=0;
            t_holding_period=R-1-c-10;
            for(t=R-1; t<T; t++) {
               S=MovingAverage1(S, t, &t_holding_period, ma_ns[i], ma_nf[j], c,
    b, DJ);
               SSS[count][t]=S;
            }
            count++;
            //DispProgress(count);
         }
      }

      //Moving average 2:
      //two MAs, time delay
      for(i=1; i<ma_nn; i++) { //slow
         for(j=0; j<i; j++) { //fast
            for(k=0; k<ma_nd; k++) {
               for(t=R-1; t<T; t++) {
                  if(t>=(R-1+ma_d[k]-1))
                     S=MovingAverage2(t, ma_n[i], ma_n[j], ma_d[k], DJ);
                  else
                     S=0;
                  SSS[count][t]=S;
               }
               count++;
               //DispProgress(count);
            }
         }
      }

cout << " MA Rules Completed!!!! /n";

      //Support and Resistance 1:
```

```
      //first defintion of extrema, constant holding period, percentage band
    filter
      for(i=0; i<sr_nn; i++) {
         for(j=0; j<sr_nb; j++) {
            for(k=0; k<sr_nc; k++) {
               S=0;
               t_holding_period=R-1-sr_c[sr_nc-1]-10;
               for(t=R-1; t<T; t++) {
                  S=SupportResistance1(S, t, &t_holding_period, sr_n[i],
    sr_b[j], sr_c[k], DJ);
                  SSS[count][t]=S;
               }
               count++;
               //DispProgress(count);
            }
         }
      }

cout << " ~~~~~~Calculation of the 5 Trading Signals or SSS is completed !!!! "
    <<endl;

//=============================================================================================

ofstream myfile;
  myfile.open ("E:\\Global
    Preparations\\MarketData\\STW_SSS\\EM\\STW_SSS_Full_02.csv"); //check!!!!

 for(t=R-1; t<TT; t++) {
  for(i=0; i<count; i++) {
      myfile<<SSS[i][t]<<",";  //Add "," for csc format
    }
    myfile<< endl;
 }

 myfile.close();

 cout << "SSS is sucessfully saved !!!! /n";

//=============================================================================================
/* Q5: Delete (clean up) temporary memory assignment*/

for (i=0; i < nb_strats; ++i)
{
delete [ ] SSS[i];
```

```
}
delete [ ] SSS;

cout << "Virtual Memory of the SSS is automatically removed !!!! /n";

//============================================================================================

return 0;
}

//===========================================================================================
/*Releted functions in detail.*/

double Sum(double Array[], long n) {
   double total=0;
   for(long t=0; t<n; t++)
      total+=Array[t];
   return total;
}

long Sum(int Array[], long n) {
   long total=0;
   for(long t=0; t<n; t++)
      total+=Array[t];
   return total;
}

double Sum(double Array[], long a, long b) {
   double total=0;
   for(long t=a; t<=b; t++)
      total+=Array[t];
   return total;
}

double Average(double Array[], long t_begin, long t_end) {
   double mu=0;
   for(long t=t_begin; t<=t_end; t++)
      mu+=Array[t];
   return mu/(t_end-t_begin+1);
}

double FindHigh(double Prices[], long t_begin, long t_end) {
   double high=Prices[t_begin];
   for(long t=t_begin+1; t<=t_end; t++) {
```

```
      if(Prices[t]>high) {
         high=Prices[t];
      }
   }
   return high;
}

double FindLow(double Prices[], long t_begin, long t_end) {
   double low=Prices[t_begin];
   for(long t=t_begin+1; t<=t_end; t++) {
      if(Prices[t]<low) {
         low=Prices[t];
      }
   }
   return low;
}


//alternative definition of extrema:
double FindHigh2(double Prices[], long t_begin, long t_end, int e) {
   double high;
   int flag=0;
   long t=0;
   int i;
   while(flag==0 && t_begin<=(t_end-t-e)) {
      flag=1;
      high=Prices[t_end-t];
      i=1;
      while(i<=e && flag==1) {
         if(high<Prices[t_end-t-i])
            flag=0;
         i++;
      }
      t++;
   }
   if(flag==1)
      return high;
   else
      return -1; //if t_begin crossed
}

double FindLow2(double Prices[], long t_begin, long t_end, int e) {
   double low;
   int flag=0;
```

```
   long t=0;
   int i;
   while(flag==0 && t_begin<=(t_end-t-e)) {
      flag=1;
      low=Prices[t_end-t];
      i=1;
      while(i<=e && flag==1) {
         if(low>Prices[t_end-t-i])
            flag=0;
         i++;
      }
      t++;
   }
   if(flag==1)
      return low;
   else
      return -1; //if t_begin crossed
}

int MovingAverage1(int oldS, long t, long * t_holding_period, int nslow, int
    nfast, int c, double b, double * Prices) {
//two MAs, constant holding period, percentage band filter
   int S;
   if((t-*t_holding_period)<c)
      S=oldS;
   else {
      double slow_avrg=Average(Prices, t-nslow+1, t);
      double fast_avrg=Average(Prices, t-nfast+1, t);
      if(fast_avrg>(1+b)*slow_avrg) {
         S=1;
         *t_holding_period=t;
      } else if(fast_avrg<(1-b)*slow_avrg) {
         S=-1;
         *t_holding_period=t;
      } else
         S=0;
   }
   return S;
}

int MovingAverage2(long t, int nslow, int nfast, int d, double * Prices) {
//two MAs, time delay
   int S=1;
   int i=0;
```

```
  double slow_avrg;
  double fast_avrg;
  while(i<d && S!=0){
    slow_avrg=Average(Prices, t-nslow+1-i, t-i);
    fast_avrg=Average(Prices, t-nfast+1-i, t-i);
    if(i==0 && fast_avrg>slow_avrg)
      S=1;
    else if(i==0 && fast_avrg<=slow_avrg)
      S=-1;
    else if((fast_avrg>slow_avrg && S==-1) || (fast_avrg<=slow_avrg && S==1))
      S=0;
    i++;
  }
  return S;
}
```

B.2 Stationary Bootstrap with R

```
library(quantreg);library(pbapply);library(foreach);library(doSNOW);library(combinat)
library(ttrTests);library(quantmod);library(TTR);library(plyr);library(snowfall)

library(doSNOW)
getDoParWorkers()
getDoParName()
registerDoSNOW(makeCluster(4, type = "SOCK"))
getDoParWorkers()
getDoParName()
getDoParVersion()

STA_Boot<-function(data,numBoot,block_size){

p=1/block_size
t=length(data)
B<-numBoot

indices = matrix(0,t,B)
index=matrix(0,t,B)
select  = matrix(0,t,B)

indices[1,]<-replicate(B,ceiling(runif(1)*t))
indices[1,]
indices  ### OK
```

```
random=replicate(B,runif(t))
select<-random<p
n.select<-random>=p

s1<-foreach(i=1:B,.combine="cbind")%dopar% select[,i]
z1<-foreach(i=1:B,.combine="cbind")%dopar% sum(s1[,i])
y1<-sapply(1:B, function(i){ceiling(runif(z1[i])*t)})

for (i in 1:B){
indices[,i][select[,i]]= y1[[i]]
indices
}

for (i in 2:t) {
   indices[i,n.select[i,]]= indices[(i-1),n.select[i,]]+1
   indices
   }

for (i in 2:t) {
   for (j in 1:B) {
    indices[i,j]<-ifelse(indices[i,j]>t, indices[i,j]-t,indices[i,j])
    indices
   }
}
indices
#bsdata<-foreach(i=1:B,.combine="cbind")%dopar% data[indices[,i]]
#bsdata
#list(bsdata,indices)
}
```

B.3 RC, SPA and Hybrid Tests Codes with Julia

This is consolidated code for three popular single step tests and Hybrid is from Song (2012). I appreciate Professor Song for sharing his hybrid test code with me. For SPA tests, visit "Bootstraps" and "Multiple Hypothesis Tests" sections of Dr. Kevin Sheppard, Oxford's **MFE Toolbox** at " https://www.kevinsheppard.com/MFE_Toolbox ".

```
function newFWERsTTR(bench,models,B,gamma,w,index)
 #This is to calculate RC,SPA and Hybrid)
 #example (bench,models,1000,0.05,0.5,10,0.0005)
```

```
# important !!, diffs= bench-models for MSE(or Min), models-bench for TTR(or
   Max);
# This is based on the SONG's Monte_Carlo Simulation code.
# To get p-value, we use "grid search" method explained on section 3.2 of
# the article
# Date of this version : 25 Aug 2013

FWER=[0.0 0.0 0.0]; #outputs

## compute test statistics
x=size(bench,1);
y=size(bench,2);
 if y>x
  error("benchmark must be a colulm vector. This means y=1 and matrix is
   x-by-1")
 end

if length(bench)!=size(models,1)
 error("dimensions must match!!, check the length of row for bench and models ")
end

t=size(models,1);
m=size(models,2);

diffs=repmat(bench,1,m)-models;
md=mean(diffs,1)';
mo=ones(t,1)*md';
nd=(t^.5)*md;

q=1/w;
i=1:t-1;
kappa=((t-i)./t).*(1-q).^i+i./t.*(1-q).^(t-i);

vars=zeros(1,m);
for i=1:m;
   workdata = diffs[:,i]-mean(diffs[:,i]);
   vars[:,i]=workdata'*vec(workdata)/t
   for j=1:t-1;
       vars[:,i] = vars[i]+2*kappa[j]*workdata[1:t-j]'*vec(workdata[j+1:t])/t
   end
 end

 w2=vars';
 wo2=ones(t,1)*w2';
```

```
# test statistics
trc=maximum(nd);
np=nd./(w2.^.5);
tsp=maximum(np);
tcm=min(maximum(np),maximum(-np));

# weed out threshold
g1=mo.*(mo.>=-((wo2/t)*2*log(log(t))).^.5);
g2=mo.*(-mo.>=-((wo2/t)*2*log(log(t))).^.5);

#Bootstrap
brc=zeros(B,1);
bsp=zeros(B,1);
bsp2=zeros(B,1);
bcm=zeros(B,1);
bprc=zeros(B,1);
bpsp=zeros(B,1);
bpcm=zeros(B,1);
bdel=zeros(B,1);
bpks=zeros(B,1);

index=stationary_bootstrap((1:t),B,w);

for b=1:B;
   bd=diffs[index[:,b],:]
   nbd=(t^.5)*mean(bd-mo)';
   nbd1=(t^.5)*mean(bd-g1)'./(w2.^.5);
   nbd2=(t^.5)*mean(-bd+g2)'./(w2.^.5);
   brc[b,1]=maximum(nbd);
   bsp[b,1]=maximum(nbd1)';
   bcm[b,1]=min(maximum(nbd1),maximum(nbd2));
end

ttrc=0;
pRC=0.0001;
while ttrc.<1
  bprc=percentile(vec(brc),(1-pRC*100));    # Bootstrap percentile
  ttrc=(trc>=bprc)
  pRC=pRC+0.0001
    if pRC>1
       pRC=1
    end
end
```

```
ttsp=0;
pSPA=0.0001
while ttsp.<1
   bpsp=percentile(vec(bsp),(1-pSPA)*100);    # Bootstrap percentile
   ttsp=(tsp>=bpsp)
   pSPA=pSPA+0.0001
     if pSPA>1
        pSPA=1
     end
end

tthb=0;
pHB=0.0001
while tthb.<1
  bpcm=percentile(vec(bcm),(1-pHB*gamma)*100);  # Bootstrap percentile
  bdel=bsp.*(bcm.<=bpcm);
  bpks=percentile(vec(bdel),(1-pHB*(1-gamma))*100);
  tthb=((tcm.>bpcm)|(tcm.<=bpcm).*(tsp.>bpks));
  pHB=pHB+0.0001
    if pHB>1
       pHB=1
    end
end

FWER= [pRC pSPA pHB];
   return FWER
end
```

B.4 How to Replicate Table 1 of the Chapter 3 with Actual Data and Codes

The purpose of this sub-section is to explain how the data and codes I introduced in previous Appendix sections are implementing.

B.4.1 Step1 : Data Collection

Among 13 time series I applied, let me give sample data of ASX200 (01Jan,1993 to 31Dec.,2012) to help your understanding. The size of the data series is 5217*1 and due to the space limit, I save the data files on my person blog.

https://wordpress.com/post/jasepark.wordpress.com/8

B.4.2 Step2 : Run C++ codes for trading signal generation

```
Find C++ code saved in MS Word at
    https://wordpress.com/post/jasepark.wordpress.com/8
```

B.4.3 Step3 : Run Matlab code for RC and SPA Test

```
% This code include 5 rules from STW

clear all; clc;

%==========================================================================%
%~~~~~~~~~~~~~~Part 1: Read Signals Generate from CPP~~~~~~~~~~~~~~~~~~~~~%
%==========================================================================%



%~~~~~~~~~~~~~~~~Files and Folders Locations ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
subName='F100' %Change!!!!!!
rateName='BBA_LIBOR.mat' %Change!!!!!!
dataColumn=[1:7] %Change!!!!!!
dataPath='C:\ASX_2016\DATA'; %Change1!!!
sssPath='C:\ASX_2016\SSS\Sub100\Equity'; % STW rules from C++
functionPath='C:\ASX_2016\Function'; %Change!!!
savePath1='C:\ASX_2016\Return\Equity\Sub100';  % for BNH,MODELChange2!!!
savePath2='C:\ASX_2016\FWER\Equity\Sub100';  % for BNH,MODELChange2!!!
%~~~~~~~~~~~~~~~~Select Folders ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~



%==========================================================================%
%~~~~~~~~~~~~~~Part 2: Generate Investment Returns~~~~~~~~~~~~~~~~~~~~~~~~%
%==========================================================================%

cd(dataPath)

% Transaction costs
TC=[0,0.0005,0.001];% {0,5,10,15,20bps}
LF= [0,0.001,0.002];% Stock borrowing costs (0.002, 0.001, 0)
```

```
% Data Alignment variavles
R=251;

% Read Price Data
file=dir('*.mat');
names={file.name};
index=strfind(names,subName);
index2=find(~cellfun(@isempty,index))
myFile =names(index2)
myFile =char(myFile);
DATA1=load(myFile);
DATA1=struct2cell(DATA1);
DATA1=cell2mat(DATA1);
DATA2=DATA1(:,dataColumn);

cd(functionPath)
%clean nan with previous row
DATA2=fill_nans(DATA2);

%~~~~~~~~~~~~~~ Load SSS Files ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

   for s=2:2; % run only ASX!!!!
   %for s=1:numel(dataColumn);
       % for cc=1:1;
         for cc=1:length(TC);

%~~~~~~~~~~~~~~~~~~~ Read Price Series Files ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

Close=DATA2(:,s);    % to convert cell format to double format.

TT= length(Close);
T=TT-1;
N = T-R +1;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Calculate Buy & Hold Return
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%~~~~~~~~~~~~ Read Interest Rate File ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

%Buy & Hold(BNH) Currency

uRet2=zeros(TT,1);
for(t=2:TT);
```

```
uRet2(1)=0;
uRet2(t) = log(Close(t)/Close(t-1));
end
BNH=uRet2(R:TT,:);


folder = savePath1;
baseFileName = sprintf('BNH_%s.mat',num2str(s,'%02i'));
fullFileName = fullfile(folder, baseFileName);
save(fullFileName,'BNH');


cd(sssPath)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Calculation of Conditional Returns based on Transaction Costs
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

 %Open signal, SSS

 file=dir('*.mat');
 names={file.name};
 sssFile=names(s)
 mySSS=char(sssFile);
 SSS=load(mySSS);
 SSS=struct2cell(SSS);
 SSS=cell2mat(SSS);
 SSS=SSS';

cd(functionPath)

LF=0;
[n m]=size(SSS);
RF=zeros(n,1);

%Calculation of daily return of each trading rule
      [MODEL] = shortTotalRet(SSS,BNH,TC(cc),RF,LF);

      folder = savePath1;
      baseFileName = sprintf('MODEL_%02d_TC_%02d.mat',s,cc);
      fullFileName = fullfile(folder, baseFileName);
      save(fullFileName, 'MODEL','-v7.3')

      BBB=mean(BNH)*251*100
```

```
      MMM=max(mean(MODEL)*251*100)


     cd(sssPath) %return to the first SSS folder

    sprintf('Now is Return series %02d with TC %02d', s,cc)
        %end
    %end


%==========================================================================%
%~~~~~~~~~~~~~~Part 3: Data Snooping Bias Tests~~~~~~~~~~~~~~~~~~~~~~~~~~%
%==========================================================================%

%inputs
  bench=BNH;
  models=MODEL;
  alpha=0.05;
  B=1000;
  gamma=0.5;
  w=10;

  cd(functionPath)


%run bootstrap and FWER test
  bsdata=stationary_bootstrap((1:n)',B,w);
  [FWER] = allFWERsSONG(-bench,-1.*models,B,gamma,w,bsdata);

      meanRet=mean(BNH);   %mean benchmark yield
      meanMODEL=mean(MODEL);  %mean yield for each model
      bestRet=max(meanMODEL); %best peforming rule's yield
      bestIDX=find(bestRet==meanMODEL);

      %run bootstrap and DM test
      model2=MODEL(:,bestIDX(1));
      bsdata2=stationary_bootstrap((1:n)',B,w);
      [DM] = allFWERsSONG(-bench,-1.*model2,B,gamma,w,bsdata2);

      ASX_Final=[BBB,MMM,bestIDX,DM(2),FWER(1:2)]; %Annual return
      sprintf('%.4f ',ASX_Final)

      folder = savePath2;
      baseFileName = sprintf('FWER_%02d_TC_%02d.mat',s,cc);
```

```
      fullFileName = fullfile(folder, baseFileName);
      save(fullFileName, 'ASX_Final','-v7.3')

     end

  cd(sssPath) %return to the first SSS folder

    sprintf('Now is FWER series %02d with TC %02d', s,cc)
end

%==========================================================================%

function A = fill_nans(A)
% Replaces the zeros in each column with
% previous non-zero values.

%clean zero with previous row
while any(A(:)==0)
  ii1=A==0;
  ii2=circshift(ii1,[-1 0]);
  A(ii1)=A(ii2);
end

% Replaces the nans in each column with
% previous non-nan values.
for ii = size(A,2):-1:1
    I = A(1,ii);
    for jj = 2:size(A,1)
        if isnan(A(jj,ii))
            A(jj,ii) = I;
        else
            I  = A(jj,ii);
        end
    end
end
```

B.5 Stepwise RC (StepM) and Generalized StepM with Matlab

This original codes are sourced from Professor Michale Wolf's http://www.econ.uzh.ch/en/faculty/wolf/publications.html#9.

```
y= net excess return ; % i.e, the difference of the model return and benchmark
    return.

[RC,SPA,test_statistic_SRC,test_statistic_SPA,ranked_boot_statistic_SRC,ranked_boot_statistic_SP
    = generalized_Gen_Statistics_SRC_SPA_Final(y,B,w,vars,bsdata);

teststatvec=-1*test_statistic_SRC;
teststatvec(isnan(teststatvec))=0;

bootteststatmat=-1*ranked_boot_statistic_SRC';
bootteststatmat(isnan(bootteststatmat))=0;

%SRC_1
k=1
[num_Rej_SRC_1,Rej_index_SRC_1, c_K_SRC_1] =
    kfwe_Mine_MQ(teststatvec,bootteststatmat,k,alpha,Nmax);

%SRC_k
k=3
[num_Rej_SRC_k,Rej_index_SRC_k, c_K_SRC_k] =
    kfwe_Mine_MQ(teststatvec,bootteststatmat,k,alpha,Nmax);

% % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % %

function [num_Rej,toplist, c_K] =
    kfwe_Mine_MQ(teststatvec,bootteststatmat,k,alph,Nmax)
%INPUTS:
%teststatvec:    1xS vector of (centered) test statistics, corresponding to the
    S null hypothesis (called z in the R routine)
%                e.g. if H0: mu=3, muhat = 1, then unstudentized test statistic
    is (1-3) or studentized (1-3)/stdhat(muhat)
%bootteststatmat:MxS vector of (centered) bootstrap test statistics (called
    z.null in the R routine)
%                Note: Here, the observed value muhat (instead of the
    null-hypothesized value)
%                needs to be used to center the bootstrap test statistic
%k:              control of k-Familywise Error Rate (k>=1)
%alph:           alpha as in k-FWE (e.g. 0.1)
%Nmax:           as in operative method of k-StepM (e.g. 20)
%
%OUTPUTS:
%toplist:        indices of null hypothesis that were rejected, according to the
    columns of teststatvec
```

```
%c_K             critical values in each step of the kStepM-routine



S=size(teststatvec,2); M=size(bootteststatmat,1);

%block-size, control of k-FWE, alpha as in GCR, R for number of rejections
Rjmin1 = 0; Rj = Inf;           %number of rejections so that while condition
    sum(rej)>=k is initially satisfied

        z_T=0;
        %global j theta_0 Rjmin1 Rj X Xbootind theta bl L r t w_Tsort w_Tboot S
    mu k alph Nmax
        %Computation of test statistic vector and reordering of X according to
    size of test statistic
      [w_Tsort,IX] = sort(teststatvec);       %IX returns vector of original
    indizes ordered in increasing order acc.t. w_T
        w_Tsort2 = flip(w_Tsort); % my modifivastion to save the RAM memory
    usage.
        %IX_sort = IX*flipdim(eye(S),1);
        IX_sort2 = flip(IX); % my modifivastion to save the RAM memory usage.
      w_Tboot = bootteststatmat(:,IX_sort2);
        [c_K,Rj] = critvalues_Mine(w_Tboot,S,w_Tsort2,k,alph,Nmax);

toplist = IX_sort2(1:Rj);
num_Rej=length(toplist);
end

  function [RC,SPA,test_statistic_SRC,
    test_statistic_SPA,ranked_boot_statistic_SRC,ranked_boot_statistic_SPA] =
    generalized_Gen_Statistics_SRC_SPA_Final(y,B,w,vars,bsdata)
  % This is code of the Hsu,Kwan & Yen (2013) titled
  % "A Generalized Stepwise Procedure with Improved Power for Multiple
    Inequalities Testing"
  % I received monte carlo simulation code from Dr.Yu-Chin Hsu
  % I modified iid boostrap to stationary method using Kevin's statonary
  % Bootstrap
  %y=diffs=models-repmat(bench,1,k);
  % This version 24 June 2015

  [t,m]=size(y);
  %~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
  % SRC statistics Based on White(2000)
  %~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
```

```
id=(1:m);
fBar=mean(y,1);

sd=zeros(1,m);
for i=1:m
  sd(i)=std(y(:,i));
end

ZdBar=zeros(m,1);
for i=1:m
  ZdBar(i)=(fBar(:,i)/sd(:,i));
end

test_statistic_SRC=sqrt(t).*ZdBar';
test_statistic_SRC(isnan(test_statistic_SRC)) =0;
isNAN=sum(isnan(test_statistic_SRC))


% bootstrap fStarSD,vectorization

fStarSD=zeros(B,m);
for i=1:m
    workdata=y(:,i);
    fStarSD(:,i)=(std(workdata(bsdata)));
end

fStarbar=zeros(B,m);
for i=1:m
    workdata=y(:,i);
    % the i'th column of perf holds the B bootstrapped statistics
    fStarBar(:,i)=mean(workdata(bsdata));
    X=['fStarBar=',num2str(i)]
   disp(X)
end

excess= fStarBar - repmat(fBar,B,1);

Zstar_dBar=zeros(B,m);
for i=1:B
Zstar_dBar(i,:)=rdivide(excess(i,:),fStarSD(i,:));
 X=['Zstar_dBar=',num2str(i)]
 disp(X)
end
```

```
boot_SRC_stats=Zstar_dBar.*sqrt(t);

model_index=(1:m)'; %this generates a vector from 1 to m

test_index=[test_statistic_SRC' model_index]; % This label the models

%%% This sort the models by the desending order of the test statistics
%%% The new column gives the rank of each model
test_index=[sortrows(test_index,[-1]) model_index];

%%%Sort the matrix according to the original labels
%%% therefore, the last column gives the ranks of original models among
%%% based on the test statistics
test_index=sortrows(test_index, [2]);

%%% THe following ranks the bootstrap statistics according to the ranks
boot_SRC_stats=boot_SRC_stats';
ranked_boot_statistic_SRC=boot_SRC_stats(test_index(:,3),:);

%~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
% SSPA statistics Based on Hansen(2005)
%~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

%Geometric probability
 q=1/w;
 stdDev = sqrt(vars);

% A new used the log(log(t)) rule
Anew = sqrt((vars/t)*2*log(log(t)));

% Only recenter if the average is reasonably small or the model is better
% (in which case mean(diffs) is negative).  If it is unreasonably large set
% the mean adjustment to 0
gc=mean(y).*(mean(y)<Anew); %Important !!!!!! not> but <<<

% Compute the test statistic,Perf will hold the boostrapped statistics for B
  iterations

boot_statistics=zeros(B,m);
stdDev = sqrt(vars);
for i=1:m
    workdata=y(:,i);
    % the i'th column of perf holds the B bootstrapped statistics
    mworkdata=mean(workdata(bsdata));
```

```
        boot_statistics(:,i)=(mworkdata-gc(i))'/stdDev(i);
        X=['Boot_SPA=',num2str(i)]
      disp(X)
  end

  boot_statistic_SPA= boot_statistics';
  test_statistic_SPA = (mean(y)./stdDev);
  test_statistic_SPA(isnan(test_statistic_SPA)) =0;
  isNAN=sum(isnan(test_statistic_SPA))

  model_index=(1:m)'; %this generates a vector from 1 to m

  test_index=[test_statistic_SPA' model_index]; % This label the models

  %%% This sort the models by the desending order of the test statistics
  %%% The new column gives the rank of each model
  test_index=[sortrows(test_index,[-1]) model_index];

  %%%Sort the matrix according to the original labels
  %%% therefore, the last column gives the ranks of original models among
  %%% based on the test statistics
  test_index=sortrows(test_index, [2]);

  %%% THe following ranks the bootstrap statistics according to the ranks
  ranked_boot_statistic_SPA=boot_statistic_SPA(test_index(:,3),:);
end
```

B.6 Stepwise SPA

We cannot open this code for copyright issue with the original author. I appreciate Dr.Hsu for sharing test codes with me.

B.7 Generalized Stepwise SPA

We cannot open this code for copyright issue with the original author. I appreciate Dr.Hsu for sharing test codes with me.

Bibliography

Achelis, S. B., 2001. Technical Analysis A-Z, 2nd Edition. McGraw-Hill, New York.

Alexander, S. S., 1961. Price movements in speculative markets: Trends or random walks. Industrial Management Review 2, 7–26.

Alexander, S. S., 1964. Price movements in speculative markets: Trends or random walks, number2. Industrial Management Review 5 (2), 25.

Allen, F., Karjalainen, R., 1999. Using genetic algorithms to find technical trading rules1. Journal of Financial Economics 51 (2), 245 – 271.
URL http://www.sciencedirect.com/science/article/pii/S0304405X9800052X

Andersen, T. G., Bollerslev, T., Meddahi, N., 2005. Correcting the errors: Volatility forecast evaluation using high-frequency data and realized volatilities. Econometrica 73 (1), 279 – 296.

Andrews, D. W. K., 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. Econometrica 59 (3), 817–858.
URL http://www.jstor.org/stable/2938229

Appel, G., 1979. The Moving AVerage Convergence-Divergence Trading Method. Signalert.

Arms, R. W., 1996. The Arms Index (TRIN) : An Introduction to Volume Analysis of Stock and Bond Market,. Market Place Book s.

Bajgrowicz, P., Scaillet, O., 2012. Technical trading revisited: False discoveries, persistence tests, and transaction costs. Journal of Financial Economics 106 (0), 473–491.
URL http://www.sciencedirect.com/science/article/pii/S0304405X1200116X

Ball, R., 1978. Filter rules: Interpretation of market efficiency, experimental problems and australian evidence. Accounting Education 18 (2), 1–17.

Bandi, F. M., Perron, B., 2008. Long-run risk-return trade-offs. Journal of Econometrics 143 (2), 349 – 374.
URL http://www.sciencedirect.com/science/article/pii/S0304407607002291

Batten, J., Ellis, C., 1996. Technical trading system performance in the australian share market: Some empirical evidence. Asia Pacific Journal of Management 13 (1), 87–99. URL http://dx.doi.org/10.1007/BF01739683

Beber, A., Pagano, M., 2013. Short-selling bans around the world: Evidence from the 2007–09 crisis. The Journal of Finance 68-1, 343–381.

Benjamini, Y., Hochberg, Y., 1995. Controlling the false discovery rate: A practical and powerful approach to multiple testing. Journal of the Royal Statistical Society. Series B (Methodological) 57 (2), 289–300.
URL http://www.tandfonline.com/doi/abs/10.1080/07350015.2012.663245

Bessembinder, H., Chan, K., 1995. The profitability of technical trading rules in the asian stock markets. Pacific-Basin Finance Journal 3 (2??3), 257 – 284.
URL http://www.sciencedirect.com/science/article/pii/0927538X95000023

Bessembinder, H., Chan, K., 1998. Market efficiency and the returns to technical analysis. Financial Management 27 (2), pp. 5–17.
URL http://www.jstor.org/stable/3666289

Bird, P. J., 1985. The weak form efficiency of the london metal exchange. Applied Economics 17 (4), 571–587.
URL http://dx.doi.org/10.1080/758534691

Blau, W., May 1991. Double-smoothed momenta. Technical Analysis of Stocks & Commodities 9 (5), 202–205.

Bollinger, J. A., February 1992. Using bollinger bands. Technical Analysis of Stocks & Commodities 10 (2), 369–374.

Botes, Etienne Siepman, D., January 2010. The vortex indicator. Technical Analysis of Stocks & Commodities 28 (1), 20–30.

Box, G. E. P., Pierce, D. A., 1970. Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. Journal of the American Statistical Association 65 (332), pp. 1509–1526.
URL http://www.jstor.org/stable/2284333

Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. Journal of Finance 47 (5), 1731–1764.
URL http://www.blackwellpublishing.com/journal.asp?ref=0022-1082

Bulkowski, T. N., May 2005. Encyclopedia of Chart Patterns, 2nd Edition. Wiley Trading.

Campbell, J. Y., Grossman, S. J., Wang, J., 1993. Trading volume and serial correlation in stock returns. Quarterly Journal of Economics 108, 905–939.

Chande, Tushar S. Kroll, S., 1994. The New Technical Trader : Boost Your Profit by Plugging into the Latest Indicators. Wiley Finance.

Chande, T. S., May 1992. Forecasting tomorrow's trading day. Technical Analysis of Stocks & Commodities 10 (5), 220–224.

Chande, T. S., 1995. The time price oscillator. Technical Analysis of Stocks & Commodities 13, 369–374, aroon indicator.

Chang, E. J., Lima, E. J., Tabak, B. M., 2004. Testing for predictability in emerging equity markets. Emerging Markets Review 5 (3), 295 – 316.
URL http://www.sciencedirect.com/science/article/pii/S1566014104000354

Chang, P. H. K., Osler, C. L., 1999. Methodical madness: Technical analysis and the irrationality of exchange- rate forecasts. The Economic Journal 109 (458), 636–661.
URL http://www.jstor.org/stable/2565638

Chen, C.-W., Huang, C.-S., Lai, H.-W., 2009. The impact of data snooping on the testing of technical analysis: An empirical study of asian stock markets. Journal of Asian Economics 20 (5), 580 – 591.
URL http://www.sciencedirect.com/science/article/pii/S1049007809000682

Cheung, Y.-W., Chinn, M. D., 2001. Currency traders and exchange rate dynamics: a survey of the {US} market. Journal of International Money and Finance 20 (4), 439 – 471.
URL http://www.sciencedirect.com/science/article/pii/S026156060100002X

Cheung, Y.-W., Chinn, M. D., Marsh, I. W., 2004. How do uk-based foreign exchange dealers think their market operates? Journal of International Money and Finance 9 (4), 289–306.
URL http://www.sciencedirect.com/science/article/pii/S026156060100002X

Cheung, Y.-W., Wong, C. Y.-P., 2000. A survey of market practitioners' views on exchange rate dynamics. Journal of International Economics 51 (2), 401 – 419.
URL http://www.sciencedirect.com/science/article/pii/S0022199699000094

Chow, K., Denning, K. C., 1993. A simple multiple variance ratio test. Journal of Econometrics 58 (3), 385 – 401.
URL http://www.sciencedirect.com/science/article/pii/030440769390051G

Clements, M., 2010. TECHNIAL ANALYSIS in the FX MARKETS. Global Matkets MEDIA LTD, UK.

Cootner, P. H., 1962. Stock prices: Random vs. systematic changes. Industrial management review 3 (2), 24–45.

Coppock, E. S., October 1962. The trendex model. Barron'sMagazzine.

Cornell, W. B., Dietrich, J. K., 1978. The efficiency of the market for foreign exchange under floating exchange rates. The Review of Economics and Statistics 60 (1), 111–120.
URL http://www.jstor.org/stable/1924339

Corrado, C. J., Lee, S.-H., 1992. Filter rule tests of the economic significance of serial dependencies in daily stock returns. Journal of Financial Research 15 (4), 369–387.
URL http://dx.doi.org/10.1111/j.1475-6803.1992.tb00119.x

Cowles, A., 1933. Can stock market forecasters forecast? Econometrica 1 (3), 309–324.

Curcio, R., Goodhart, C., Guillaume, D., Payne, R., 1997. Do technical trading rules generate profits? conclusions from the intra-day foreign exchange market. International Journal of Finance & Economics 2 (4), 267–280.

Dale, C., Workman, R., 1980. The arc sine law and the treasury bill futures market. Financial Analysts Journal, 71–74.

Davutyan, N., Pippenger, J., 1989. Excess returns and official intervention: Canada 1952–1960. Economic Inquiry 27 (3), 489–500.

Dawson, E. R., Steeley, J. M., 2003. On the existence of visual technical patterns in the uk stock market. Journal of Business Finance & Accounting 30 (1-2), 263–293.

Day, T. E., Wang, P., 2002. Dividends, nonsynchronous prices, and the returns from trading the dow jones industrial average. Journal of Empirical Finance 9 (4), 431 – 454.
URL http://www.sciencedirect.com/science/article/pii/S092753980200004X

DeMark, T. R., 1997. Market Timing Techniques: Innovative Studies in Market Rhythm & Price Exhaustion. Wiley.

Dempster, M., Jones, C., 2001. A real-time adaptive trading system using genetic programming. Quantitative Finance 1 (4), 397–413.

Dewachter, H., 2001. Can markov switching models replicate chartist profits in the foreign exchange market? Journal of International Money and Finance 20 (1), 25 – 41.
URL http://www.sciencedirect.com/science/article/pii/S0261560600000462

Diebold, F. X., Mariano, R. S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13-3 (1), 253–263.

Donchian, R. D., 1960. Commodities: High finance in copper. Financial Analysts Journal.

Dooley, M. P., Shafer, J., 1984. Analysis of short-run exchange rate behavior: March 1973 to november 1981. Floating exchange rates and the state of world trade and payments, 43–70.

Dudoit, S., Shaffer, J. P., Boldrick, J. C., 2003. Multiple hypothesis testing in microarray experiments. Statistical Science 18 (1), pp. 71–103.
URL http://www.jstor.org/stable/3182872

Dueker, M., Neely, C. J., 2007. Can markov switching models predict excess foreign exchange returns? Journal of Banking & Finance 31 (2), 279 – 296.
URL http://www.sciencedirect.com/science/article/pii/S037842660600166X

Ehlers, H. F., 2004. Cybenetic Analysis for Stocks & Futures: Cutting-Edge DSP Technology to Improve Your Trading. Wiley, Ch. Chapter 5.

Ehlers, J., 2002a. MESA and Trading Market Cycles. Wiley Trading.

Ehlers, J., 2002b. Relative vigor index. Technical Analysis of Stocks & Commodities 20 (1), 16–20.

Elder, A., 1993. Trading for a Living : Psychology, Trading Tactics, Money Management. Wiley, Ch. Chapter 13, p. 227 234.

Ellis, C. A., Parbery, S. A., 2005. Is smarter better? a comparison of adaptive, and simple moving average trading strategies. Research in International Business and Finance 19 (3), 399 – 411.
URL http://www.sciencedirect.com/science/article/pii/S0275531905000310

Eremee, V., Kositsin, N., 2010. True rvi - relative strength index (liveliness) of market - indicator for metatrader 5. Original version is in Russian and later version is translated into English.
URL https://www.mql5.com/ru/code/9726(https://www.mql5.com/en/code/1157)

Eremeev, V., 2010. Trvi - true rvi - relative strength index (liveliness) market - an indicator for metatrader 4.
URL https://www.mql5.com/ru/code/9726(https://www.mql5.com/en/code/1157)

Escanciano, J. C., Lobato, I. N., 2009a. An automatic portmanteau test for serial correlation. Journal of Econometrics 151 (2), 140 – 149, recent Advances in Time Series Analysis: A Volume Honouring Peter M. Robinson.
URL http://www.sciencedirect.com/science/article/pii/S0304407609000773

Escanciano, J. C., Lobato, I. N., 2009b. Testing the martingale hypothesis. Palgrave Hand-book of Econometrics. Palgrave MacMillan, New York, 972–1003.

Escanciano, J. C., Velasco, C., 2006. Generalized spectral tests for the martingale difference hypothesis. Journal of Econometrics 134 (1), 151 – 185.
URL http://www.sciencedirect.com/science/article/pii/S0304407605001417

Fama, E. F., Blume, M. E., 1966. Filter rules and stock-market trading. The Journal of Business 39 (1), 226–241.
URL http://www.jstor.org/stable/2351744

Fang, J., Jacobsen, B., Qin, Y., 2014. Predictability of the simple technical trading rules: An out-of-sample test. Review of Financial Economics 23 (1), 30 – 45.
URL http://www.sciencedirect.com/science/article/pii/S1058330013000396

Fernandez-Rodriguez, F., Sosvilla-Rivero, S., Andrada-Felix, J., 2003. Technical analysis in foreign exchange markets: evidence from the ems. Applied Financial Economics 13 (2), 113–122.
URL http://dx.doi.org/10.1080/09603100210100891

Fifield, S. G. M., Power, D. M., Knipe, D. G. S., 2008. The performance of moving average rules in emerging stock markets. Applied Financial Economics 18 (19), 1515–1532.
URL http://dx.doi.org/10.1080/09603100701720302

Gartley, H. M., 1935. Profits in the Stock Market. Lambert-Gann Publishing, Pomeroy,Washington.

Gehrig, T., Menkhoff, L., 2006. Extended evidence on the use of technical analysis in foreign exchange. International Journal of Finance and Economics 11 (4), 327–338.
URL http://www.sciencedirect.com/science/article/pii/S026156060100002X

Gencay, R., 1998. The predictability of security returns with simple technical trading rules. Journal of Empirical Finance 5, 347–359.

Gencay, R., 1999. Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. Journal of International Economics 47 (1), 91 – 107.
URL http://www.sciencedirect.com/science/article/pii/S0022199698000178

Getmansky, M., Lo, A. W., Makarov, I., 2004. An econometric model of serial correlation and illiquidity in hedge fund returns. Journal of Financial Economics 74 (3), 529 – 609.
URL http://www.sciencedirect.com/science/article/pii/S0304405X04000698

Granville, J., 1963. Granville's New Key to Stock Market Profits. Prentice Hall, Englewood Cliffs, N.J.

Gu, A., Finnerty, J., 2002. The evolution of market efficiency: 103 years daily data of the dow. Review of Quantitative Finance and Accounting 18 (3), 219–237.
URL http://dx.doi.org/10.1023/A%3A1015300817043

Gulen, H., Mayhew, S., 2000. Stock index futures trading and volatility in international equity markets. Journal of Futures Markets 20-7, 661–685.

Gunasekarage, A., Power, D. M., 2001. The profitability of moving average trading rules in south asian stock markets. Emerging Markets Review 2 (1), 17 – 33.
URL http://www.sciencedirect.com/science/article/pii/S1566014100000170

Hansen, P. R., 2005. A test for superior predictive ability. Journal of Business & Economic Statistics 23 (4), 365–380.
URL http://www.jstor.org/stable/27638834

Hansen, P. R., Lunde, A., Nason, J. M., 2005. Testing the significance of calendar effects. SSRN.

Hatgioannides, J., Mesomeris, S., 2007. On the returns generating process and the profitability of trading rules in emerging capital markets. Journal of International Money and Finance 26 (6), 948 – 973.
URL http://www.sciencedirect.com/science/article/pii/S0261560607000629

Haurlan, P., 1968. Measuring Trend Values. Trade Levels.

Hawtrey, K., Nguyen, J., 2006. Trading rule profit and the australian dollar. Economic Papers: A journal of applied economics and policy 25 (3), 272–283.
URL http://dx.doi.org/10.1111/j.1759-3441.2006.tb00400.x

Hong, Y., Lee, T.-H., 2003. Inference on predictability of foreign exchange rates via generalized spectrum and nonlinear time series models. Review of Economics and Statistics 85 (4), 1048–1062.

Horne, J. C. V., Parker, G. G., 1967. The random-walk theory: An empirical test. Financial Analysts Journal 23 (6), 87–92.

Horne, J. C. V., Parker, G. G. C., 1968. Technical trading rules: A comment. Financial Analysts Journal 24 (4), 128–132.
URL http://simsrad.net.ocs.mq.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=buh&AN=6935594&site=ehost-live

Houthakker, H. S., 1961. Systematic and random elements in short-term price movements. The American Economic Review 51 (2), 164–172.
URL http://www.jstor.org/stable/1914481

Hsu, P.-H., Hsu, Y.-C., Kuan, C.-M., 2010. Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias. Journal of Empirical Finance 17 (3), 471–484.

Hsu, P.-H., Kuan, C.-M., 2005. Reexamining the profitability of technical analysis with data snooping checks. Journal of Financial Econometrics 3 (4), 606–628.

Hsu, P.-H., Taylor, M. P., 2014. Forty years, thirty currencies and 21,000 trading rules: A large-scale, data-snooping robust analysis of technical trading in the foreign exchange market.
URL https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=AMES2014&paper_id=160

Hsu, Y.-C., Kuan, C.-M., Yen, M.-F., 2014. A generalized stepwise procedure with improved power for multiple inequalities testing. Journal of Financial Econometrics 12 (4), 730–755.

Hudson, R., Dempsey, M., Keasey, K., 1996. A note on the weak form efficiency of capital markets: The application of simple technical trading rules to {UK} stock prices - 1935 to 1994. Journal of Banking & Finance 20 (6), 1121 – 1132.
URL http://www.sciencedirect.com/science/article/pii/0378426695000437

Hutson, J. K., May/June 1984. Triple exponential smoothing oscillator. Technical Analysis of Stocks & Commodities 2 (3), 91–93.

Ito, A., 1999. Profits on technical trading rules and time-varying expected returns: evidence from pacific-basin equity markets. Pacific-Basin Finance Journal 7 (3-4), 283 – 330.
URL http://www.sciencedirect.com/science/article/pii/S0927538X99000086

Ito, M., Sugiyama, S., 2009. Measuring the degree of time varying market inefficiency. Economics Letters 103 (1), 62 – 64.
URL http://www.sciencedirect.com/science/article/pii/S0165176509000408

Jain, A., Jain, P. K., McInish, T. H., McKenzie, M., 2013. Worldwide reach of short selling regulations. Journal of Financial Economics 109 (1), 177 – 197.
URL http://www.sciencedirect.com/science/article/pii/S0304405X1300055X

James, F. E., 9 1968. Monthly moving averages—an effective investment tool? Journal of Financial and Quantitative Analysis 3, 315–326.
URL http://journals.cambridge.org/article_S0022109000016252

Jensen, M. C., Benington, G. A., 1970. Random walks and technical theories: Some additionall evidence. The Journal of Finance 25 (2), 469–482.
URL http://dx.doi.org/10.1111/j.1540-6261.1970.tb00671.x

John, D. S., 2010. Technical analysis based on moving average convergence and divergence. Ph.D. thesis, University of Illinois, Chicago.

Keltner, C. W., 1960. How to Make Money in Commodities. Keltner Statistical Service.

Kho, B.-C., 1996. Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets. Journal of Financial Economics 41 (2), 249 – 290.
URL http://www.sciencedirect.com/science/article/pii/0304405X95008618

Kim, J. H., 2006. Wild bootstrapping variance ratio tests. Economics Letters 92 (1), 38 – 43.
URL http://www.sciencedirect.com/science/article/pii/S0165176506000140

Kim, J. H., Shamsuddin, A., 2008. Are asian stock markets efficient? evidence from new multiple variance ratio tests. Journal of Empirical Finance 15 (3), 518 – 532.
URL http://www.sciencedirect.com/science/article/pii/S0927539807000692

Kim, J. H., Shamsuddin, A., Lim, K.-P., 2011. Stock return predictability and the adaptive markets hypothesis: Evidence from century-long u.s. data. Journal of Empirical Finance 18 (5), 868 – 879.
URL http://www.sciencedirect.com/science/article/pii/S0927539811000612

Kinnunen, J., 2014. Risk-return trade-off and serial correlation: Do volume and volatility matter? Journal of Financial Markets 20, 1 – 19.
URL http://www.sciencedirect.com/science/article/pii/S1386418114000226

Kirkpatrick, C. D., Dajlquist, J. R., 2011. Technical Analysis: The Complete Resource for Financial Market Technicians, 2nd Edition. PearWiley Trading, Inc., NJ.

Kozhan, R., Salmon, M., 2008. On uncertainty, market timing and the predictability of tick by tick exchange rates, wP08-06, Warwick Business School.

Lai, M.-M., Lau, S.-H., 2006. The profitability of the simple moving averages and trading range breakout in the asian stock markets. Journal of Asian Economics 17 (1), 144 – 170.
URL http://www.sciencedirect.com/science/article/pii/S1049007805001788

Lambert, D. R., 1980. Commodities channel index: Tools for trading cyclical trends. Technical Analysis of Stocks & Commodities 1 (5), 120–122.

Lane, G. C., May/June 1984. Lane's stochastics. Technical Analysis of Stocks & Commodities 2 (3), 87–90.

LeBaron, B., 1992. Some relations between volatility and serial correlations in stock market returns. The Journal of Business 65 (2), 199–219.
URL http://www.jstor.org/stable/2353162

LeBaron, B., 1999. Technical trading rule profitability and foreign exchange intervention. Journal of International Economics 49 (1), 125 – 143.
URL http://www.sciencedirect.com/science/article/pii/S0022199698000610

Lebeau, Charles Lucas, D., 1991. Technical Traders Guide to Computer Analysis of the Futures Markets. McGrow-Hill.

Lee, C. I., Pan, M.-S., Liu, Y. A., 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 (2), 199–214.

Leigh, W., Paz, N., Purvis, R., 2002. Market timing: a test of a charting heuristic. Economics Letters 77 (1), 55 – 63.
URL http://www.sciencedirect.com/science/article/pii/S0165176502001106

Lento, C., Gradojevic, N., Wright, C. S., 2007. Investment information content in bollinger bands? Applied Financial Economics Letters 3 (4), 263–267.
URL http://www.ingentaconnect.com/content/routledg/rafl/2007/00000003/00000004/art00012

Leuthold, R. M., 1972. Random walk and price trends: The live cattle futures market. The Journal of Finance 27 (4), 879–889.
URL http://dx.doi.org/10.1111/j.1540-6261.1972.tb01318.x

Levich, R. M., 1986. Empirical studies of exchange rates: Price behavior, rate determinationand market efficiency. Tech. rep., National Bureau of Economic Research.

Levich, R. M., Thomas, L. R., 1993. The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach. Journal of International Money

and Finance 12 (5), 451 – 474.
URL http://www.sciencedirect.com/science/article/pii/0261560693900349

Levy, R. A., 1967. Relative strength as a criterion for investment selection. Journal of Finance 22 (4), 959–610.

Levy, R. A., 1971. The predictive significance of five-point chart patterns. The Journal of Business 44 (3), 316–323.
URL http://www.jstor.org/stable/2351345

Lo, A. W., 2004a. The adaptive markets hypothesis. The Journal of Portfolio Management 30 (5), 15–29, 30th Anniversary.

Lo, A. W., 2004b. The adaptive markets hypothesis. The Journal of Portfolio Management 30 (5), 15–29, 30th Anniversary.

Lo, A. W., MacKinlay, A., 1990. Data-snooping biases in tests of financial asset pricing models. Review of Financial Studies 3 (3), 431–467.
URL http://rfs.oxfordjournals.org/content/3/3/431.abstract

Lo, A. W., Mamaysky, H., Wang, J., 2000. Foundations of technical analysis:computational algorithms, statistical inference, and empirical implementation. The Journal of Finance 55-4, pp. 1705–1770.

Lobato, I., Nankervis, J. C., Savin, N. E., 2001. Testing for autocorrelation using a modified box-pierce q test. International Economic Review 42 (1), pp. 187–205.
URL http://www.jstor.org/stable/2648724

Logue, D. E., Sweeney, R. J., Willett, T. D., 1978. Speculative behavior of foreign exchange rates during the current float. Journal of Business Research 6 (2), 159 – 174.
URL http://www.sciencedirect.com/science/article/pii/0148296378900061

Loh, E., 2004. Technical trading rules and market efficiency: Evidence from the australian stock exchange 1980-2002.
URL http://www.animals.uwa.edu.au/__data/assets/pdf_file/0020/102548/04_14_Loh.pdf

Lovell, M. C., 1983. Data mining. The Review of Economics and Statistics 65 (1), pp. 1–12.
URL http://www.jstor.org/stable/1924403

Lucke, B., 2003. Are technical trading rules profitable? evidence for head-and-shoulder rules. Applied Economics 35 (1), 33–40.
URL http://dx.doi.org/10.1080/00036840210150884

Lui, Y.-H., Mole, D., 1998. The use of fundamental and technical analyses by foreign exchange dealers: Hong kong evidence. Journal of International Money and Finance 17 (3), 535 – 545.
URL http://www.sciencedirect.com/science/article/pii/S0261560698000114

Lukac, L. P., Brorsen, B. W., 1990. A comprehensive test of futures market disequilibrium. Financial Review 25 (4), 593–622.

Lukac, L. P., Brorsen, B. W., Irwin, S. H., 1988. A test of futures market disequilibrium using twelve different technical trading systems. Applied Economics 20 (5), 623–639.
URL http://dx.doi.org/10.1080/00036848800000113

Mahi, 2004. Indicators, smoothed movinbg average.
URL https://mahifx.com/indicators/smoothed-moving-average-smma

Marshall, B. R., Cahan, R. H., Cahan, J. M., 2008. Does intraday technical analysis in the u.s. equity market have value? Journal of Empirical Finance 15 (2), 199–210.

Marshall, B. R., Cahan, R. H., M., C. J., 2010. Technical analysis around the world, massey University.
URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1181367

Marshall, B. R., Cahan, R. M., 2005. Is the 52-week high momentum strategy profitable outside the us? Applied Financial Economics 15 (18), 1259–1267.
URL http://dx.doi.org/10.1080/09603100500386008

MATLAB, 2014. version 8.4 (R2014b). The MathWorks Inc., Natick, Massachusetts.

McKenzie, M. D., Faff, R. W., 2003. The determinants of conditional autocorrelation in stock returns. Journal of Financial Research 26 (2), 259–274.
URL http://dx.doi.org/10.1111/1475-6803.00058

Menkhoff, L., 1997. Examining the use of technical currency analysis. International Journal of Finance & Economics 2 (4), 307–318.

Menkhoff, L., 2010. The use of technical analysis by fund managers: International evidence. The Journal of Banking and Finance 23(11), 2573–2586.

Menkhoff, Lukas; Taylor, M. P., 2007. The obstinate passion of foreign exchange professionals: Technical analysis. Journal of Economic Literature 45-4, 936–972.

Metghalchi, M., Chang, Y.-H., Garza-Gomez, X., 2012a. Technical analysis of the taiwanese stock market. International Journal of Economics and Finance 4 (1), 90–102.

Metghalchi, M., Chang, Y.-H., Marcucci, J., 2008a. Is the swedish stock market efficient? evidence from some simple trading rules. International Review of Financial Analysis 17 (3), 475 – 490.
URL http://www.sciencedirect.com/science/article/pii/S1057521907000257

Metghalchi, M., Garza-Gomez, X., Yung-Ho, C., 2008b. Are moving average trading rules profitable? evidence from the mexican stock market. Journal of Applied Business Research 2.

Metghalchi, M., Marcucci, J., Chang, Y.-H., 2012b. Are moving average trading rules profitable? evidence from the european stock markets. Applied Economics 44 (12), 1539–1559.
URL http://dx.doi.org/10.1080/00036846.2010.543084

Mills, T. C., 1997. Technical analysis and the london stock exchange: Testing trading rules using the ft30. Int. J. Fin. Econ 2, 319–331.
URL http://web.ist.utl.pt/~adriano.simoes/tese/referencias/Papers%20-%20Adriano/Technical%20Analysis.pdf

MQL5, 2005. Moving averages, ma - indicator for metatrader 4. MetaQuotes Software Corp.
URL www.mql5.com/en/code/7534

Mulloy, P. G., 1994a. Calculate tema1 and dema1. Technical Analysis of Stocks & Commodities 12 (2).

Mulloy, P. G., January 1994b. Smoothing data with faster moving average. Technical Analysis of Stocks & Commodities 12 (1), 11–19.

Murphy, J. J., 1998. Technical Analysis of the Financial Markets. No. 228-234. PHP Investment Analysis.

Neely, C. J., 1997. Technical analysis in the foreign exchange market: A layman's guide. Federal Reserve Bank of St. Louis Review 79 (5), 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 (1), 211 – 232.
URL http://www.sciencedirect.com/science/article/pii/S0022199601001635

Neely, C. J., 2003. Risk-adjusted, ex ante, optimal technical trading rules in equity markets. International Review of Economics & Finance 12 (1), 69 – 87.
URL http://www.sciencedirect.com/science/article/pii/S1059056002001296

Neely, C. J., Weller, P. A., 1999. Technical trading rules in the european monetary system. Journal of International Money and Finance 18 (3), 429 – 458.
URL http://www.sciencedirect.com/science/article/pii/S0261560699850050

Neely, C. J., Weller, P. A., 2001. Technical analysis and central bank intervention. Journal of International Money and Finance 20 (7), 949 – 970.
URL http://www.sciencedirect.com/science/article/pii/S026156060100033X

Neely, C. J., Weller, P. A., 2011. Technical analysis in the foreign exchange market, federal Reserve Bank of St. Louis.

Neely, C. J., Weller, P. A., Ulrich, J. M., 4 2009. The adaptive markets hypothesis: Evidence from the foreign exchange market. Journal of Financial and Quantitative Analysis 44, 467–488.
URL http://journals.cambridge.org/article_S0022109009090103

Oberlechner, T., 2001. Importance of technical and fundamental analysis in the european foreign exchange market. International Journal of Finance & Economics 6 (1), 81–93.

Oberlechner, T., Osler, C., 4 2012. Survival of overconfidence in currency markets. Journal of Financial and Quantitative Analysis 47, 91–113.
URL http://journals.cambridge.org/article_S0022109012000038

Okamoto, H., 1978. Sonar momentum chart.
URL http://swing-trade.net/trade193.htmlhttp://booja.blogspot.com.au/2012/12/sonar.html

Olson, D., 2004. Have trading rule profits in the currency markets declined over time? Journal of Banking & Finance 28 (1), 85 – 105.
URL http://www.sciencedirect.com/science/article/pii/S0378426602003990

Omrane, W., Van Oppens, H., 2008. The performance analysis of chart patterns: Monte carlo simulation and evidence from the euro/dollar foreign exchange market. In: Bauwens, L., Pohlmeier, W., Veredas, D. (Eds.), High Frequency Financial Econometrics. Studies in Empirical Economics. Physica-Verlag HD, pp. 199–223.
URL http://dx.doi.org/10.1007/978-3-7908-1992-2_9

Park, C.-H., Irwin, S. H., 2007. What do we know about the profitability of technical analysis? Journal of Economic Surveys 21 (4), 786–826.

Park, C.-H., Irwin, S. H., 2010. A reality check on technical trading rule profits in the u.s. futures markets. Journal of Futures Markets 30 (7), 633–659.

Park, J.-S., Heaton, C., 2014. Technical trading rules in australian financial markets. International Journal of Economics and Finance 6 (10), 67–75.

Park, J. Y., Whang, Y.-J., 2005. A test of the martingale hypothesis. Studies in Nonlinear Dynamics & Econometrics 9 (2).

Pavlov, V., Hurn, S., 2012. Testing the profitability of moving-average rules as a portfolio selection strategy. Pacific-Basin Finance Journal 20 (5), 825 – 842.
URL http://www.sciencedirect.com/science/article/pii/S0927538X12000327

Phillips, P. C. B., Jin, S., 2014. Testing the martingale hypothesis. Journal of Business & Economic Statistics 32 (4), 537–554.
URL http://dx.doi.org/10.1080/07350015.2014.908780

Politis, D. N., Romano, J. P., 1994. The stationary bootstrap. Journal of the American Statistics Association 89 (428), 1303–1313.

Poole, W., 1967. Speculative prices as random walks: An analysis of ten time series of flexible exchange rates. Southern Economic Journal 33 (4), 468–478.
URL http://www.jstor.org/stable/1055642

Pring, M. J., May 1985. Technical Analysis Explained : An Illustrated Guide for the Investor, 2nd Edition. McGraw-Hill, US.

Qi, M., Wu, Y., 2006. Technical trading-rule profitability, data snooping, and reality check: Evidence from the foreign exchange market. Journal of Money, Credit and Banking 30, 2135–2158.

Quong, Gene Soudack, A., 1989. Volume-weighted rsi: Money flow. Technical Analysis of Stocks & Commodities 7 (3), 76–77.

R Core Team, 2013. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
URL http://www.R-project.org/

Raj, M., Thurston, D., 1996. Effectiveness of simple technical trading rules in the hong kong futures markets. Applied Economics Letters 3 (1), 33–36.
URL http://dx.doi.org/10.1080/758525512

Ratner, M., Leal, R. P., 1999. Tests of technical trading strategies in the emerging equity markets of latin america and asia. Journal of Banking & Finance 23 (12), 1887 – 1905.
URL http://www.sciencedirect.com/science/article/pii/S0378426699000424

Ready, M. J., 2002. Profits from technical trading rules. Financial Management 31 (3), pp. 43–61.
URL http://www.jstor.org/stable/3666314

Reitz, S., Taylor, M. P., 2008. The coordination channel of foreign exchange intervention: A nonlinear microstructural analysis. European Economic Review 52 (1), 55 – 76.
URL http://www.sciencedirect.com/science/article/pii/S0014292107001018

Romano, J. P., Shaikh, A. M., Wolf, M., 2008. Formalized data snooping based on generalized error rates. Econometric Theory 24 (2), pp. 404–447.
URL http://www.jstor.org/stable/20142498

Romano, J. P., Wolf, M., 2005. Stepwise multiple testing as formalized data snooping. Econometrica 73 (4), 1237–1282.

Romano, J. P., Wolf, M., 2007. Control of generalized error rates in multiple testing. The Annals of Statistics 35 (4), pp. 1378–1408.

Saacke, P., 2002. Technical analysis and the effectiveness of central bank intervention. Journal of International Money and Finance 21 (4), 459–479.

Sapp, S., 2004. Are all central bank interventions created equal? an empirical investigation. Journal of Banking & Finance 28 (3), 443 – 474.
URL http://www.sciencedirect.com/science/article/pii/S0378426602004107

Savin, G., Weller, P., Zvingelis, J., 2007. The predictive power of "head-and-shoulders" price patterns in the u.s. stock market. Journal of Financial Econometrics 5 (2), 243–265.
URL http://jfec.oxfordjournals.org/content/5/2/243.abstract

Scarborough, B., 2008a. Stochastic
URL https://www.amibroker.com/library/detail.php?id=1144

Scarborough, B., 2008b. Stochastic
URL http://www.amibroker.com/library/detail.php?id=1144

Schulmeister, S., 2008. Components of the profitability of technical currency trading. Applied Financial Economics 18 (11), 917–930.
URL http://dx.doi.org/10.1080/09603100701335416

Schulmeister, S., 2009. Profitability of technical stock trading: Has it moved from daily to intraday data? Review of Financial Economics 18 (4), 190 – 201.
URL http://www.sciencedirect.com/science/article/pii/S1058330008000372

Schwage, J. D., 1997. Technical Analysis. Wiley.

Shynkevich, A., 2012. Performance of technical analysis in growth and small cap segments of the us equity market. Journal of Banking and Finance 36 (1), 193 – 208.

Silber, W. L., 1994. Technical trading : When it works and when it doesn't. The Journal of Derivatives 1 (3), 39–44.

Smidt, S., 1965. A test of the serial independence of price changes of soybean futures. Food Research Institute studies.

Song, K., 2012. Testing predictive ability and power robustification. Journal of Business and Economic Statistics 30 (2), 288–296.

Sullivan, R., Timmermann, A., White, H., 2001. Dangers of data mining: The case of calendar effects in stock returns. Journal of Econometrics 105 (1), 249 – 286, forecasting and empirical methods in finance and macroeconomics.
URL http://www.sciencedirect.com/science/article/pii/S030440760100077X

Sullivan, R., Timmermann, A., White, H., 2003. Forecast evaluation with shared data sets. International Journal of Forecasting 19 (2), 217 – 227.
URL http://www.sciencedirect.com/science/article/pii/S0169207001001406

Sullivan, R., Timmermann, A. G., White, H., 1999. Data-snooping, technical trading rule performance and the bootstrap. Journal of Finance.

Sweeney, R. J., 1986. Beating the foreign exchange market. The Journal of Finance 41 (1), 163–182.
URL http://www.jstor.org/stable/2328350

Sweeney, R. J., 9 1988. Some new filter rule tests: Methods and results. Journal of Financial and Quantitative Analysis 23, 285–300.
URL http://journals.cambridge.org/article_S0022109000013120

Swenlin, C., 1997. Decisionpoint.com-stock market technical analysis & timing. Http://decisionpoint.com/.
URL http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:dppmo

Szakmary, A. C., Mathur, I., 1997. Central bank intervention and trading rule profits in foreign exchange markets. Journal of International Money and Finance 16 (4), 513 – 535.
URL http://www.sciencedirect.com/science/article/pii/S026156069700017X

Taylor, N., 2014. The rise and fall of technical trading rule success. Journal of Banking & Finance 40, 286 – 302.
URL http://www.sciencedirect.com/science/article/pii/S0378426613004664

Taylor, S. J., 1992. Rewards available to currency futures speculators: Compensation for risk or evidence of inefficient pricing? Economic Record 68, 105–116.
URL http://dx.doi.org/10.1111/j.1475-4932.1992.tb02298.x

Tian, G., Wan, G., Guo, M., 2002. Market efficiency and the returns to simple technical trading rules: New evidence from u.s. equity market and chinese equity markets. Asia-Pacific Financial Markets 9 (3-4), 241–258.
URL http://dx.doi.org/10.1023/A%3A1024181515265

Timmermann, A., Granger, C. W., 2004. Efficient market hypothesis and forecasting. International Journal of Forecasting 20 (1), 15 – 27.
URL http://www.sciencedirect.com/science/article/pii/S0169207003000128

Ulku, N., Prodan, E., 2013. Drivers of technical trend-following rules' profitability in world stock markets. International Review of Financial Analysis 30, 214 – 229.
URL http://www.sciencedirect.com/science/article/pii/S1057521913001269

Ulrich, J., 2013. Ttr : Technical trading rules. Package version 0.22-0, R Foundation for Statistical Computing.
URL #https://github.com/joshuaulrich/TTR#

Vigfusson, R., 1996. Switching between chartists and fundamentalists, bank of Canada Working Paper 96-1.

Wang, J., 2000. Trading and hedging in s&p 500 spot and futures markets using genetic programming. Journal of Futures Markets 20 (10).

White, H., 2000. A reality check for data snooping. Econometrica 68 (5), 1097–1126.

Wilder, J. W., 1978. New Concepts in Technical Tradings System,Trend Research. Trend Research, Ch. Chapter 3, pp. 21–23.

Williams, B., 1967. The Secrete of Selecting Stocks for Immediate and Substantial Gains. Windor Books, NY.

Williams, B., 1995. Trading Chaos: Applying Expert Techniques to Maximize Your Profits. Wiley.

Williams, L., July/August 1985. The ultimate oscillator. Technical Analysis of Stocks & Commodities 3 (4), 140–141.

Wyckoff, R., 1910. Studies in Tape Reading. The Ticker Publishing Company, NY.

Yamamoto, R., 2012. Intraday technical analysis of individual stocks on the tokyo stock exchange. Journal of Banking & Finance 36 (0), 3033–3047.
URL http://www.sciencedirect.com/science/article/pii/S1059056012000767

Yu, H., Nartea, G. V., Gan, C., Yao, L. J., 2013. Predictive ability and profitability of simple technical trading rules: Recent evidence from southeast asian stock markets. International Review of Economics & Finance 25, 356 – 371.
URL http://www.sciencedirect.com/science/article/pii/S1059056012000767