Essays on Technical Analysis in Stock Markets

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To my husband Yu Li

and my son Anthony Fangbo Li

Abstract

Although technical analysis is widely used by practitioners, current academic evidence on its efficiency is largely mixed. This thesis carries out four independent studies to contribute to this strand of literature.

In a true out-of sample test, the first study finds no evidence that several well-known technical trading strategies predict stock markets over the period from 1987 to 2011. Further analysis shows that this poor out-of-sample performance most likely is not due to the market becoming more efficient – instantaneously or gradually over time – but is probably a result of bias.

Moreover, current studies largely concentrate on price-based technical indicators. In contrast, the widely used technical market indicators have drawn limited attention. This raises the risk of data snooping, since so many indicators are proposed. The second study reviews and examines the profitability of a wide range of 93 market indicators. I[1] give these technical market indicators the benefit of the doubt, but even then I find little evidence that they predict stock market returns.

Many so-called return predictability anomalies disappear over time because investors arbitrage profits away through their trading. Is this the case in technical analysis? The third study investigates what would happen if a completely new technical trading rule – Bollinger Bands – appeared that investors had never used before but which became more popular over time. I find although trading on Bollinger Bands had been extremely profitable before their introduction to public in 1983, its profitability has gradually decreased ever since and has largely disappeared since the influential publication on Bollinger Bands in 2001. Moreover, the profitability

[1] The first three studies of this thesis are joint work with my supervisors Professor Ben Jacobsen and Dr. Yafeng Qin, while the last study is my individual work. Therefore as individual papers, it should be "we" instead of "I". In this thesis, however, I use "I" throughout for the sake of consistency.

disappeared in the US market first, where Bollinger Bands originated, and then in other international markets.

The last study finds while commonly used technical trading strategies generate positive returns in most of the 50 sample countries, the same strategies show no merit in countries such as the United States and the United Kingdom. Further cross-country investigation shows that the returns of technical analysis are higher in countries where investors are less culturally individualistic, in markets that are less developed and/or integrated, and where information uncertainty is greater.

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Chapter 1 Overview

Researchers have long debated the efficiency of technical analysis – one of the oldest tools used to forecast returns. The root of the debate is probably that technical analysis primarily uses non-fundamental information, such as past prices, to predict future returns, which breaches the classic market efficiency theories.

Beginning in 1965, Fama argues that stock prices follow random walks, and for the first time the term “efficient market” is defined. Fama defines an efficient market as the market where prices have fully reflected all available information. Samuelson (1965) documents strong supportive evidence for this concept by showing that if the market is efficient, prices will follow random walks. Later studies by Roberts (1967) and Fama (1970) further extend and refine the “efficient market theory”, with financial market efficiency defined in three forms; weak, semi-strong, and strong. The market efficiency theory spreads rapidly thereafter and many researchers document supportive evidence for the conjecture. Among many others, using a sample of 115 mutual funds from 1955 to 1964, Jensen (1968) finds that any trading opportunities that the fund managers have are offset by fees and expenses. Fama, Fisher, Jensen and Roll (1969) show that prices adjust rapidly and accurately when news is released during stock splits and earnings announcements. Scholes (1972) examines stock price movements when the seller in secondary offerings may possess non-public information, and he finds that share prices accurately fall by an amount that reflects the value of the non-public information.

If the market is efficient, all methods that try to predict future returns should have no value since the prices follow a random walk that is unpredictable. Certainly technical analysis should then have no practical value at all since it breaches even the weak-form efficiency theory. However, the strand of literature on stock market anomalies seems to show that returns are somewhat predictable. Ball (1978) summarises twenty studies of post-earnings announcement “drift” in the direction indicated by an earnings surprise, and concludes that the anomaly is strong. Rozeff and Kinney (1976) uncover the January effect on the New York Stock Exchange from 1904 to 1974. The January effect refers to the phenomenon of statistically significant differences in mean returns among different months due primarily to large January returns. Lakonishok and Smidt (1988) document persistently anomalous returns around the turn of the week, the turn of the month and the turn of the year, and around holidays on the DJIA from 1896 to 1986. Banz (1981) and Reinganum (1983) document the size effect that refers to small-capitalisation firms earning higher average returns than those predicted by the capital asset pricing model, or CAPM. Keim (1983) and Reinganum (1983) show that much of the abnormal return to small firms (measured relative to the CAPM) occurs during the first two weeks in January. This anomaly is now known as the small-firm turn of the year effect. French (1980) notices the weekend effect and documents that the average return to the S&P composite portfolio is reliably negative over weekends in the period from 1953 to 1977. Basu (1977, 1983) notes that firms with high earnings-to-price ratios earn positive abnormal returns relative to the CAPM, which is referred to as the value effect. Jensen (1978, p8) engages in a detailed discussion of the anomalous evidence regarding market efficiency and concludes that, “Unlike much of the ‘inefficiency literature’ of the past, each and every one of these studies is a carefully done scientific piece. Each of the authors displays in varying degrees a commonly held allegiance to the efficient Market Hypothesis—witness the general reluctance to reject the notion of market efficiency".

Although some studies argue that anomalies can be gradually arbitraged away so that the market is still efficient (e.g. Schwert, 2003; Dimson & Marsh, 1999), many anomalies persist. For instance, the momentum effect, which is first documented by Jegadeesh and Titman (1993), seems to persist. This effect refers to the anomaly that winner stocks tend to be winners in the future, while loser stocks tend to be losers. Researchers argue the momentum anomaly persists since it is practically difficult for investors to buy or sell a large cross-section of stocks (the winner stocks or the loser stocks) simultaneously. As another example, studies such as Andrade, Chhaochharia and Fuerst (2012), Grimbacher, Swinkels and van Vliet (2010), Jacobsen and Visaltanachoti (2009), and Zhang and Jacobsen (2014) confirm the out of sample persistence of the Halloween indicator, since it is first documented by Bouman and Jacobsen (2002). The Halloween effect refers to the anomaly that stock returns from November to April are significantly higher than returns from May to October. As Bouman and Jacobsen (2002) suggest, if the Halloween effect is caused by investors taking vacations during the summer, it may persist if that behavior does not change. Furthermore, Peyer and Vermaelen (2009) suggest that the buyback anomaly persists in the US market in a fresh sample from 1991 to 2001, and suggest that open market repurchases are a response to market overreactions to bad news. Since a repurchase is a unique event in the life of a company, individual shareholders cannot learn from their mistakes. Moreover, tender offers are too infrequent an event to attract professional arbitrageurs, which may well explain the persistence of this anomaly.

Other reasons suggested by the literature as to why an anomaly can persist; in other words, why stock prices can be predictable; include limits-to-arbitrage, institutional or psychological barriers in place, high transaction or information costs, political restrictions, and short-sales constraints. All these studies show that stock prices contain a predictable component, such that even investors learn about the anomalies.

On the other hand, studies also find that, rather than following a random walk, stock returns exhibit some statistically predictable patterns. Lo and Mackinlay (1988) reject the random walk model by using variance-ratio testing on weekly stock market data. Jegadeesh (1990) also documents results that reject the random walk model and he further documents strong evidence of predictable behavior of stock returns. Poterba and Summers (1988) show that stock returns exhibit positive autocorrelation over short periods and negative autocorrelation over longer horizons. For individual stocks, Lehmann (1990), French and Roll (1986), and Lo and Mackinlay (1990) document negative serial correlation for daily and weekly returns. Chopra, Lakonishok and Ritter (1992), De Bondt and Thaler (1985), and Fama and French (1988) also document negative serial correlation in returns of individual stocks and portfolios over three to ten year intervals. In addition, Fama and French (1988) conclude that the negative serial correlation discovered implies 25 to 40% of the variation of longer-horizon returns is predictable from past returns. To summarise, this strand of the literature points to the possibility that stock returns can be predictable through an examination of past returns.

Despite the scrutiny received from believers of the market efficiency theory, the above literature seem to provide some theoretical ground to why technical analysis based on using past information may have some practical value. A study on technical analysis may be further motivated by the popularity of technical analysis in practice despite the on-going debate on its effectiveness. For example, a survey of 692 fund managers shows that 87% of the fund managers place some importance on technical analysis when making their investment decisions (Menkhoff, 2010). Therefore, how useful is technical analysis? This thesis seeks to extend the current literature on this question by carrying out four independent studies from different perspectives. The four studies are in Chapters 2, 3, 4 and 5, respectively.[2]

A major concern on existing evidence that supports the profitability of technical strategies is the danger of data-snooping bias. That is, the positive results may simply be a spurious outcome of searching for profitable trading strategies with hindsight. And this concern has drawn increasing attention with the rising number of studies carried out in the field of technical analysis. My first study (Chapter 2) performs a rigorous out-of-sample test of the predictive ability of 26 well-known technical strategies on a fresh sample from 1987 to 2011. I find little predictability of the 26 technical trading strategies out-of-sample, which is in strong contrast with the in-sample findings by Brock, Lakonishok and LeBaron (1992). Further analysis of these out-of-sample results shows that the profitability of these strategies does not gradually disappear, suggesting the market becomes more efficient over time, but trading strategies based on these rules underperform the market from the beginning of my out-of-sample period. While it is possible that all investors started using these technical rules and made the market instantaneously more efficient, it seems more likely that the earlier results are caused by

[2] Chapter 2 of this thesis is largely based on my paper titled “Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test” published on *Review of Financial Economics*. Chapter 3 of this thesis is based on my paper titled “Technical Market Indicators: An Overview” that is forthcoming in *Journal of Behavioral and Experimental Finance*.

some sort of statistical biases; particularly because I also find no evidence in another 12 year out-of-sample period from 1885 to 1896.

The 26 technical strategies used in the first study are all price-based technical indicators. While many studies in this field pay attention to the classic price-based technical indicators only, such as moving average rules and trading range breakout rules, this might raise the problem of data-snooping as a consequence of fitting the same rules into different samples while seeking positive evidence. More importantly, price-based technical indicators are just a subset of all technical indicators—drawing a conclusion from this subset only seems premature. There are other types of technical indicators—so called technical market indicators—that investors and media and finance professionals use frequently as well, such as advance/decline lines, the Arms Index, and volatility indices. The second study (Chapter 3) reviews and examines the predictive ability of these technical market indicators on the longest sample possible in the US market. Intriguingly, I find these technical market indicators largely show no merit in predicting future returns. This conclusion holds continuously even if I allow predictability to be state dependent on business cycles or sentiment regimes.

With the first two studies suggesting that technical analysis seems to show no predictive ability in the US stock markets, one may wonder whether it is possible that using technical analysis was historically profitable, or whether investors' overuse gradually arbitraged the profits away. I can best verify this conjecture by investigating the predictive ability of a completely new technical trading rule that investors had never used before but which became increasingly popular over time. In the third study (Chapter 4), I test the predictive ability of such a "new" rule – Bollinger Bands. Bollinger Bands were first introduced to investors in the United States in 1983. Bollinger Bands gradually gained popularity among investors especially following the publication of “Bollinger on Bollinger Bands” in 2001. In contrast, I find although a Bollinger Bands-based strategy used to generate superior returns before 1983 in 14 international stock markets, its profitability seems to have gradually decreased and has largely disappeared since the publication of “Bollinger on Bollinger Bands” in 2001. Moreover, their profitability disappeared in the US market first, where Bollinger Bands originated, and then in other international markets.

The first three studies show that technical analysis largely has no predictive ability in the US. But is it possible that it is still useful in other markets? If it is, why does the profitability vary across countries? The fourth study (Chapter 5) of the thesis answers these questions. I firstly replicate the analysis in the first study (Chapter 2) in 50 international stock markets on a 20-year sample from 1994 to 2014. With the finding that exactly the same strategies generate substantially different profits across the countries, my cross-country analysis shows that technical trading profits are higher in countries where investors are less culturally individualistic, in less developed and/or integrated markets and also in markets that exhibit greater information uncertainty.

All in all, despite the previous academic debates on technical analysis, this thesis suggests that technical analysis still has considerable practical value in international stock markets. Nevertheless, the danger of data-snooping and investors’ overuse should be carefully considered before the results are interpreted. Moreover, it should be kept in mind that the growing overall international stock market integration could gradually eliminate the trading opportunities of technical analysis in the future, although the statistical results from Chapter 5 seem to suggest that such integration does not seem to affect the results so far. Lastly, it should also be noted that much of the profitability of technical analysis is dependent on investors' ability to short sell, although this possibility does not appear to drive the results in this thesis.

Chapter 2 Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test[3]

2.1 Introduction

Technical analysis studies patterns in historical stock market series generated by day-to-day market activities, with the aim to predict future market movements. The key information technical analysts use is volume and price. I evaluate the profitability of 26 classic technical trading strategies that are formed by using the underlying price on the Dow Jones Industrial Average (DJIA) during the period from 1987 to 2011. These trading rules were first tested extensively by Brock, Lakonishok and LeBaron (1992) which allows me to perform a comprehensive out-of-sample test by using exactly the same trading rules on a fresh new data set that minimises the effect of any possible statistical biases. With the benefit of a fresh dataset, I find little predictability of the 26 technical trading strategies out-of-sample, which is in strong contrast with their in-sample findings. Further analysis of these out-of-sample results shows that the profitability of these strategies does not gradually disappear suggesting the market becomes more efficient over time, but trading strategies based on these rules underperform the market from the beginning of my out-of-sample period. While it is possible that all investors started using these technical rules and made the market instantaneously more efficient, it seems more likely that the earlier results are caused by some sort of statistical biases. Particularly because I also find no evidence in another 12 year out-of-sample period from

[3] Chapter 2 of this thesis is largely based on my paper titled "Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test" published on *Review of Financial Economics*.

1885 to 1896. Moreover, the in-sample success of the technical trading strategies does not alter in several robustness tests. It changes neither when the OLS robust regression method is used to limit the impact of outliers, nor when the rolling window regression is used to check if any particular period would drive the results. Also it does not change when using the S&P 500 Index as a different proxy for the stock market. Similarly, the out-of-sample failure stay unchanged to the robustness checks too, and additionally the 2008 financial crisis period does not appear to drive the out-of-sample results as the profitability of the 26 technical trading rules also does not persist out-of-sample when I remove the crisis period from my sample. No other alternative hypothesis seems to explain the difference between in-sample and out-of-sample results, but the statistical biases. Last but not least, the inclusion of transaction cost that further eliminates the profitability of technical trading strategies may cast even stronger doubts on the efficiency of the technical trading strategies. My study shows the importance of studying new data to safeguard against the danger of possible statistical biases.

The possible danger of biases of all sorts is well known. Jensen and Bennington (1970) indicate that superior trading rule performance is often a consequence of survivorship bias. Merton (1985) points out the danger of selection bias and cognitive bias that could affect the results, while studying the behavior of stock market returns; Lo and Mackinlay (1990) state that the degree of data snooping bias in a particular field increases with the number of studies published on the topic. Others like Denton (1985), Black (1993), and Ferson, Sarkissian and Simin (2003) also emphasis the threats from the common statistical biases. In the field of technical analysis, Sullivan, Timmermann and White (1999) utilise the White's Reality Check technique to check for any data snooping bias in particular, and Bajgrowicz and Scaillet (2012) employ the False Discovery Rate strategy to deal with the same problem. However, it is difficult to guard against other statistical biases that could affect the results. Fama (1991) and Lakonishok and Smidt (1988) both provide me with the best solution for these statistical biases: The use of new data. Fama (1991, p 1587) states that: “We should also keep in mind that the CRSP data… are mined on a regular basis by many researchers. Spurious regularities are a sure consequence. Apparent anomalies in returns thus warrant out-of-sample tests before being accepted as regularities likely to be present in future returns”. Lakonishok and Smidt (1988) prescribe long and new data series as the best remedy against data snooping, noise and ‘boredom’ (selection bias). Fortunately, with the passage of time many earlier studies can now be replicated with fresh data. My study is, therefore, primarily motivated to perform such an out-of-sample test, by having access to another 25 years of out-of-sample data other than that used in Brock, Lakonishok and LeBaron (1992).

The study of Brock, Lakonishok and LeBaron (1992) is an important milestone in the field of technical analysis. Not only because they tested a large number of popular technical trading rules but also because it marks a turning point in the academic view on technical analysis. Before the publication of their work, technical analysis was largely dismissed by academics in the 1960s and 1970s. Although Alexander (1964) provides supportive evidence for the profitability of technical analysis on stock markets by utilising the filter rules, Fama (1965) and Samuelson (1965) both question the value of technical analysis by providing evidence in favor of random walk models. The debate on the usefulness of technical analysis has continued since these studies. But it suffered a relatively quiet period until the beginning of the 1990s. Modern studies in the field of technical analysis are boosted from the beginning of the 1990s, which coincides with the publication of Brock, Lakonishok and LeBaron (1992). According to Park and Irwin (2004, p 17): “The number of technical trading studies over the 1995-2004 period amounts to about half of all empirical studies conducted since 1960”. Following the strength of their findings, many studies further confirm the predictive power of their set of technical trading rules in many different economic circumstances. These trading strategies are found to beat the buy-and-hold strategy in different stock markets across the world. For example, Raj and Thurston (1996), Parisi and Vasquez (2000) and Vasiliou, Eriotis and Papathanasiou (2008) provide supportive evidence from the Hong Kong, Chile and Greek markets, respectively. Bessembinder and Chan (1995) take transaction costs into account on six Asian stock markets (Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan) during the period of 1975 to 1991, with these trading rules again found to significantly beat the buy-and-hold strategy across all markets and all trading rules. Previous literature also confirms the predictive ability of the technical trading strategies when different forecasting techniques are employed. Fernandez-Rodriguez, Gonzalez-Martel and Sosvilla-Rivero (2000) use the Artificial Neutral Networks and they discover predictability in the Madrid stock market from 1966 to 1997. Gencay (1996) and Gencay and Stengos (1998) both use the Feedforward Networks and report positive results on the DJIA during the period 1963 to 1988 and the later also argue that past information on volume improves the forecast accuracy. Using the same data, Gencay and Stengos (1997) additionally apply the Nearest Neighbors Regression technique and reach similar conclusion. For a longer sample period from 1897 to 1988, Gencay (1998) also provides supportive evidence by using the same Feedforward

Networks method on the DJIA. Lastly, not just in the stock markets, Gencay, Dacorogna, Olsen and Pictet (2003), Gencay, Ballocchi, Dacorogna, Olsen and Pictet (2002) and Gencay (1999) further report the merit of the technical trading strategies in the forex markets.

The concern of data snooping arises with the increasing supportive evidence reported in the field of technical analysis. Sullivan, Timmermann and White (1999) find that the results of Brock, Lakonishok and LeBaron (1992) are not altered after taking into account the quantified data snooping effects. They also show that the same significant profitability is not realised in a shorter out-of-sample tests on either the DJIA 1987 to 1996 data, or the S&P 500 futures data. They state at the end of their study that: "…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" (Sullivan, Timmermann and White, 1999, p 1684). Bajgrowicz and Scaillet (2012) also show that technical trading rules do not outperform after 1986. Their study uses a different method to account for the data snooping effects. These two studies focus on examining the data snooping adjusted predictability of a large number of technical trading rules (in both cases, they use the same universe of 7,846 technical trading rules). My study differs as I do not consider a large universe of trading rules but focus on what would have happened to an investor had he or she implemented the 26 trading rules that seemed to performed so well in the past. My paper also uses a substantially longer new sample of 25 years, which best prevent the danger of statistical biases with respect to the Brock Lakonishok and LeBaron set of trading rules. Last but not least I investigate why these specific technical trading rules might not work. Is that caused by bias or a market becoming (gradually) more efficient with respect to these trading rules over time?

2.2 Out-of-sample Test

Like Fama (1991), many researchers have stressed the need for out-of-sample tests against common statistical biases, and they presented a number of different techniques to conduct out-of-sample tests while new data is not available (see for example, Elliott and Timmermann (2008), Rapach and Zhou (2012), Goyal and Welch (2003) and Hansen and Timmermann (2012)). However we should keep in mind that only the *true* out-of-sample tests using fresh data best prevents the statistical biases. Some methods themselves are subject to ongoing debates. For instance, researchers sometimes validate the in-sample results by using the sample-split method - using one part of the sample for calibration and the other for verification. However some studies question the efficiency of such method (Faraway (1992), Camstra and Boomsma (1992) and Inoue and Kilian (2004)), and Chatfield (1995) considers the use of new data as irreplaceable: "Statisticians sometimes think that they can overcome the need for new data by splitting a sample into two parts... this is a poor substitute for true replication and the same sentiment also applies to techniques like cross-validation. 'The only real validation of a statistical analysis, or of any statistical enquiry, is confirmation by independent observations' (Anscombe (1967), p. 6) and so model validation needs to be carried out on a completely new set of data" (Chatfield, 1995, p 439). Moreover, we should also distinguish between using completely fresh new data from those using the appended *new* dataset. In the latter case, only small amount of new data is added to the original data set, and the resulting longer dataset is used for the *out-of-sample* confirmation. Conrad, Cooper and Kaul (2003) argue that such *out-of-sample* experiment is likely to be affected by any snooping bias that is present in the original results.

Besides, while some out-of-sample tests provide measures for a particular type of statistical biases (for instance, Sullivan, Timmermann and White (1999) and Bajgrowicz and Scaillet (2012) for data snooping), the use of fresh sample help to avoid many common statistical biases simultaneously. Sullivan, Timmermann and White (2003) state the standard assumptions underlying statistical inference need not be violated if forecasters subsequently use fresh data samples; Neely and Weller (2012) consider fresh data based out-of-sample study as the most certain solution against data snooping, data mining and publication bias; Cooper and Gulen (2006) report that many features of a researcher's *out-of-sample* experiment such as the choice of assets, predictive variables, length of the in-sample window used to obtain forecast parameters, and model selection methods are typically exogenously determined by the researcher after having obtained familiarity with the entire data, whereas it does not induce a bias when out-of-sample tests are performed on new data. Additionally, Andrikopoulos, Daynes, Latimer and Pagas (2008), Davis (1994), Foster, Smith and Whaley (1997), Rapach and Wohar (2006), Hand, Mannila and Smyth (2001), McQueen and Thorley (1999), Ilmanen (2011), DeFusco, McLeavey, Pinto, Runkel and Anson (2007), and Cortes, Mohri, Riley and Rostamizadeh (2008) all claim the cleanness of the results that the *true* out-of-sample studies could provide.

Specifically to my case, I best avoid the sample selection problem by including all truly out-of-sample data available to the in-sample period of 1897-1986 used by Brock, Lakonishok and LeBaron (1992). My out-of-sample data comprises two parts: a 25 year period 1987-2011 that starts immediately after and a 12 year period 1885-1896 that starts right before their in-sample counterpart. In other words, I do not select any particular sample to conduct my out-of-sample test, but I include everything available out-of-sample. The out-of-sample data has not been studied previously for the topic of technical analysis, and this prevents the results away from any hindsight bias- I do not know the predictability in such fresh sample until the out-of-sample test take place. And the clean data also suggests it has not been mined or snooped under this subject in order to reach any favorable conclusion. Overall, the fresh dataset allows me clean hands to start my evaluation of technical trading strategies. In addition to the fresh sample, I strictly limit the trading strategies to the entire set of 26 rules studied in-sample by Brock, Lakonishok and LeBaron (1992) and report all the results to allow direct out-of-sample comparison, this would further eliminate any potential concern on data snooping, hindsight bias or survivorship bias by not searching for any ex-post profitable trading strategies.

2.3 Empirical Approach

2.3.1 Technical Trading Rules

By precisely restricting the settings of the 26 trading rules in line with the original work of Brock, Lakonishok and LeBaron (1992), I aim to deliver a true out-of-sample test. By studying the same trading rules that have been studied extensively in previous research, I mitigate the data snooping problem by not searching for ex-post successful trading rules. Another benefit of my choosing to replicate their work is that the selected 26 trading rules are themselves representative, being widely used in practice in the long run, as they are basically formulated from the historical stock price patterns, which ensures easy access to data and sufficiently long data series. The 26 trading rules can be further divided into three groups: Variable-Length Moving Average Rules; Fixed-Length Moving Average Rules; and Trading Range Break Rules. I briefly discuss these groups here, as well as trading rules with filters that help to generate more reliable signals.

a) Variable-Length Moving Average Rules

Simply put, a long-term moving average and a short-term moving average of the underlying prices are each calculated for Variable-Length Moving Average rules. If the short-term moving average is below (above) the long-term moving average, a sell (buy) signal is generated. The underlying theory is straightforward: A falling (rising) long-term moving average indicates that the prices are periodically falling (up-trending). Thus, comparing the long-term moving average with the short-term moving average that reflects the current market position produces buy, or sell, trading signals. The difference between the short- and long-term moving averages provides an indication of the strength of the trend and, hence, the trading signal.

Moving averages are customized indicators, with adjustable time frames according to the investor’s preference. There are an unlimited number of combinations of the short- and long-term cycles. In my study I apply five combinations following Brock, Lakonishok and LeBaron (1992), namely 1-50, 1-150, 5-150, 1-200 and 2-200. The term Variable-Length refers to the fact that the holding period after trading on the signals is flexible. In other words, it is not forced to hold the position for a certain time period. I hold the current buy (sell) position until a different sell (buy) trading signal is generated. I then study the daily returns conditional on these trading signals.

It is not easy to define the best moving average rules, as economic circumstances vary and investors' behaviors differ. However, the convention is normally that 5-20 periods, 20-60 periods and 100-200 periods are often used to detect short-, medium- and long-term cycles of price movements, respectively.[4] The longer the time period, the less sensitive the trading rule is to current price fluctuations, with less trading signals being generated.

In addition, I also examine - again in line with Brock, Lakonishok and LeBaron (1992) - these five moving average trading strategies, with a percentage filter of 1%. The filter is added to eliminate whipsaws that may generate *fake* trading signals without the support of a solid underlying trend. The filter is defined as the percentage difference between the long-term and short-term moving averages, which has to be greater than 1% for a trading signal to become valid. Hence, there are a total of 10 Variable-Length Moving Average Rules.

b) Fixed-Length Moving Average Rules

Fixed-Length Moving Average rules work similarly to Variable-Length Moving Averages, the key difference being that a trading signal is only generated when a

[4] The choice of the underlying cycles differs between investors. I describe the convention according to the websites http://www.incrediblecharts.com/indicators/moving_average.php and http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:moving_averages#lengths_and_timefram

crossover is discovered. Also, on top of the settings for Variable-Length Moving Average rules, the term *fixed-length* refers to a fixed holding period being required after a trading signal is generated. I use a holding period of 10 days. That is, once a trading signal is generated, I will hold the position for 10 days and all other signals within this 10 day period will be ignored.

This type of time filter is another widely used technique for eliminating whipsaws. The choices of short- and long-term intervals are the same as those for Variable-Length Moving Average rules. I apply the time filter to all of my Fixed-Length Moving Average rules and a 1% filter is also applied at the second stage along with the time filter. There are a total of 10 Fixed-Length Moving Average rules.

c) Trading Range Break Rules

While moving averages give the current price a benchmark for comparison, Trading Range Break rules form a channel for the price to fluctuate. The channel is formed by local extremes; namely support and resistance over the same period, which are defined as moving periodic minimum and maximum prices, respectively. If the price goes beyond either support, or resistance, this signals a possible change in the current trend. A buy signal is generated when the current price rises over the resistance and a sell signal is generated when the current price goes below the support.

I study the same Trading Range Break rules as Brock, Lakonishok and LeBaron (1992): 1-50, 1-150 and 1-200. To illustrate, taking the 1-50 rule as example, when the 1 day price rises over the previous 50 days' maximum price, this signals a buy and when the 1 day price falls below the previous 50 days' minimum price, this signals a sell. Again, I also limit the holding period to 10 days to all three Trading Range Break rules and in the second step the 1% filter is also applied. This gives me six Trading Range Break rules for examination.

2.3.2 Data

I cover both the Dow Jones Industrial Index (DJIA) and the S&P 500 Composite Price Index in this study. Results generated upon these two series are reliable and meaningful for several reasons. They are both US indices, where the market is widely considered to be more efficient and less subject to problems such as political instability and government intervention than many other markets. The US is also the most important and the largest economy worldwide and both of these indices are historically extensive.

I study the DJIA first in order to link my study directly Brock, Lakonishok and LeBaron (1992). To make sure that my results are not index dependent, I also replicate the same evaluation on the S&P 500. As well as providing for double checking of my results, the S&P 500 is often considered to be a better proxy for studying the US stock markets than is the DJIA. The S&P 500 contains 500 large companies, which together account for over 75% of the market value of the US stock markets, while the DJIA contains only 30 companies that are the leaders in their particular industries.

I source both the DJIA and the S&P 500 price data from Global Financial Data. I try to gather the longest data where possible, in order to cover all economic circumstances and to, as much as possible, prevent my results from suffering from any sample selection bias.

The sample periods for the DJIA can be separated into three parts. The first part covers the period from January 1897 to December 1986. This is the in-sample period studied by Brock, Lakonishok and LeBaron (1992) and I use this sample to provide a brief discussion for their in-sample findings. The second part is my out-of-sample test. It starts directly following the data used in Brock, Lakonishok and LeBaron (1992), that is, it runs from January 1987 to the latest data available for March 2011, giving a 25 year period. The third part is also out-of-sample and serves as a robustness check. It begins in February 1885, which is the starting point of the earliest US stock market index data available at a daily frequency. This sample period lasts until December 1896, just before the start of the sample period of Brock, Lakonishok and LeBaron (1992), totaling a 12 year period. The sample period for the S&P 500 starts from the earliest available daily data; which is for January 1928; to the latest data available (March 2011). Returns are calculated as the log differences of the current period and the last period's closing prices. In order to detect the impact, if any, of the 2008 financial crisis on my results I also apply the trading strategies on the sub-sample periods after removing the crisis period of 2008 to 2011[5].

Table 2.1 presents detailed summary statistics for both the DJIA and the S&P 500 in the daily and 10-day holding periods. Across the three samples of the DJIA, I can see that both the mean returns and volatilities increase through time. The daily mean return of the DJIA during the period of 1885 to 1896 of 0.003% is the lowest across all three sample periods, with the return ten times that during the recent 25 year sample period, indicating the vigorous development of the stock market.

[5] I try as best as possible to set my sample period in line with Brock, Lakonishok and LeBaron (1992), however, the S&P 500 data is only available from 1928, while the DJIA data is available from 1897.

The average daily and 10-day returns for the DJIA for 1987 to 2011 are 0.031% and 0.30%, respectively, across the 25 year period. The returns on the S&P 500 are 0.0169% and 0.266%, respectively, on daily and 10-day basis, which are lower compared with those of the DJIA, while the volatilities are higher. Not surprisingly, the inclusion of the 2008 financial crisis generates lower returns and higher volatilities.

Table 2.1: Summary Statistics

	The S&P 500			The DJIA			
Sample Period	1928-1986	1987-2011	1987-2007	1885-1896	1897-1986	1987-2011	1987-2007
	Panel A: Daily Returns						
Mean (%)	0.016	0.027	0.033	0.003	0.017	0.031	0.036
Std Dev	0.011	0.012	0.011	0.008	0.011	0.012	0.011
Minimum	-0.132	-0.229	-0.229	-0.068	-0.137	-0.256	-0.256
Maximum	0.154	0.110	0.087	0.055	0.143	0.105	0.097
N	15885	6170	5359	3592	25086	6139	5296
	Panel B: 10-days Returns						
Mean (%)	0.166	0.266	0.328	0.019	0.166	0.301	0.359
Std Dev	0.038	0.034	0.031	0.027	0.036	0.034	0.032
Minimum	-0.374	-0.378	-0.378	-0.163	-0.396	-0.418	-0.418
Maximum	0.291	0.196	0.143	0.161	0.305	0.172	0.153
N	15876	6161	5350	3583	25077	6130	5287

2.3.3 Methodology

The selected 26 technical trading rules all generate clear buy, or sell, trading signals. Therefore, I perform my evaluation of their profitability based on studying the mean returns conditional on trading signals across each sample period. The procedure can be separated into two steps, as outlined below.

1) In the first step, buy and sell signals are studied separately. I perform the t-tests to study the differences between the mean buy/sell returns and the same period

unconditional indices' returns. This gives me 52 groups of buy/sell signals to study. If the null hypothesis that returns conditional on technical trading signals are not statistically different from the unconditional returns cannot be rejected, the economic value of technical trading rules should be carefully considered.

2) I test the differences between the mean buy returns and the mean sell returns generated by the same trading strategy. This is achieved by using the regression model below with two dummy variables; D_{t-1}^{Buy} and D_{t-1}^{Sell}:

$$r_t = \alpha + \beta_1 D_{t-1}^{Buy} + \beta_2 D_{t-1}^{Sell} + \varepsilon_t \qquad (1)$$

- r_t represents the daily/10 days log returns of the DJIA/ the S&P 500;
- D_{t-1}^{Buy} is a dummy variable that equals 1 when a buy signal is generated and 0 otherwise;
- D_{t-1}^{Sell} is a dummy variable that equals 1 when a sell signal is generated and 0 otherwise; and
- ε_t represents the residual term.

According to the regression model, the average buy and sell returns are captured by $\alpha + \beta_1$ and $\alpha + \beta_2$ respectively. Then, the difference between the average buy and sell returns is captured by $\beta_1 - \beta_2$.

I then test the null hypothesis of equality between mean buy returns and mean sell returns by applying the Wald test. Under the null hypothesis that technical trading strategies do not produce useful trading signals, buy signals should not differ statistically from sell signals in terms of returns conditional on these trading signals and, thus, β should not be statistically different from zero. I employ the above regression to test the spread between returns conditional on buy and sell signals rather than following the original t-test utilised by Brock, Lakonishok and LeBaron (1992). This allows me to easily implement the Newey-West correction on the standard errors to avoid autocorrelation and heteroskedasticity effects to influence significance levels, while Brock, Lakonishok and LeBaron (1992) utilise the bootstrap methodology to address these statistical aspects.

2.4 Empirical Results

2.4.1 In-sample results on the DJIA 1897-1986

Before reporting my out-of-sample findings, I first provide some brief discussion here on the in-sample findings of Brock, Lakonishok and LeBaron (1992). I duplicate their results by using my methodology on the same DJIA 1897 to 1986. The Wald test statistics, rather than the original t-statistics, are reported, with the conclusions drawn from these two statistical tests being basically the same. I ensure the accuracy of the settings of the 26 trading strategies by doing this. This also allows me to link and compare the in-sample and out-of-sample results. Table 2.2 contains my results.

The first and second columns of Table 2.2 give the time period and the trading rules examined. For each group of trading rules, I test these both with and without the 1% percentage filters. For each trading rule, the first and second figure in brackets represent the underlying long- and short-term cycles in days, respectively, and the third figure

Table 2.2: Results on the DJIA 1897-1986

This table reports the results on the DJIA 1897-1986. Trading rules are written as (short, long, band), where short and long represent the short and long moving averages, respectively. A 1% price change is used as the band. N (buy) and N (sell) represent the number of buy/sell trading signals. Buy/Sell represents the mean returns conditional on buy/sell trading signals and the associated t-statistics report the t-test results of the differences of the buy/sell returns from the buy-and-hold returns. The last two columns report βs, which are differences between mean buy and sell returns, and the associated Wald-statistics. β equals the differences of β_1 and β_2, which are estimated by the Regression Model $R_t = \alpha + \beta_1 D_{t-1}^{Buy} + \beta_2 D_{t-1}^{Sell} + \varepsilon_t$, where R_t represents the returns conditional on buy/sell signals, and D_{t-1}^{Buy} and D_{t-1}^{Sell} are dummy variables that equal 1 when a buy, or sell, signal is generated and 0 otherwise. The Wald-statistic is Newey-West corrected and marked in bold if it is significant at the 10% level.

Period	Trading Rules	N (Buy)	Buy ($*10^{-3}$)	t-statistics	N (Sell)	Sell ($*10^{-3}$)	t-statistics	β ($*10^{-3}$)	Wald-stats
				VMA Daily					
1897-1986	**(1,50,0)**	14420	0.50	**3.01**	10617	-0.29	**-3.71**	0.79	**29.63**
	(1,150,0)	15042	0.43	**2.37**	9895	-0.24	**-3.18**	0.66	**18.90**
	(5,150,0)	15037	0.38	**1.96**	9900	-0.17	**-2.64**	0.55	**12.87**
	(1,200,0)	15348	0.41	**2.20**	9539	-0.25	**-3.20**	0.65	**17.40**
	(2,200,0)	15362	0.39	**2.04**	9525	-0.22	**-3.00**	0.61	**14.83**
				VMA Band=1% Daily					
1897-1986	**(1,50,0.01)**	11810	0.64	**4.02**	8201	-0.35	**-3.77**	0.99	**32.97**
	(1,150,0.01)	13713	0.45	**2.51**	8622	-0.30	**-3.47**	0.75	**19.60**
	(5,150,0.01)	13650	0.41	**2.15**	8610	-0.21	**-2.84**	0.62	**13.60**
	(1,200,0.01)	14233	0.42	**2.28**	8539	-0.31	**-3.60**	0.74	**19.09**
	(2,200,0.01)	14223	0.39	**2.04**	8532	-0.25	**-3.08**	0.64	**14.16**
Average			0.44			-0.26		0.70	
				FMA Holding Period=10 days					
1897-1986	**(1,50,0)**	342	3.33	0.86	347	-4.35	**-3.12**	7.67	**7.98**
	(1,150,0)	158	6.26	1.62	189	-0.74	-0.92	7.00	**2.88**
	(5,150,0)	133	7.13	**1.77**	141	-0.38	-0.68	7.52	**3.32**
	(1,200,0)	115	4.76	0.93	158	-2.51	-1.47	7.28	**3.13**
	(2,200,0)	110	4.26	0.76	143	-4.73	**-2.14**	8.99	**4.22**
				FMA Band=1% Holding Period=10 days					
1897-1986	**(1,50,0.01)**	313	5.58	**1.94**	324	-4.54	**-3.11**	10.12	**12.49**
	(1,150,0.01)	172	6.74	**1.87**	159	-4.59	**-2.20**	11.34	**7.00**
	(5,150,0.01)	128	5.91	1.35	126	-4.42	**-1.91**	10.32	**4.62**
	(1,200,0.01)	133	5.24	1.16	129	-9.46	**-3.53**	14.70	**10.24**
	(2,200,0.01)	118	1.39	0.08	118	-10.19	**-3.60**	11.58	**4.82**
Average			5.06			-4.59		9.65	
				TRB Holding Period=10 days					
1897-1986	**(1,50,0)**	733	4.92	**2.44**	417	-0.24	-1.08	5.15	**4.12**
	(1,150,0)	520	4.89	**2.05**	218	-3.23	**-2.02**	8.13	**4.52**
	(1,200,0)	473	4.63	**1.80**	187	-2.61	-1.63	7.24	**2.92**
				TRB Band=1% Holding Period=10 days					
1897-1986	**(1,50,0.01)**	252	8.26	**2.93**	253	-1.88	-1.57	10.14	**6.52**
	(1,150,0.01)	161	8.49	**2.42**	144	-3.94	**-1.88**	12.43	**5.14**
	(1,200,0.01)	149	7.04	**1.84**	126	-5.18	**-2.15**	12.22	**4.41**
Average			6.18			-3.10		9.22	

represents the percentage filter. For example, the Variable-Length Moving Average rule (2, 200, 0.01) tells me that buy (sell) signals are generated when the 2 day moving average of the DJIA is above (below) the 200 day moving average, and that the trading signal is only valid when the difference between the two moving averages is over 1%. The results show that the introduction of filters eliminates some weak trading signals. Also, the longer the time frame of the underlying moving averages, the greater the number of variations on the prices that are smoothed out, hence the lower the number of trading signals generated.

The following three columns report the number of buy trading signals generated by each trading rule, the mean returns conditional on these buy signals, and the t statistics of testing the difference between buy returns and the unconditional buy-and-hold returns. I then repeat this for sell trading signals in the next three columns. The results reveal that buy (sell) signals consistently produce positive (negative) returns across the 90 year sample period. Most of these conditional returns are also found to be statistically different from the buy-and-hold returns at the 10% significance level, with the rest being marginally significant. The Variable-Length Moving Average strategies outperform the Fixed-Length Moving Average strategies and the Trading-Range Break strategies, with all 20 groups of trading signals beating the buy-and-hold strategy.

The last two columns report the Wald test results for testing the differences between buy returns and sell returns. These results are even stronger. Across all 26 trading strategies, I consistently find that buy returns are significantly different from the same period sell returns at the 10% level of significance. The in-sample results provide strong supportive evidence -for the argument that technical trading strategies produce useful trading signals.

My results are not surprisingly similar to Brock, Lakonishok and LeBaron (1992). For example, I find that the Variable-Length Moving Average rule (1, 50, 0) generates 14420 buy signals and 10617 sell signals that totals 25037 signals across the 90 year sample period, and Brock, Lakonishok and LeBaron (1992) reports 14240 buy signals and 10531 sell signals. My mean buy (sell) return for this trading rule is 0.050% (-0.027%) while they report 0.047% (-0.029%). Overall across all 26 trading strategies, I find 19 (20) groups of buy (sell) signals producing returns higher than the buy-and-hold returns at the 10% significance level, while Brock, Lakonishok and LeBaron (1992) report 19 (19) groups of buy (sell) signals. Moreover, my Wald test results indicates that all the 26 trading rules produce different buy returns from sell returns, while Brock, Lakonishok and LeBaron (1992) provides the answer of 25 to the same question although they use a t-test instead.

2.4.2 Out-of-sample Results on the DJIA 1987-2011

I report my results on the DJIA from 1987 to 2011 in Table 2.3. Overall, I find no evidence supporting the predictability of the technical trading rules. My out-of-sample findings are in sharp contrast with the findings of the in-sample results.

The out-of-sample results are tabulated in the same way as the in-sample results. Again there are generally more buy signals than sell signals, which is consistent with the overall uptrending of the DJIA. The Variable-Length Moving Average strategies generate significantly more trading signals across all three categories of my trading strategies, with an average of 223.38 trading signals per year, compared with only 4.35 signals per year

Table 2.3: Results on the DJIA 1987-2011

This table reports the results on the DJIA 1987-2011. Trading rules are written as (short, long, band), where short and long represents the short and long moving averages, respectively. A 1% price change is used as the band. N(buy) and N(sell) represents the number of buy/sell trading signals. Buy/Sell represents the mean returns conditional on buy/sell trading signals and the associated t-statistics report the t-test results of the differences of the buy/sell returns from the buy-and-hold returns. The last two columns report βs, which are difference between mean buy and sell returns, and the associated Wald-statistics. β equals the difference of β_1 and β_2, which is estimated by the regression model $R_t = \alpha + \beta_1 D_{t-1}^{Buy} + \beta_2 D_{t-1}^{Sell} + \varepsilon_t$, where R_t represents the returns conditional on buy/sell signals, and D_{t-1}^{Buy} and D_{t-1}^{Sell} are dummy variables that equal 1 when a buy or sell signal is generated and 0 otherwise. The Wald-statistic is Newey-West corrected and marked in bold if it is significant at the 10% level.

Period	Trading Rules	N(Buy)	Buy ($*10^{-3}$)	t-statistics	N(Sell)	Sell ($*10^{-3}$)	t-statistics	B ($*10^{-3}$)	Wald-stats
				VMA Daily					
1987-2011	**(1,50,0)**	3931	0.22	-0.36	2159	0.40	0.31	-0.18	0.27
	(1,150,0)	4108	0.22	-0.37	1882	0.37	0.21	-0.15	0.16
	(5,150,0)	4102	0.20	-0.45	1888	0.41	0.34	-0.21	0.35
	(1,200,0)	4186	0.27	-0.16	1754	0.31	0.02	-0.04	0.01
	(2,200,0)	4184	0.23	-0.30	1756	0.40	0.29	-0.16	0.18
				VMA Band=1% Daily					
1987-2011	**(1,50,0.01)**	3231	0.13	-0.69	1555	0.48	0.52	-0.35	0.63
	(1,150,0.01)	3752	0.24	-0.25	1525	0.46	0.45	-0.22	0.24
	(5,150,0.01)	3742	0.28	-0.12	1518	0.45	0.43	-0.18	0.17
	(1,200,0.01)	3851	0.30	-0.03	1450	0.54	0.69	-0.24	0.30
	(2,200,0.01)	3832	0.28	-0.13	1438	0.51	0.58	-0.23	0.27
Average			0.24			0.43		-0.20	
				FMA Holding Period=10 days					
1987-2011	**(1,50,0)**	81	3.01	0.00	111	4.44	0.44	-1.43	0.10
	(1,150,0)	58	-0.12	-0.70	50	-4.93	-1.66	4.81	0.38
	(5,150,0)	48	0.44	-0.53	39	-7.43	**-1.93**	7.87	1.43
	(1,200,0)	48	2.87	-0.03	45	1.43	-0.31	1.44	0.03
	(2,200,0)	40	3.22	0.04	45	3.37	0.07	-0.15	0.00
				FMA Band=1% Holding Period=10 days					
1987-2011	**(1,50,0.01)**	96	-0.69	-1.07	87	7.00	1.09	-7.69	**2.80**
	(1,150,0.01)	45	-2.67	-1.13	52	3.60	0.12	-6.27	0.59
	(5,150,0.01)	37	3.55	0.10	43	1.49	-0.29	2.06	0.10
	(1,200,0.01)	36	-2.66	-1.01	47	9.71	1.35	-12.37	2.06
	(2,200,0.01)	41	-2.64	-1.07	38	9.42	1.17	-12.06	2.59
Average			0.43			2.81		-2.38	
				TRB Holding Period=10 days					
1987-2011	**(1,50,0)**	208	-0.48	-1.47	79	5.92	0.76	-6.40	1.03
	(1,150,0)	163	-0.14	-1.18	30	23.49	**3.31**	-23.63	**4.03**
	(1,200,0)	149	0.84	-0.77	21	24.16	**2.87**	-23.32	2.42
				TRB Band=1% Holding Period=10 days					
1987-2011	**(1,50,0.01)**	69	2.81	-0.05	49	2.37	-0.13	0.45	0.00
	(1,150,0.01)	47	0.87	-0.43	20	19.28	**2.15**	-18.41	1.60
	(1,200,0.01)	42	1.37	-0.31	18	27.27	**3.04**	-25.89	**3.05**
Average			0.82			15.04		-14.23	

generated by the Fixed-Length Moving Average rules and 5.97 signals per year generated by the Trading-Range Break rules. The average frequencies of the trading signals do not vary much from the in-sample period. The Variable-Length Moving Average strategies produces 37 more signals per year in-sample (260.91 signals annually), the Fixed-Length Moving Average strategies and the Trading-Range Break Rules generate 3.95 and 6.73 trading signals annually in-sample, respectively.

Brock, Lakonishok and LeBaron (1992) find that buy (sell) signals during their sample period from 1897 to 1986 are consistently generating positive (negative) returns, which are significantly higher than the same period buy-and-hold returns. In my case, however, I find that, out of the total 52 groups of signals, only five groups of trading signals produce statistically different returns from the unconditional returns and are all sell signals. None of the buy returns are found to be different from the buy-and-hold returns.

The findings on the sell signals from the Trading Range Break rules are especially remarkable: The trading rules (1,150), (1,200), (1,150, 0.01) and (1,200, 0.01) produce predictable sell signals with positive mean returns that are statistically significant at the 90% level. The mean returns of these sell signals range from 1.93% to 2.73%, all being quite substantial compared with the 10-day unconditional mean return of 0.30%. The positive mean returns of the sell signals indicate that the sell signals inversely predict the market. Brock, Lakonishok and LeBaron (1992) documented in their study that:

> "The negative returns in Table II for sell signals are especially noteworthy. These returns cannot be explained by various seasonalities since they are based on about 40 percent of all trading days. Many previous studies found as

> we did that returns are predictable. This predictability can reflect either: (1) changes in expected returns that result from an equilibrium model, or (2) market inefficiency. In general, it is difficult to distinguish between these two alternative explanations. Although rational changes in expected returns are possible it is hard to imagine an equilibrium model that predicts negative returns over such a large fraction of trading days" (p. 1740).

In contrast, it is interesting that in my case, through examining the same DJIA index out-of-sample data from 1987 to 2011, instead of the negative returns detected in their study, I find that most sell returns are positive.

The Wald test results from the last two columns show that, among the 26 trading rules, three trading rules are found to generate significantly different buy and sell returns at the 90% significance level. The spread between the signals is, however, negative, which actually indicates that the buy, the sell, or both signals predict the market in the opposite direction. These negative values are again in contrast with the findings of Brock, Lakonishok and LeBaron (1992), in which positive spreads are always discovered. Nevertheless, such negative values of mean buy-sell spreads would not be surprising with the positive mean sell returns that I detected earlier.

2.4.3 Three Hypotheses

My out-of-sample findings differ largely with what is found in-sample. I present three hypotheses in attempting to explain why the predictability of the 26 simple technical trading strategies disappears:

(1) The 26 simple technical trading strategies simply do not work. The in-sample results with predictability discovered are subject to possible statistical biases. In this case I would not find significant results in both my sample from 1987 to 2011, and during the earlier sample periods from 1885 to 1896.

(2) While the 26 simple technical trading strategies could have been profitable during the 90 year in-sample period, the stock market is gradually becoming more efficient with respect to the information of technical trading rules after the Brock, Lakonishok and LeBaron (1992). Thus, the predictability of these trading rules is gradually eliminated. The outperformance of these trading strategies would gradually disappear over time in my 1987-2011 sample but still be present from 1885 to 1896.

(3) The 26 simple technical trading strategies do generate superior returns during the 90 year period; however, investors are informed immediately of the Brock, Lakonishok and LeBaron (1992) results and discover the profitability of the 26 trading strategies. They implement these strategies straightaway, to the extent when these trading strategies are no longer profitable. The predictability disappears immediately in 1987 but is still present in my earlier sample period of 1885 to 1896.

2.4.4 The Profitability Over Time

To illustrate the changed predictability over time, Figures 2.1, 2.2 and 2.3 present the cumulative wealth of investing on the Variable-Length Moving Average strategy (1, 50). I also plot the cumulative wealth for the buy-and-hold strategy for comparison. To save space, I use this as an example to illustrate the profitability of the technical trading strategies over time, while the results on the remaining 25 trading strategies are similar.

Figure 2.1: Cumulative Wealth of the Variable-Length Moving Average Rule (1, 50) on the DJIA 1987-1991

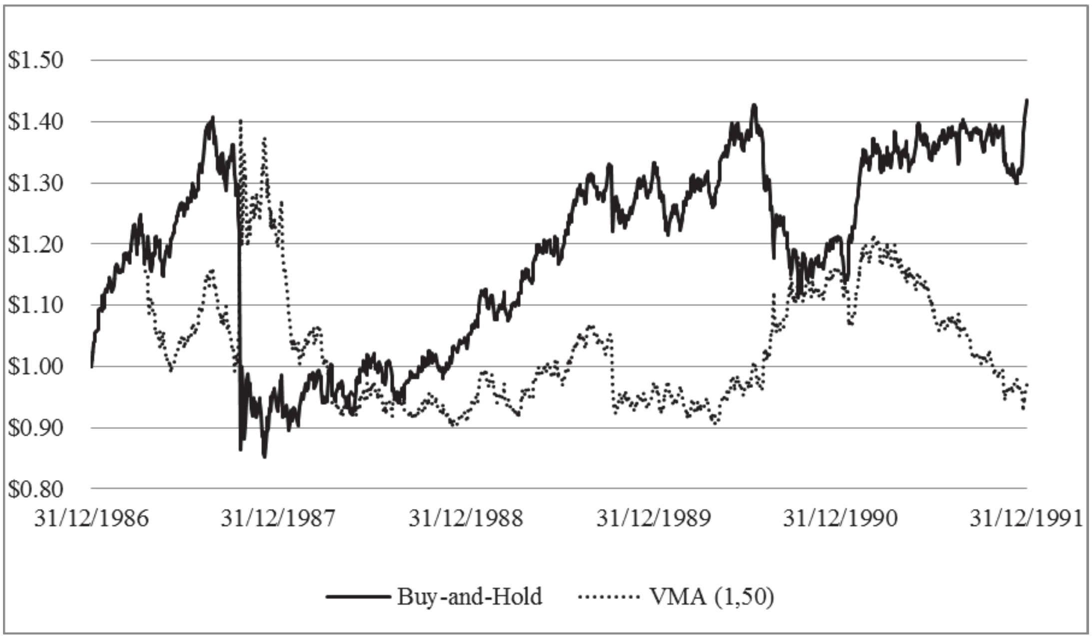


Figure 2.2: Cumulative Wealth of the Variable-Length Moving Average Rule (1, 50) on the DJIA 1987-1995

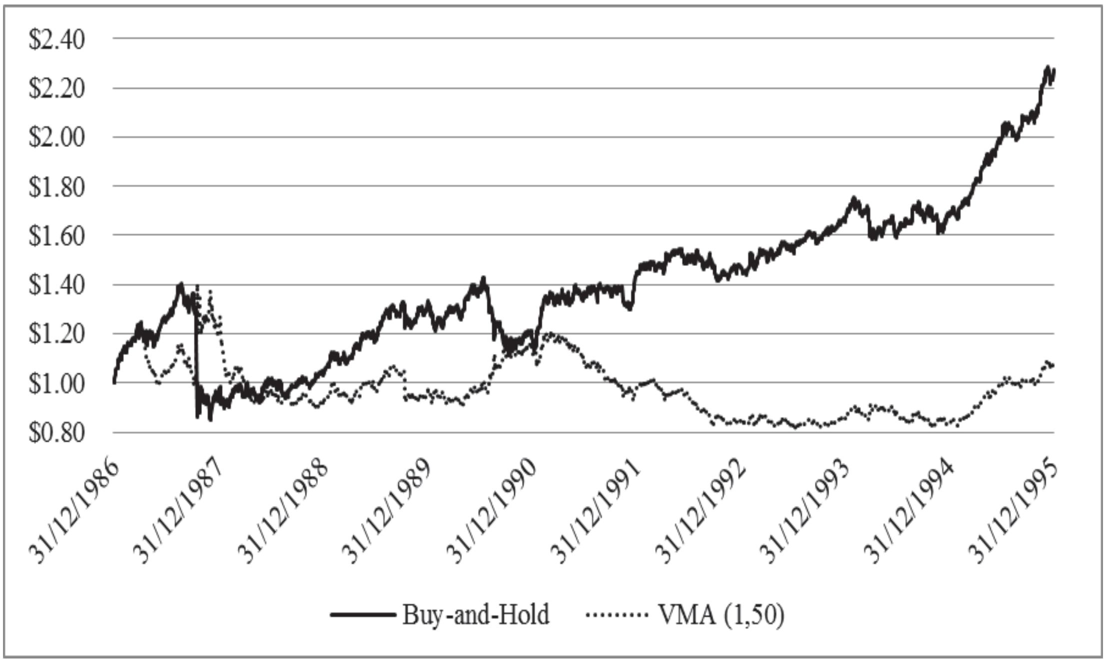
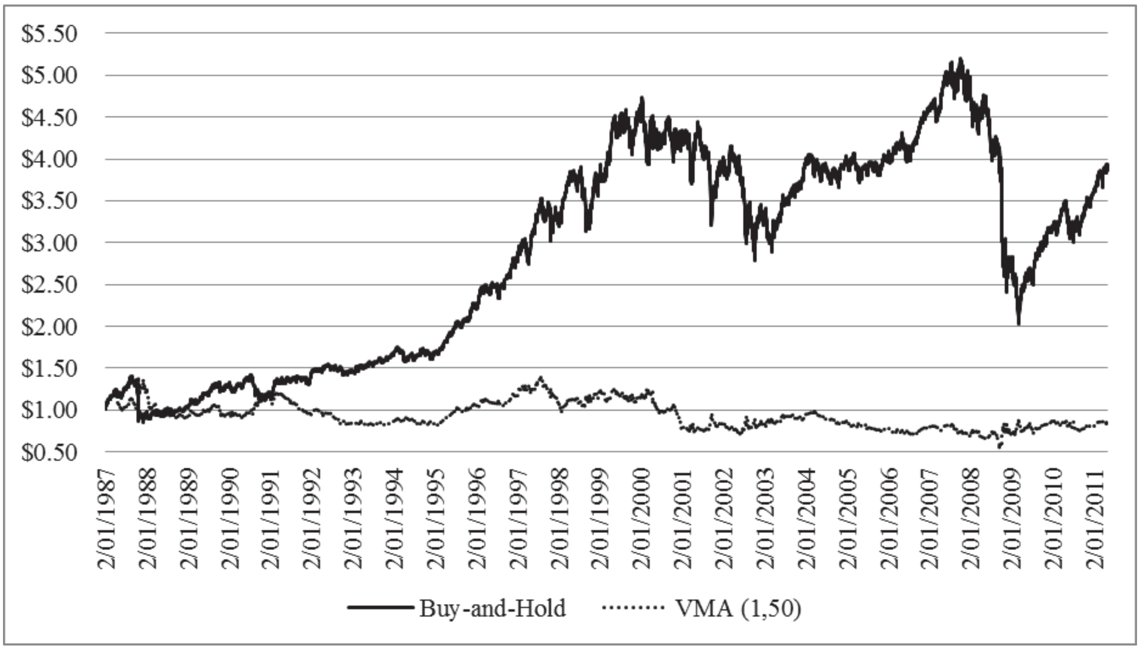


Figure 2.3: Cumulative Wealth of the Variable-Length Moving Average Rule (1, 50) on the DJIA 1987-2011



The plots are given on a 5 year panel, a 10 year panel and the full 25 year panel since 1987. I assume that I invest one dollar on the DJIA on the first trading day of 1987, that I long on buy trading signals and that I short sale on sell trading signals. I invest in risk-free assets when there is no trading signal. The 3-month US T-bill rate is used as the risk-free rate.

Figure 2.1 shows that during the 5 year period from 1987 to 1991, the technical trading strategy does not beat the buy-and-hold strategy over most of the period. It wins the buy-and-hold strategy only during the 1987 financial crisis period. I then extend the underlying period to 10 years from 1987 to 1995 in Figure 2.2. The cumulative wealth of the buy-and-hold strategy gradually increases, associated with the stock markets' growth during this period. At the same time, however, the cumulative wealth of the technical trading strategy remains flat. This causes the gap in the cumulative wealth between the buy-and-hold strategy and the Variable-Length Moving Average strategy (1, 50) to expand more and more during this period. At the end of 1995, the cumulative wealth of the buy-and-hold strategy and the technical trading strategy are \$2.27 and \$1.08 respectively, from the \$1 initial investment. Last, in Figure 2.3, it is observed that the cumulative wealth of the buy-and-hold strategy fluctuates across the full 25 year sample period. The end-of-period wealth reaches \$3.87 by investing on the buy-and-hold strategy, while at the same time the cumulative wealth line over time remains flat for the (1, 50) rule with an end-of-period wealth of \$0.85 by the end of March in 2011. Overall, the cumulative wealth of the variable-length moving average rule ranges between \$0.55 and \$1.41, which is relatively flat across the full 25 year period and seldom beats the market.

While lower returns could be a result of lower risk. I next examine the profitability of the technical trading strategies on a risk-adjusted basis by estimating Jensen's α:

$$r_t^p - r_t^f = \alpha + \beta\,(r_t^m - r_t^f) + \varepsilon_t \qquad (2)$$

- r_t^p represents the log return on technical trading strategies;
- r_t^f represents the risk free rate, which is set as the US 3-month Treasury Bill rate;
- r_t^m represents the return on the DJIA index; and
- ε_t represents the residual term.

The excess return over what is expected and the systematic risk of the technical trading strategy are captured by α and β, respectively. I report the results in Table 2.4 with the t-statistics (based on White standard errors) in brackets.

Table 2.4: Results for Jensen's α Estimation 1987-2011

This table reports results for the regression model: $r_t^p - r_t^f = \alpha + \beta\ (r_t^m - r_t^f) + \varepsilon_t$ for the DJIA 1987-2011, where r_t^p represents the returns of technical trading strategies, r_t^f represents the risk free rates which is set as the US 3-month Treasury Bill rate, and r_t^m represents the return on the DJIA index. The excess returns and the systematic risks of the technical trading strategies are captured by α and β, respectively. Trading rules are written as (short, long, band) where short and long represents the short and long moving averages, respectively. A 1% price change is used as the band. The t-statistics are reported in brackets, and marked in bold if significant at the 10% level.

		Buy		Sell		Buy&Sell	
Period	**Trading Rules**	**α ($*10^{-4}$)**	**β**	**α ($*10^{-4}$)**	**β**	**α ($*10^{-4}$)**	**β**
				VMA Daily			
1987-2011	**(1,50,0)**	0.15	0.35	-0.568	-0.65	-0.42	-0.30
		(0.21)	**(10.94)**	(-0.77)	**(-20.44)**	(-0.28)	**(-4.73)**
	(1,150,0)	0.25	0.35	-0.33	-0.65	-0.08	-0.29
		(0.34)	**(10.83)**	(-0.45)	**(-19.84)**	(-0.05)	**(-4.48)**
	(5,150,0)	0.10	0.37	-0.48	-0.63	-0.38	-0.26
		(0.13)	**(10.87)**	(-0.64)	**(-18.53)**	(-0.25)	**(-3.81)**
	(1,200,0)	0.31	0.39	-0.20	-0.61	0.11	-0.23
		(0.43)	**(20.77)**	(-0.28)	**(-32.88)**	(0.08)	**(-6.05)**
	(2,200,0)	0.14	0.39	-0.37	-0.61	-0.23	-0.21
		(0.19)	**(20.83)**	(-0.51)	**(-32.13)**	(-0.16)	**(-5.65)**
				VMA Daily Band=1%			
1987-2011	**(1,50,0.01)**	-0.35	0.28	-0.38	-0.58	-0.73	-0.30
		(-0.51)	**(10.60)**	(-0.50)	**(-15.7)**	(-0.54)	**(-4.84)**
	(1,150,0.01)	0.42	0.32	-0.34	-0.60	0.08	-0.28
		(0.57)	**(10.70)**	(-0.44)	**(-16.66)**	(0.06)	**(-4.25)**
	(5,150,0.01)	0.59	0.33	-0.33	-0.59	0.26	-0.26
		(0.81)	**(10.71)**	(-0.43)	**(-15.87)**	(0.18)	**(-3.85)**
	(1,200,0.01)	0.50	0.35	-0.56	-0.57	-0.06	-0.22
		(0.70)	**(19.98)**	(-0.77)	**(-28.89)**	(-0.05)	**(-6.19)**
	(2,200,0.01)	0.33	0.35	0.00	-0.57	-0.13	-0.21
		(0.47)	**(19.92)**	(-0.63)	**(-28.42)**	(-0.09)	**(-5.82)**
				FMA 10-days			
1987-2011	**(1,50,0)**	0.15	0.01	-0.67	-0.01	-0.52	0.00
		(0.30)	**(3.93)**	(-1.40)	**(-6.07)**	(-0.75)	(0.05)
	(1,150,0)	-0.27	0.01	0.57	-0.02	0.31	-0.01
		(-0.57)	**(2.69)**	(0.83)	(-1.51)	(0.37)	(-0.58)
	(5,150,0)	-0.11	0.00	0.53	-0.01	0.41	0.00
		(-0.40)	**(4.10)**	(1.29)	**(-2.55)**	(0.83)	(-1.02)
	(1,200,0)	-0.04	0.01	-0.37	-0.01	-0.41	0.00
		(-0.09)	**(2.93)**	(-1.01)	**(-2.81)**	(-0.73)	(0.50)
	(2,200,0)	-0.03	0.01	-0.43	0.00	-0.46	0.00
		(-0.06)	**(2.21)**	(-1.51)	**(-4.06)**	(-0.88)	(0.95)
				FMA 10-days Band=1%			
1987-2011	**(1,50,0.01)**	-0.49	0.02	-0.85	-0.01	-1.34	0.00
		(-0.84)	**(3.67)**	**(-1.88)**	**(-5.70)**	**(-1.81)**	(1.06)
	(1,150,0.01)	-0.41	0.01	-0.17	-0.02	-0.57	-0.01
		(-0.96)	**(2.31)**	(-0.24)	(-1.53)	(-0.70)	(-0.73)
	(5,150,0.01)	0.10	0.00	-0.09	-0.01	0.01	0.00
		(0.40)	**(3.21)**	(-0.23)	**(-2.55)**	(0.03)	(-1.09)
	(1,200,0.01)	-0.48	0.01	-0.95	-0.01	-1.43	0.01
		(-0.93)	**(2.64)**	**(-3.08)**	**(-4.54)**	**(-2.37)**	(1.34)
	(2,200,0.01)	-0.41	0.01	-0.76	-0.01	-1.17	0.00
		(-1.05)	**(2.93)**	**(-2.52)**	**(-4.07)**	**(-2.36)**	(0.74)

Period	Trading Rules	Buy α (*10^{-4})	Buy β	Sell α (*10^{-4})	Sell β	Buy&Sell α (*10^{-4})	Buy&Sell β
				TRB 10-days			
1987-2011	**(1,50,0)**	-0.70	0.02	-0.45	-0.03	-1.15	-0.02
		(-1.28)	**(7.12)**	(-0.53)	**(-3.26)**	(-1.13)	(-1.68)
	(1,150,0)	-0.41	0.01	-1.06	-0.02	-1.47	-0.01
		(-0.86)	**(6.39)**	**(-1.90)**	**(-3.16)**	**(-1.98)**	(-1.17)
	(1,200,0)	-0.19	0.01	-0.65	-0.02	-0.84	-0.01
		(-0.42)	**(6.01)**	(-1.38)	**(-2.59)**	(-1.29)	(-0.89)
				TRB 10-days Band=1%			
1987-2011	**(1,50,0.01)**	0.09	0.01	0.35	-0.03	0.44	-0.02
		(0.27)	**(4.31)**	(0.40)	**(-2.51)**	(0.47)	(-2.00)
	(1,150,0.01)	-0.09	0.00	-0.37	-0.01	-0.46	-0.01
		(-0.31)	**(3.67)**	(-0.78)	**(-2.66)**	(-0.83)	(-1.81)
	(1,200,0.01)	-0.07	0.00	-0.46	-0.01	-0.54	-0.01
		(-0.28)	**(3.33)**	(-1.04)	**(-2.49)**	(-1.04)	(-1.73)

I study technical trading strategies that employ buy signals only, or sell signals only, or both buy and sell signals separately, in comparison with a buy-and-hold strategy:

- Buy Only: I only long when there is a buy trading signal generated; otherwise I invest in risk-free assets.
- Sell Only: I only short sell when there is a sell trading signal generated; otherwise I invest in risk-free assets.
- Buy and Sell: I long on buy trading signals and short on sell trading signal; I invest in risk-free assets when there is no trading signal.
- Buy and Hold: I invest on the DJIA throughout.

Table 2.4 gives α and β estimates for each of these trading rules separately. No matter whether I employ buy signals only, or sell signals only, none of these 26 trading strategies are shown to generate positive significant α. In addition, a few trading strategies, namely the Fixed-Length Moving Average rule (1,50,0.01), (1,200, 0.01), (2,200,0.01) and the Trading Range Break rule (1,150,0) are found to generate negative significant α when I invest on both buy and sell trading signals. These negative significant α indicate that, for a given risk level, investing on these technical trading strategies is not as profitable as investing on the market. Overall, the absence of positive significant α reveals that technical trading strategies do not generate superior returns on a risk-adjusted basis either. I also calculate the Henriksson & Merton (1981) market timing coefficient and the Sharpe ratios; they capture different perspectives of the risk/return trade-off. The results are available in Appendix 1, with similar findings that do not favor the technical trading strategies on a risk-adjusted basis. This suggests that I can rule out the hypothesis that technical trading rules were gradually implemented by traders. This leaves me with two alternatives. Either a large group of investors immediately acted upon a trading strategy in 1987 when the sample period of Brock, Lakonishok and LeBaron (1992) ends and this made the market more efficient, or the results are caused by statistical bias.

2.4.5 Results on the DJIA 1885-1896

I further test the profitability of the same 26 technical trading rules on the DJIA from 1885 to 1896, which totals a 12 year period. As well as double checking whether the in-sample results are sample specific, it could also help in identifying the role that a more efficient market is playing in the changed predictability. That is, if the disappearing predictability of the technical trading strategies is the result of a more efficient market, I should not be able to detect similar disappearing predictability during the period from 1885 to 1896.

The results are presented in Table 2.5. Again, the technical trading strategies show limited predictability during this period. At the 10% significance level, only seven out of the total fifty-two groups of buy/sell trading signals are found to produce higher mean returns than the simple buy-and-hold returns. This seems only slightly more than one would expect under the null hypothesis of no predictability. It is also noteworthy that even for the seven significant results; nearly all of them come from the Fixed-Length Moving Average rules and the Trading range Break rules. Both of these two types of trading rules have relatively less trading signals due to a fixed holding period of 10 days. For instance, the Trading Range Break rule (1, 200, 0.01) only generates 7 buy signals and 12 sell signals during the 12 year period. The predictability of the seven groups of trading signals may be further challenged when I realize that this may be due to a limited number of signals for many of these trading rules.

Moreover, I find none of the sell signals shows any predictability in the 12 year period, which contrasts with the in-sample findings that sell signals tend to show more predictability. And the Wald test results in the last column indicate that in nineteen cases out of twenty-six in total, the buy-sell spreads are not different from zero, showing that the majority of the simple technical trading strategies do not produce useful signals.

I present the results for Jensen's α estimation for the period 1885 to 1896 in Table 2.6. Out of seventy-eight trading strategies only twelve produce positive αs. Again this number might even be biased upward as most of the twelve trading strategies only generate a small number of signals during the 12 year period. This provides evidence that the reduced predictability of the simple technical trading strategies is not associated with a reduced risk level neither during the period from 1885 to 1896.

Table 2.5: Results on the DJIA 1885-1896

This table reports the results on the DJIA 1885-1896. Trading rules are written as (short, long, band), where short and long represent the short and long moving averages, respectively. A 1% price change is used as the band. N (buy) and N (sell) represents the number of buy/sell trading signals. Buy/Sell represents the mean return conditional on buy/sell trading signals and the associated t-statistics report the t-test results of the difference of the buy/sell returns from the buy-and-hold returns. The last two columns report βs, which is difference between mean buy and sell returns, and the associated Wald-statistics. β equals the difference of β_1 and β_2, which is estimated by the regression model $R_t = \alpha + \beta_1 D_{t-1}^{Buy} + \beta_2 D_{t-1}^{Sell} + \varepsilon_t$, where R_t represents the returns conditional on buy/sell signals, and D_{t-1}^{Buy} and D_{t-1}^{Sell} are dummy variables that equals 1 when a buy or sell signal is generated and 0 otherwise. The Wald-statistic is Newey-West corrected and marked in bold if it is significant at the 10% level.

Period	Trading Rules	N (Buy)	Buy ($*10^{-3}$)	t-statistics	N(Sell)	Sell ($*10^{-3}$)	t-statistics	β ($*10^{-3}$)	Wald-stats
				VMA Daily					
1885-1896	**(1,50,0)**	1787	0.28	1.02	1756	-0.23	-1.10	0.51	**3.45**
	(1,150,0)	1792	0.04	0.03	1651	-0.04	-0.29	0.08	0.07
	(5,150,0)	1776	0.09	0.25	1667	-0.10	-0.52	0.19	0.44
	(1,200,0)	1786	-0.08	-0.44	1607	0.05	0.09	-0.13	0.19
	(2,200,0)	1776	-0.01	-0.17	1617	-0.02	-0.19	0.01	0.00
				VMA Band=1% Daily					
1885-1896	**(1,50,0.01)**	1295	0.47	**1.65**	1241	-0.30	-1.21	0.77	**4.96**
	(1,150,0.01)	1493	0.03	0.02	1278	0.05	0.07	-0.02	0.00
	(5,150,0.01)	1487	0.08	0.20	1258	0.03	0.00	0.05	0.02
	(1,200,0.01)	1505	-0.04	-0.29	1359	0.01	-0.09	-0.05	0.02
	(2,200,0.01)	1501	0.03	0.00	1355	0.02	-0.04	0.01	0.00
Average			0.09			-0.05		0.14	
				FMA Holding Period=10 days					
1885-1896	**(1,50,0)**	44	7.24	**1.73**	55	2.85	0.73	4.39	0.74
	(1,150,0)	38	-3.40	-0.82	26	0.72	0.10	-4.11	0.41
	(5,150,0)	25	5.76	1.04	20	-3.84	-0.67	9.61	2.44
	(1,200,0)	25	1.63	0.27	29	4.65	0.89	-3.02	0.31
	(2,200,0)	24	8.16	1.45	24	-0.78	-0.18	8.94	1.98
				FMA Band=1% Holding Period=10 days					
1885-1896	**(1,50,0.01)**	47	3.13	0.75	43	0.85	0.16	2.28	0.17
	(1,150,0.01)	25	9.05	**1.65**	35	-3.44	-0.80	12.49	**4.63**
	(5,150,0.01)	18	8.34	1.29	22	-0.70	-0.15	9.04	**2.79**
	(1,200,0.01)	26	11.41	**2.12**	24	1.39	0.22	10.02	2.40
	(2,200,0.01)	19	16.11	**2.58**	24	-2.30	-0.45	18.42	**5.33**
Average			6.75			-0.06		6.81	
				TRB Holding Period=10 days					
1885-1896	**(1,50,0)**	70	7.50	**2.26**	69	-3.20	-1.04	10.70	**5.64**
	(1,150,0)	36	6.46	1.40	36	-3.04	-0.72	9.50	2.28
	(1,200,0)	29	6.53	1.27	31	1.51	0.27	5.02	0.61
				TRB Band=1% Holding Period=10 days					
1885-1896	**(1,50,0.01)**	20	15.07	**2.47**	29	-0.51	-0.14	15.58	**3.18**
	(1,150,0.01)	10	8.71	1.00	19	4.41	0.68	4.30	0.16
	(1,200,0.01)	7	1.81	0.16	18	7.40	1.14	-5.59	0.25
Average			7.55			0.93		6.62	

Table 2.6: Results for Jensen's α Estimation 1885-1896

This table reports results for the regression model: $r_t^p - r_t^f = \alpha + \beta\,(r_t^m - r_t^f) + \varepsilon_t$ for the DJIA 1885-1896, where r_t^p represents the returns of technical trading strategies, r_t^f represents the risk free rates which is set as the US 3-month Treasury Bill rate, and r_t^m represents the return on the DJIA index. The excess returns and the systematic risks of the technical trading strategies are captured by α and β, respectively. Trading rules are written as (short, long, band) where short and long represents the short and long moving averages, respectively. A 1% price change is used as the band. The t-statistics are reported in brackets, and marked in bold if significant at the 10% level.

		Buy		Sell		Buy&Sell	
Period	**Trading Rules**	**α (*10^{-4})**	**β**	**α (*10^{-4})**	**β**	**α (*10^{-4})**	**β**
				VMA Daily			
1885-1896	**(1,50,0)**	1.170	0.388	0.146	-0.612	1.315	-0.224
		(1.73)	**(16.5)**	(0.22)	**(-26.00)**	(0.97)	**(-4.75)**
	(1,150,0)	0.015	0.374	-0.945	-0.626	-0.930	-0.252
		(0.02)	**(15.67)**	(-1.39)	**(-26.21)**	(-0.68)	**(-5.27)**
	(5,150,0)	0.300	0.377	-0.669	-0.623	-0.369	-0.246
		(0.44)	**(15.74)**	(-0.98)	**(-26.03)**	(-0.27)	**(-5.14)**
	(1,200,0)	-0.547	0.361	-1.481	-0.639	-2.028	-0.278
		(-0.81)	**(15.12)**	**(-2.18)**	**(-26.75)**	(-1.49)	**(-5.81)**
	(2,200,0)	-0.210	0.361	-1.150	-0.639	-1.360	0.000
		(-0.31)	**(15.13)**	(-1.69)	**(-26.75)**	(-1.00)	**(-5.81)**
				VMA Daily Band=1%			
1885-1896	**(1,50,0.01)**	1.594	0.310	0.246	-0.542	1.840	-0.231
		(2.48)	**(14.36)**	(0.36)	**(-21.39)**	(1.48)	**(-5.07)**
	(1,150,0.01)	0.021	0.328	-1.142	-0.566	-1.121	-0.238
		(0.03)	**(14.41)**	(-1.64)	**(-22.29)**	(-0.87)	**(-5.05)**
	(5,150,0.01)	0.223	0.323	-1.048	-0.552	-0.824	-0.229
		(0.34)	**(14.29)**	(-1.50)	**(-21.39)**	(-0.65)	**(-4.88)**
	(1,200,0.01)	-0.301	0.320	-1.124	-0.595	-1.425	-0.275
		(-0.46)	**(13.95)**	(-1.62)	**(-23.78)**	(-1.10)	**(-5.83)**
	(2,200,0.01)	0.016	0.315	-1.175	-0.589	-1.159	-0.274
		(0.02)	(13.84)	**(-1.69)**	**(-23.38)**	(-0.90)	**(-5.82)**
				FMA 10-days			
1885-1896	**(1,50,0)**	0.878	0.012	-0.721	-0.013	0.157	-0.001
		(1.69)	**(3.14)**	(-1.36)	**(-3.19)**	(0.21)	(-0.10)
	(1,150,0)	-0.360	0.012	-0.204	-0.006	-0.563	0.006
		(-0.73)	**(2.85)**	(-0.57)	**(-2.95)**	(-0.92)	(1.32)
	(5,150,0)	0.415	0.007	0.135	-0.002	0.550	0.004
		(1.08)	**(3.03)**	(0.63)	**(-2.72)**	(1.25)	**(1.89)**
	(1,200,0)	0.105	0.005	-0.550	-0.005	-0.445	0.000
		(0.33)	**(2.65)**	**(-1.71)**	**(-3.01)**	(-0.98)	(-0.05)
	(2,200,0)	0.607	0.008	-0.048	-0.002	0.559	0.005
		(1.38)	**(2.08)**	(-0.22)	**(-2.61)**	(1.13)	(1.40)
				FMA 10-days Band=1%			
1885-1896	**(1,50,0.01)**	0.42	0.016	-0.312	-0.009	0.103	0.007
		(0.71)	**(3.72)**	(-0.71)	**(-3.59)**	(0.14)	(1.37)
	(1,150,0.01)	0.635	0.005	0.155	-0.008	0.790	-0.003
		(1.83)	**(2.64)**	(0.41)	**(-1.96)**	(1.53)	(-0.57)
	(5,150,0.01)	0.416	0.003	-0.036	-0.001	0.380	0.002
		(1.51)	**(2.09)**	(-0.21)	**(-2.90)**	(1.17)	(1.17)
	(1,200,0.01)	0.931	0.011	-0.195	-0.002	0.736	0.008
		(1.75)	**(1.66)**	(-0.89)	**(-3.33)**	(1.27)	(1.29)
	(2,200,0.01)	0.969	0.010	0.050	-0.003	1.019	0.006
		(1.88)	(1.51)	(0.20)	**(-2.90)**	**(1.77)**	(0.98)

Period	Trading Rules	Buy α (*10^-4)	Buy β	Sell α (*10^-4)	Sell β	Buy&Sell α (*10^-4)	Buy&Sell β
			TRB 10-days				
1885-1896	**(1,50,0)**	1.418	0.017	0.237	-0.023	1.655	-0.005
		(2.29)	**(2.87)**	(0.36)	**(-3.86)**	**(1.82)**	(-0.64)
	(1,150,0)	0.626	0.006	0.042	-0.016	0.668	-0.010
		(1.79)	**(3.26)**	(0.08)	**(-3.41)**	(1.04)	**(-2.07)**
	(1,200,0)	0.515	0.004	-0.392	-0.013	0.124	-0.009
		(1.78)	**(3.49)**	(-0.80)	**(-3.16)**	(0.22)	**(-2.10)**
			TRB 10-days Band=1%				
1885-1896	**(1,50,0.01)**	0.86	0.007	-0.153	-0.013	0.707	-0.006
		(2.11)	**(2.32)**	(-0.31)	**(-3.52)**	(1.09)	(-1.15)
	(1,150,0.01)	0.244	0.002	-0.433	-0.012	-0.189	-0.010
		(1.25)	**(2.37)**	(-0.87)	**(-3.17)**	(-0.36)	**(-2.65)**
	(1,200,0.01)	0.029	0.001	-0.598	-0.012	-0.569	-0.011
		(0.20)	**(1.88)**	(-1.24)	**(-3.06)**	(-1.13)	**(-2.79)**

In general, I find that strong supportive results in-sample could not be realized out-of-sample in the most recent 25 years. The consistently lower profit across the 25 year period compared with the simple buy-and-hold strategy could also not be explained by lower risk. Furthermore, the results on the 12 year period from 1885 to 1896 confirm that the results of Brock, Lakonishok and LeBaron (1992) tend to be sample specific, and that a more efficient market does not also appear to cause the disappearing profitability out-of-sample. Among the three hypotheses possible statistical bias seems the most likely explanation for the absence of profitability of these trading rules out-of-sample.

2.4.6 Transaction Cost

Technical trading strategies often produce frequent trading signals, for example, the VMA in its simplest form without band basically generate a trading signal each day and this can induce heavy transaction costs. My analysis above suggests consistent weak predictability from all the 26 technical trading strategies, and taking account into the transaction cost can even reinforce my point by further eliminating the predictability of the technical trading strategies.

Bajgrowicz and Scaillet (2012) discuss the role of transaction costs on the profitability of technical trading strategies extensively. They include transaction costs as selection criteria for the *best rules* from a universe of 7846 technical rules to address the data snooping problem. Then they evaluate the efficiency of technical trading strategies by studying performance of the *best rules.* The *best rules* selected differ in several sub-periods of their sample, also under different hypotheses on transaction costs (high or low transaction costs regimes are both tested). Nevertheless, they find even the *best rules* do not outperform the market largely after taking account into the transaction costs on the DJIA 1897 to 2008. I use a different approach that do not involve selecting the *best rules* or defining the *universe of technical trading rules*, but reach a similar conclusion that also seriously doubts the predictability of technical trading strategies. I focus only on the entire set of the 26 trading strategies studied in-sample by Brock, Lakonishok and LeBaron (1992). Before transaction costs, none of the 26 trading strategies beat the market. And without doubt, the inclusion of transaction costs - no matter high or low - would even lower the profitability of the technical rules.

2.5 Further Checks

2.5.1 OLS Outlier Robust Regressions

Both the in-sample and the out-of-sample periods cover several extreme events that the U.S. stock market has experienced. Like the Wall Street Crash of 1929 and the Recession of 1937-1938 happened during the in-sample period, and the most recent 2008 Financial Crisis took place during the out-of-sample period. The stock returns fluctuate dramatically in these cases. For example, on the *Black Monday* of 28th October 1929, the Dow Jones suffered a record loss of 13.7%. To check whether any extreme observation as such would affect the results, I employ the OLS outlier robust regressions which limit the influence of outliers. I adopt the M estimation method introduced by Huber (1973) that suits when the outliers mainly come from the response direction (the returns).

The results in Table 2.7 suggest that the in-sample predictability is generally robust to any outlier. Specifically, I receive positive buy returns that beat the market from 20 trading strategies; such findings are largely consistent with those of the original OLS. Whereas it is noteworthy that I discover only 7 groups of efficient sell signals compared to the 20 groups under the OLS. And a few trading strategies like the VMA (1,150) produce positive sell returns instead of the consistent negative sell returns claimed earlier. Consequently, the average sell returns largely decreases, to give an example, the average sell return of the TRB drops from -0.31% to -0.029% after controlling for outliers. Nonetheless discard the somewhat weaker evidence from the sell side, in 20 cases out of the 26 I still receive significant positive returns if I follow every signal the trading strategies generate (both buy and sell signals). Also, the results of sell signals are not surprising as the OLS robust regression majorly limits the impact of several major market downturns like those mentioned above, and it will not alter the general conclusion of strong in-sample predictability.

Moving out-of-sample, I discover similar collapse of the predictability as to those under the OLS too. The results probably become even stronger, suggesting use of the technical

Table 2.7: Robust Regression Results on the DJIA 1897-1986

This table reports the OLS outlier robust regression results on the DJIA 1897-1986, I adopt the M-estimation method introduced by Huber (1973). Trading rules are written as (short, long, band), where short and long represent the short and long moving averages, respectively. A 1% price change is used as the band. N (buy) and N (sell) represent the number of buy/sell trading signals. Buy/Sell represents the mean returns conditional on buy/sell trading signals and the associated t-statistics report the t-test results of the differences of the buy/sell returns from the buy-and-hold returns. The last two columns report βs, which are differences between mean buy and sell returns, and the associated Wald statistics. β equals the differences of β_1 and β_2, which are estimated by the Regression Model $R_t = \alpha + \beta_1 D_{t-1}^{Buy} + \beta_2 D_{t-1}^{Sell} + \varepsilon_t$, where R_t represents the returns conditional on buy/sell signals, and D_{t-1}^{Buy} and D_{t-1}^{Sell} are dummy variables that equal 1 when a buy, or sell, signal is generated and 0 otherwise. The Wald statistics is marked in bold if it is significant at the 10% level.

Period	**Trading Rules**	**N (Buy)**	**Buy ($*10^{-3}$)**	**t-statistics**	**N (Sell)**	**Sell ($*10^{-3}$)**	**t-statistics**	**β ($*10^{-3}$)**	**Wald-stats**
				VMA Daily					
1897-1986	**(1,50,0)**	14420	0.63	**4.21**	10617	0.01	-1.26	0.62	**36.41**
	(1,150,0)	15042	0.62	**4.12**	9895	-0.01	-1.38	0.63	**35.91**
	(5,150,0)	15037	0.58	**3.81**	9900	0.06	-0.85	0.53	**25.22**
	(1,200,0)	15348	0.61	**4.04**	9539	-0.03	-1.52	0.64	**36.54**
	(2,200,0)	15362	0.59	**3.90**	9525	0.00	-1.30	0.59	**31.70**
				VMA Band=1% Daily					
1897-1986	**(1,50,0.01)**	11810	0.73	**4.78**	8201	-0.02	-1.35	0.75	**38.60**
	(1,150,0.01)	13713	0.64	**4.22**	8622	-0.06	**-1.73**	0.71	**38.93**
	(5,150,0.01)	13650	0.61	**3.92**	8610	0.00	-1.27	0.61	**28.95**
	(1,200,0.01)	14233	0.63	**4.15**	8539	-0.11	**-2.03**	0.74	**42.58**
	(2,200,0.01)	14223	0.60	**3.89**	8532	-0.04	-1.54	0.64	**32.34**
Average			0.63			-0.02		0.65	
				FMA Holding Period=10 days					
1897-1986	**(1,50,0)**	342	5.76	**2.12**	347	-2.85	**-2.34**	8.62	**12.76**
	(1,150,0)	158	5.41	1.32	189	4.66	1.15	0.75	0.06
	(5,150,0)	133	6.83	**1.67**	141	5.05	1.13	1.78	0.30
	(1,200,0)	115	4.71	0.91	158	1.60	-0.02	3.10	0.85
	(2,200,0)	110	4.93	0.96	143	2.77	0.37	2.16	0.39
				FMA Band=1% Holding Period=10 days					
1897-1986	**(1,50,0.01)**	313	6.55	**2.41**	324	-2.55	**-2.11**	9.10	**13.37**
	(1,150,0.01)	172	7.21	**2.04**	159	1.27	-0.14	5.94	**4.01**
	(5,150,0.01)	128	6.06	1.39	126	5.11	1.08	0.95	0.07
	(1,200,0.01)	133	6.73	1.64	129	-4.14	**-1.84**	10.87	**9.54**
	(2,200,0.01)	118	1.78	0.04	118	-4.12	**-1.76**	5.90	**2.44**
Average			5.60			0.68		4.92	
				TRB Holding Period=10 days					
1897-1986	**(1,50,0)**	733	5.18	**2.64**	417	3.24	0.90	1.94	1.13
	(1,150,0)	520	5.05	**2.15**	218	-1.01	-1.10	6.05	**5.85**
	(1,200,0)	473	5.14	**2.11**	187	-0.37	-0.78	5.52	**4.40**
				TRB Band=1% Holding Period=10 days					
1897-1986	**(1,50,0.01)**	252	7.79	**2.72**	253	2.20	0.24	5.59	**3.64**
	(1,150,0.01)	161	9.42	**2.76**	144	-2.75	-1.48	12.18	**9.52**
	(1,200,0.01)	149	7.90	**2.13**	126	-4.01	**-1.78**	11.90	**8.92**
Average			6.58			-0.29		7.20	

Table 2.8: Robust Regression Results on the DJIA 1987-2011

This table reports the OLS outlier robust regression results on the DJIA 1987-2011, I adopt the M-estimation method introduced by Huber (1973). Trading rules are written as (short, long, band), where short and long represent the short and long moving averages, respectively. A 1% price change is used as the band. N (buy) and N (sell) represent the number of buy/sell trading signals. Buy/Sell represents the mean returns conditional on buy/sell trading signals and the associated t-statistics report the t-test results of the differences of the buy/sell returns from the buy-and-hold returns. The last two columns report βs, which are differences between mean buy and sell returns, and the associated Wald statistics. β equals the differences of β_1 and β_2, which are estimated by the Regression Model $R_t = \alpha + \beta_1 D_{t-1}^{Buy} + \beta_2 D_{t-1}^{Sell} + \varepsilon_t$, where R_t represents the returns conditional on buy/sell signals, and D_{t-1}^{Buy} and D_{t-1}^{Sell} are dummy variables that equal 1 when a buy, or sell, signal is generated and 0 otherwise. The Wald statistics is marked in bold if it is significant at the 10% level.

Period	Trading Rules	N (Buy)	Buy (*10^{-3})	t-statistics	N (Sell)	Sell (*10^{-3})	t-statistics	B (*10^{-3})	Wald-stats
				VMA Daily					
1987-2011	**(1,50,0)**	3931	0.46	0.63	2159	0.75	1.52	-0.30	1.55
	(1,150,0)	4108	0.44	0.57	1882	0.79	1.56	-0.35	**1.98**
	(5,150,0)	4102	0.42	0.47	1888	0.85	**1.77**	-0.44	**3.11**
	(1,200,0)	4186	0.48	0.72	1754	0.74	1.36	-0.26	1.08
	(2,200,0)	4184	0.47	0.68	1756	0.78	1.48	-0.31	1.53
				VMA Band=1% Daily					
1987-2011	**(1,50,0.01)**	3231	0.33	0.10	1555	0.91	**1.80**	-0.58	**4.22**
	(1,150,0.01)	3752	0.47	0.67	1525	1.02	**2.12**	-0.55	**4.09**
	(5,150,0.01)	3742	0.49	0.73	1518	0.93	**1.84**	-0.44	2.67
	(1,200,0.01)	3851	0.50	0.82	1450	0.99	**1.98**	-0.48	**3.12**
	(2,200,0.01)	3832	0.49	0.76	1438	0.94	**1.83**	-0.45	2.64
Average			0.45			0.87		-0.42	
				FMA Holding Period=10 days					
1987-2011	**(1,50,0)**	81	8.23	1.38	111	6.20	0.98	2.03	0.24
	(1,150,0)	58	3.48	0.11	50	-0.48	-0.73	3.97	0.52
	(5,150,0)	48	0.61	-0.49	39	-0.82	-0.71	1.42	0.06
	(1,200,0)	48	4.55	0.31	45	7.40	0.87	-2.85	0.23
	(2,200,0)	40	7.26	0.79	45	6.41	0.67	0.85	0.02
				FMA Band=1% Holding Period=10 days					
1987-2011	**(1,50,0.01)**	96	3.17	0.04	87	8.30	1.45	-5.13	1.41
	(1,150,0.01)	45	0.52	-0.49	52	9.74	1.43	-9.23	**2.76**
	(5,150,0.01)	37	1.92	-0.20	43	4.89	0.36	-2.97	0.25
	(1,200,0.01)	36	5.48	0.44	47	13.12	**2.04**	-7.64	1.26
	(2,200,0.01)	41	1.34	-0.32	38	14.16	**2.03**	-12.82	**3.74**
Average			3.66			6.89		-3.24	
				TRB Holding Period=10 days					
1987-2011	**(1,50,0)**	208	0.43	-1.09	79	10.09	**1.85**	-9.66	**6.96**
	(1,150,0)	163	1.13	-0.70	30	31.27	**4.57**	-30.14	**35.48**
	(1,200,0)	149	2.17	-0.30	21	27.90	**3.37**	-25.74	**23.59**
				TRB Band=1% Holding Period=10 days					
1987-2011	**(1,50,0.01)**	69	2.93	-0.02	49	14.46	**2.36**	-11.53	**3.69**
	(1,150,0.01)	47	1.28	-0.35	20	25.73	**3.00**	-24.44	**8.54**
	(1,200,0.01)	42	1.91	-0.21	18	33.89	**3.87**	-31.98	**16.48**
Average			1.93			21.46		-22.25	

trading strategies will bring significant loss. I present the results in Table 2.8. None of the buy returns beats the market returns, and in more than half of the cases (14 out of 26) the sell returns even generate significantly lower returns than the market returns - the positive sell returns indicate the market actually goes upward when the trading strategies suggest sells. Not surprisingly, none of the buy-sell returns is significantly positive; but being actually significantly negative in half of the cases. Generally, limiting the impact of extreme observations weakens the sell signals' predictability for both the in-sample and the out-of-sample periods, but the overall findings out-of-sample remains strongly contradictory to that in-sample under the OLS outlier robust estimation method.

2.5.2 Rolling Window Returns

In addition, I perform rolling window regressions to check the stability of the predictability in-sample and out-of-sample on 10-year moving windows that roll ahead 1 month each time. Using the in-sample period to illustrate, I use the same methodology as those above in the full sample on the first 10 years of the in-sample period (a 10-year period from 1897:01 to 1906:12), next I repeat the steps on the second 10-year period from 1897:02 to 1907:01 – the first fixed 10-year window is rolled forward by 1 month. I continue the rolling process until the last month of the in-sample period (1986:12) is included in the last 10-year regression. For every 10-year moving window period, I record the estimated returns conditional on using buy signals or sell signals only, and those conditional on following both buy and sell signals. I plot the estimates to observe their variations across time.

I use the results of the VMA (1, 50) in-sample and out-of-sample in Figure 2.4&2.5 as an example, and the results from the rest 25 rules remain similar. I indicate the buy (sell) returns in grey dotted (solid) lines, the buy-sell returns in black solid lines and the S&P 500 market returns in black dotted lines. For the in-sample period, the buy (sell) returns generate stable positive (negative) returns that are always higher (lower) than the market returns for each 10-year period, and as expected the buy-sell returns consistently rise above the market returns. In contrast, the story changes dramatically out-of-sample, both the buy and the sell returns are largely positive, and the buy (sell) returns locate below (above) the market returns at most times. That is, the VMA (1, 50) produces signals moving in the opposite direction with the market, and not surprisingly the overall buy-sell returns are lower than the market returns. The rolling window regressions provide closer look on the persistence of my results overtime, and the results well complies with my main findings, the technical trading strategies consistently outperform the market in-sample but underperform out-of-sample. It clearly suggests that no matter any particular time period in-sample or out-of-sample is likely to drive the results.

Figure 2.4: 10-year Rolling Window Returns of the Variable-Length Moving Average Rule (1, 50) on the DJIA 1897-1986

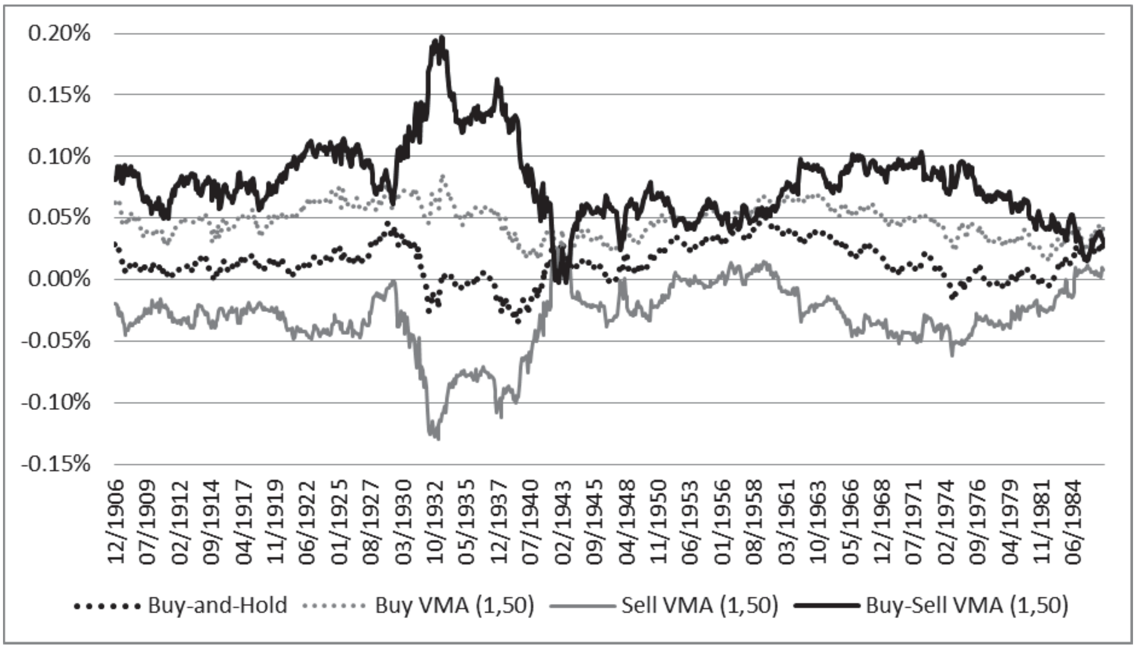
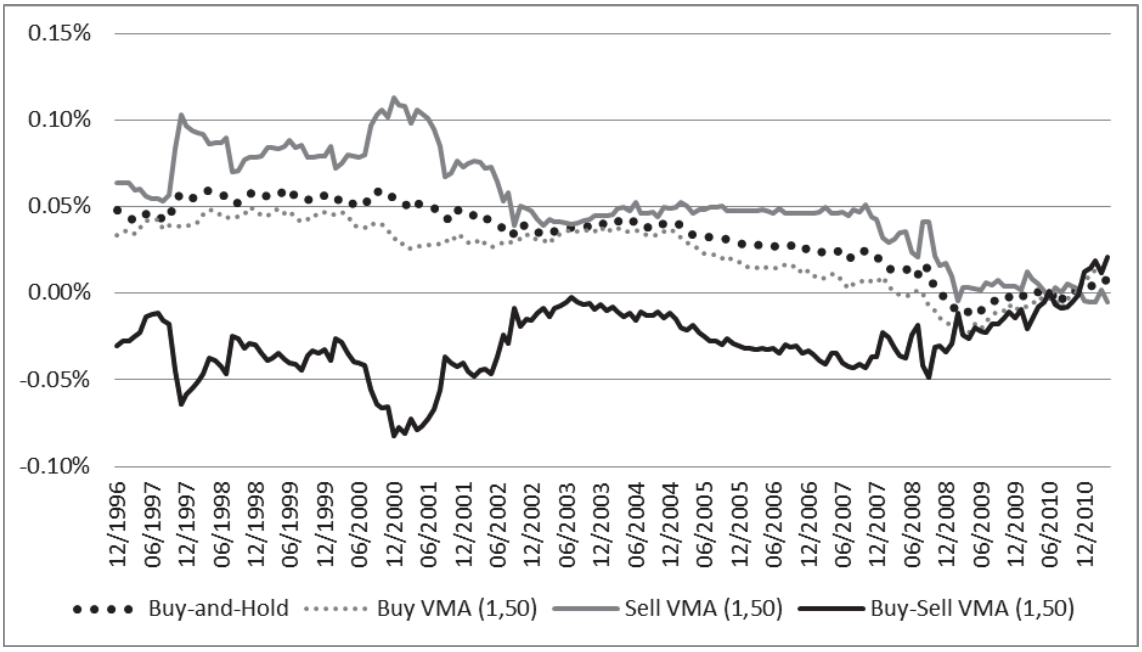


Figure 2.5: 10-year Rolling Window Returns of the Variable-Length Moving Average Rule (1, 50) on the DJIA 1987-2011



2.5.3 Other Robustness Checks

I also perform my evaluation excluding the 2008 financial crisis period from January 2008 to March 2011, with the results found to be robust. Together with the robust regression results above, this could probably lend some support to the concern of Sullivan, Timmermann and White (1999), that the 1987 financial crisis could also alter their findings of decreased predictability of the technical trading rules.[6]

Also, by considering the S&P 500 as a more popular proxy to construct a full story across time, I duplicate the evaluations for the trading rules on the S&P 500 data for the period of 1928 to 2011. To save space, the results are not reported. Nonetheless, the findings are similar: The technical trading strategies do work during the period before 1986, whereas such profitability disappears since 1987. With the robustness check results, I eliminate a few more possibilities that might explain the in-sample and the out-of-sample difference, and the most likely explanation - to the difference - is the statistical biases.

2.6 Conclusion

With the benefit of a fresh 25 year out-of-sample period I am able to perform a truly out-of-sample test of Brock, Lakonishok and LeBaron (1992). I find no evidence that 26 popular technical trading rules tested by Brock, Lakonishok and LeBaron (1992) have statistically significant predictability out-of-sample. The predictability is gone at the beginning of my 25 year sample, when their sample ends. As I also find no evidence in an earlier fresh sample from 1885 to 1896, this suggests not the market has become more

[6] As the results are similar whether, or not, the 2008 financial crisis period is included, I do not report them here in this study for either the DJIA, or the S&P 500, due to space restraints.

efficient over time but more likely that the exposure to the danger of statistical biases might have caused the in-sample predictability result. Last but not least, several further tests suggest that the conclusion is not likely to be driven by any extreme observation or any particular time period either in-sample or out-of-sample.

Chapter 3 Technical Market Indicators: An Overview[7]

3.1 Introduction

Technical analysis, a methodology for forecasting the direction of security prices through the study of past market data, is widely used by practitioners. A survey on 692 fund managers shows that 87% of the fund managers place some importance on technical analysis when making their investment decisions (Menkhoff, 2010). However, there has been controversy over whether technical analysis actually helps to predict the markets. Some previous studies (e.g., Brock, Lakonishok, & LeBaron, 1992; Fama & Blume, 1996; Jensen & Bennington, 1970) try to examine the predictability of classic price-based technical indicators. However, these studies cannot provide affirmative evidence of the usefulness of technical analysis because the conclusions are mixed. In a review study, Irwin and Park (2007) find that 56 out of 95 modern studies on technical analysis produce supportive evidence of its profitability.

However, as discussed in Chapter 2, some academics consider that much of the positive evidence is pseudoscience or dubious (Paulos, 2003) because of problems such as data snooping and sample bias. More importantly, most studies only consider price-based technical indicators (for example, the 26 trading rules used in Chapter 2) that are just a subset of all technical indicators. There are other types of technical indicators—so called technical market indicators—that investors and media and finance professionals use frequently as well, such as advance/decline lines, the Arms Index, and volatility indices.

[7] Chapter 3 of this thesis is mainly based on my paper titled "Technical Market Indicators: An Overview" that is forthcoming in *Journal of Behavioral and Experimental Finance*.

Contrary to price-based indicators that use only historical prices information to predict future price movements of individual stocks or the aggregate market, market indicators use a variety of other financial market information, such as trading volumes, investor sentiment survey results, and implied market volatility, to predict the aggregate market.

Market indicators are very important to practitioners. A popular technical analysis book, Achelis (2001, p. 38), states, “Market indicators add significant depth to technical analysis, because they contain much more information than price and volume … the analogy being ‘all boats rise in a rising tide’.” Many major data vendors, such as MarketWatch and Bloomberg, report these indicators regularly as key market statistics. For example, MarketWatch, among many other data vendors, presents analysis on the Chicago Board Options Exchange (CBOE) volatility index nearly every day. In contrast to the popularity and acceptance these technical market indicators have received from practitioners, however, limited academic scrutiny has been presented on the predictability of these market indicators. My study tries to fill the gap in the literature by examining the predictability of a wide range of market indicators. I look at all 93 market indicators from the Global Financial Data database,[8] which, to my best knowledge, is one of the most comprehensive ranges of market indicators.

Branch (1976), which comes closest to my work, reviews the predictability of a range of 10 market indicators and documents mixed results. The author points out that the study is limited by insufficient data access, even many more indicators are proposed. Nearly 40

[8] See www.globalfinancialdata.com. I exclude a few indicators from the Global Financial Database, including New York Stock Exchange (NYSE) money borrowed and NYSE debit balances, since the data end in 1967 and 1970, respectively. I exclude most CBOE volatility indices except that for the Standard & Poor’s (S&P) 500, since their sample periods are shorter than 10 years, most not actually starting until 2011. For similar reasons, I do not include the S&P total dividend declarations, the S&P monthly dividend declarations, the S&P 500 monthly advancing/declining stocks, or the S&P 500 index sales per share.

years later, with access to a much broader set of market indicators, including those introduced during those 40 years, I can now conduct a comprehensive study on market indicators. Using a wide range of 93 market indicators, however, I find no evidence that they show predictability for future stock returns. This conclusion consistently holds even if I allow predictability to be state dependent on business cycles or sentiment regimes.

My range of indicators covers nearly all those available in the Global Financial Data database except a few that do not have sufficient data. In addition, I add common transformations of the raw indicators provided by Global Financial Data. The idea is that the raw data may contain both signal and noise and the technical transformations might reduce the noise in those series. However, I find no significant predictability either from the raw data or from the popular technical transformations. Moreover, following Chapter 2, I use the longest sample for each indicator available from the database to best avoid the data-snooping problems pointed out by many previous studies (e.g., Lakonishok & Smidt, 1988). The longest sample in my study is nearly 200 years and the overall average sample length is 54 years.

Accounting for the data-snooping bias is particularly important in the field of technical analysis. In particular, the predictability of technical analysis can change over time - like what I documented in Chapter 2. Hence, using the longest sample available best prevents such data-driven results. On the other hand, predictability also varies greatly across different market indicators. Hence, using the widest range of market indicators I can obtain also safeguards my results against data-snooping issues.

My preliminary analysis shows that at a conservative 10% significance level, 30 out of 93 indicators show possible predictability. However, only 10 of these remain significant after I conduct sub-sample robustness checks.[9] Since some indicators exhibit sign-switching predictability in the sub-sample test, I employ rolling window regressions to take a closer look at the stability of indication. This further reduces the number of possible predictive indicators to eight. I then conduct economic significance tests to account for risk and transaction costs and none of the technical trading strategies beats the naïve buy and hold strategy in terms of either the Sharpe ratio or Jensen's α.

I make no conclusions on the predictability of market indicators yet. A recent strand in the literature documents that some return-predicting models are time varying and state dependent (Dangl & Halling, 2009; Henkel, Martin, & Nardari, 2010; Jacobsen, Marshall, & Visaltanachoti, 2010; Yu & Yuan, 2011). For example, Jacobsen, Marshall, and Visaltanachoti (2010) show that an increasing industrial metal index can significantly predict higher stock market returns during contractions but lower market returns during expansions. These two effects offset each other. As a result, the industrial metal index does not show any predictability if not contingent on states of the economy. The underlying reason for the time variation of return predictability is that the same news may be interpreted differently by investors across business cycles (Boyd, Hu, & Jagannathan, 2005; Jacobsen, Marshall, & Visaltanachoti, 2010; McQueen & Roley, 1993).

In the case of technical analysis, the same information can also be interpreted differently across different states of the economy. For instance, a rising value of investors' bearish

[9] These 10 market indicators are the NYSE short sales volumes–members/specialist/total, the NYSE short interest ratio, the NYSE advances/declines/new highs, the Alternext declines/new highs, and weekly NYSE cumulative highs.

sentiment index during contractions often indicates a bearish sentiment extreme that signals a potential market reversal. In contrast, a rising value of bearish sentiment during market expansions can signal investors' fear about the future market and thus a decreased market. If that is the case, the observed non-predictability of the market indicators could be due to their time variation or state dependency. This conjecture has been recognized by practitioners[10] and supported by the empirical findings on price-based indicators of Han, Yang, and Zhou (2013), who show that moving average strategies generate much higher abnormal returns in recessions. I hence explicitly test if there is any time variation or state dependency that could also shadow the real predictability of market indicators by using the regime-switching methodology of Jacobsen, Marshall, and Visaltanachoti (2010).

I define my business cycles by using National Bureau of Economic Research (NBER) data. My results show that 26 (21) market indicators show possible predictability in expansion (contraction) periods in the first place and the numbers are both smaller than the 30 I find in the full sample. Further *F*-test results testing the statistical difference in predictability between expansion and contraction periods reveal that only 19 indicators show significantly different predictability in one of the business states over the other. That is, most indicators (74 out of 93) do not seem to suffer from the problem where they potentially exhibit predictability in one of the business states but this predictability is shadowed by insignificant predictability in the other business state in the full-sample test. Nevertheless, I continue my economic significance test for those possible 26 (21)

[10] Edwards, Magee, and Bassetti (2007, p. 17) point out, "One of the keys in long-term chart analysis is realizing that market behaves differently in different economic cycle. … Identifying where you are in an economic cycle … is critical to interpreting the chart patterns evolving at that time."

predictors under expansions (contractions) separately. During expansion periods, I find one market indicator has a higher Sharpe ratio than the buy and hold strategy and another market indicator has a significant positive Jensen's α.[11] During contraction periods, none of the 93 indicators show any economic value. Although it remains possible the two indicators have some predictive value in expansion periods only, my overall results generally do not seem to suggest the business cycle-dependent predictability of the market indicators.

Besides testing the possible time-varying predictability on business cycles that many return predictability studies have considered, I also look at the sentiment cycles recently introduced by Yu and Yuan (2011). They find that the mean–variance tradeoff differs across high- and low-sentiment periods. The intuition for the differences between high- and low-sentiment periods on returns is as follows. During a high-sentiment period, when more irrational investors participate, the price deviates more from its fundamental value, whereas during a low-sentiment period, the price more accurately reflects its fundamentals, with less sentimental noise. I thus am motivated to test if technical market indicators' predictability can differ across sentiment cycles, considering a fundamental belief of technical analysis that the price has already reflected all information and investors' aggregate sentiment is the main driver of price deviation from its fundamental value (Kirkpatrick & Dahlquist, 2010). The test results on sentiment cycles remain largely similar to those on business cycles: 21 (25) indicators show possible predictability in high-sentiment (low-sentiment) periods, while only 10 of them show significantly different predictability across these two regimes. Moreover, after I consider economic

[11] The indicator U.S. mutual fund equity fund redemptions has a higher Sharpe ratio than the buy and hold strategy and the NYSE new highs indicator has a significantly positive Jensen's α.

significance, none of the market indicators remain predictive. These findings further eliminate the possibility of the state-dependent predictability of the market indicators.

I try to give my market indicators the benefit of the doubt as much as possible. In that sense, my linear regression tests with a general correction for heteroscedasticity may be too restrictive. Therefore, as a robustness check, I verify whether these technical market indicators might work if I reduce noise in the data. I model the heteroscedasticity more explicitly using a GARCH (1, 1) model. I follow the same steps above as those under ordinary least squares (OLS) and find consistent results of no predictability. I also check if outliers could affect my results by using robust regressions, particularly because I observe problems such as widening confidence bounds under the OLS rolling window regressions. Only one indicator may possess predictive value when the effect of extreme observations is controlled for. Moreover, I use the Chicago Fed National Activity Index (CFNAI) data alternatively to define business cycles; I also check the possible impact of the recent 2008 financial crisis by omitting this period from my sample; lastly, I also replicate my analysis excluding the top and bottom 5% extreme observations. My finding of weak predictability remains similar.

Can we rely on technical analysis? My results, from evaluating a comprehensive range of technical market indicators using the longest sample available, do not seem to suggest an affirmative answer to this question. My main contribution lays in filling the gap in the literature on a comprehensive study of the technical market indicators by providing strong statistical and economic evidence on their practical usage. My study has particularly important implications for practitioners who rely heavily on technical analysis in making investment decisions.

The rest of the paper is organized as follows. To best serve the overview role of this paper, Section 2 first explicitly reviews current evidence on my market indicators before a formal analysis, including those from the sentiment field. This provides an overall understanding and expectation of the predictability of the market indicators. I then introduce my data and methodology in Section 3, followed by a presentation of the empirical results in Section 4. Section 5 explicitly examines the time-varying predictability of the market indicators and Section 6 provides various robustness checks. I conclude the paper in Section 7.

3.2 Technical Market Indicators

Fundamentally, technical analysis believes that stock prices follow trends because investors collectively repeat their patterned trading behavior, which is the major driver of stock price fluctuations (Murphy, 1999). Although the patterned behavior may be irrational, by exploring the pattern—the trend—one can effectively anticipate future price movements.

Market indicators can be classified into two groups: market sentiment indicators and market strength indicators. The market sentiment indicators predict market movements based on tracking the bullish or bearish psychology of the market. When bullish (bearish) sentiment dominates the market, stock prices will rise (decline), associated with an increasing demand for (supply of) securities. Market strength indicators measure the strength—the breadth—of market movements. A strong movement with a high breadth reading will last longer and take the market to higher highs or lower lows. Market indicators expand the information set of technicians beyond classic price and volume data to a variety of financial information. Although market indicators are sometimes used in other markets, such as the futures market, they primarily analyze aggregate stock market movements (Achelis, 2001, p. 31). While evaluating overall market conditions remains important even when investing in individual stocks, the measurements of individual stocks' sentiment or the strength of price movements are generally noisy and less reliable with limited data access.

Among the 93 market indicators my paper studies, 65 are raw indicators that extract information from market data directly, such as total market advance/decline issues in a trading day, and the other 28 are transformed indicators that manipulate raw information through some formula. For example, net advances equal raw decline issues deducted from raw advance issues. This has a benefit for the practitioner. One may favor a few particular transformed indicators when one believes that the transformation can provide further indications over what the raw information can. For instance, in the above example, net advances indicate the strength of a trend on a relative basis, comparing the up and down trend strengths, while the raw advances/declines focus solely on the up/down trend. While many previous studies use transformed indicators only—for example, on advance/decline information, Brown and Cliff (2004) use the advance/decline ratio and Zakon and Pennypacker (1968) use the advance/decline line—my study may shed light on whether using such a transformation has an advantage over using the raw information or whether it actually masks the raw information's true predictability.

Table 3.1 summarises my indicators. Panels A and B report my reviews of market sentiment indicators and market strength indicators, respectively. I further classify my indicators into 14 sub-groups based on the type of information they use. As mentioned earlier, many indicators can use the same raw information. For example, my first group of sentiment indicators uses option volumes to proxy for aggregate sentiment, with a rising call (put) volume indicating investors' bullish (bearish) sentiment since they are hedging against a potential market rise (fall). Global Financial Data provides the information from two sources, the CBOE and the OEX. The last indicator is a transformed indicator that uses the ratio of the traded value of put to call options to measure the relative strength of bearish sentiment to bullish sentiment. This gives me a total of five indicators for this group. In the remainder of the paper, I discuss my results by such a grouping. To save space, I review the underlying theory and existing evidence of my indicators explicitly in Table 3.1 and give a brief overview in the following.

Table 3.1: Overview of Technical Market Indicators

Market Indicators	Sample Period	Notes and Formulars	More References
		Panel A: Market Sentiment Indicators	
1. Option Volumes:			
CBOE Calls Volume CBOE Puts Volume OEX Calls Volume OEX Puts Volume CBOE Ratio of Traded Value of Puts to Calls*	1989 - 2011 1989 - 2011 1989 - 2011 1989 - 2011 1986 - 2011	This group of indicators uses data from closely-related option market instead of from stock market itself to predict returns. Due to financial institutions' larger presence in the derivatives market, these indicators are viewed as primarily a measure of institutional sentiment (Brown & Cliff, 2004). A call (put) option gives its holder the right, but not the obligation to buy (sell) the underlying security at a pre-specified price. Therefore, a rising call (put) volume indicates investors' fear about a potential price increase (decrease), and reflects their bullish (bearish) sentiment. I study volumes of put/call options listed on Chicago Board of Exchange (CBOE) and Standard & Poor's 100 index (OEX), the volumes are published daily in their dollar values. Different from using the volumes directly, the ratio of traded value of puts to calls is calculated from dividing the CBOE daily dollar puts volume to the corresponding calls volume. It compares the relative strength of bullish/bearish sentiment. The ratio is lower (higher) during bullish (bearish) sentiment periods. While previous studies mainly focus on the put/call ratio only, Brown and Cliff (2004) and Wang, Keswani and Taylor (2006) both document that the put/call ratio does not predict stock returns.	Dennis & Mayhew (2002); Feldman (2010); Kurov (2010); Simon & Wiggins (2001).
2. Odd-lots Volumes:			
NYSE Odd Lot Purchases NYSE Odd Lot Sales NYSE Odd Lot Shorts	1970 - 2011 1970 - 2011 1970 - 2011	The odd-lotters refer to small individual investors who usually trade at an amount less than the standard unit of trading. Their trading activities became popular contrarian indicators in the 1960s and the 1970s. When they turn bullish (bearish), odd lot purchases (sales) increase in contrast to actual market declines (increases). NYSE publishes its odd lot trading statistics daily since 1970. Studies including Lakonishok and Maberly (1990), Zweig (1973), and Gup (1973) confirm the accuracy of odd-lot trading indicators. In contrast, Brown and Cliff (2004) find that the odd-lot sales to purchases ratio does not predict market returns, Neal and Wheatly (1998) also find that the ratio does not predict the size premium while the other two sentiment proxies they use do.	Abraham & Ikenberry (1994); Branch (1976); Brown & Cliff (2005); Dyl & Maberly (1992); Gup (1973); Kaish (1969); Kewley & Stevenson (1967).
3. Short Sales Volumes:			
NYSE Short Sales-Members NYSE Short Sales-General Public NYSE Short Sales-Specialists NYSE Short Sales-Total	1940 - 2008 1940 - 2008 1940 - 2008 1940 - 2008	Investors short sell to hedge against a future market decline. Technical theory insists that informed investors (for example, NYSE members and specialists) always build their short selling decisions on reliable savvy analysis, such that their short selling activities indicate future market declines. However the exact opposite holds for uninformed investors (general public), the market moves upwards when they short sale. I study the weekly short sales information published by the NYSE. After 2008, The NYSE is no longer compiling this data on a weekly basis. Instead, they report daily data of non-specialist, specialist and total short sales. Since the definitions remain similar, and the weekly data before 2008 gives me a much longer sample period, I focus on data before 2008. Reilly and Whitford (1982) find the specialist short sales ratio (specialists' short sales/total short sales) has no merit in predicting stock returns from 1971 to 1979, while Fosback (1993) suggests the contrary that the ratio predicts the market during 1941 to 1975. However, Bowlin and Rozeff (1987) argue the above two studies can be misleading since they both use nonindependent observations, they correct this problem and find that the specialist short-interest ratio is inversely related to subsequent NYSE stock returns. Nevertheless, Brown and Cliff (2004) and Branch (1976) both study the specialists shorts and conclude they fail in predicting the stock returns. Branch (1976) also studies the members' short sales and finds no merit of it in predicting stock returns. Zweig (1973) on the other hand, finds that floor traders (NYSE members) are subject to the same overemotional pressures as individual investors so that they sell (buy) at bottoms (peaks) too. Lastly, the public short sales have drawn much less attention in the literature, although practical technical analysis textbooks like Summa (2004) and Kirkpatrick and Dahlquist (2010) view it as a contrarian indicator.	Glushkov (2006); Lamont & Stein (2004).

4. Short Interests:			
NYSE Short Interest Ratio* NYSE Short Interest Shares	1931 - 2010 1931 - 2010	NYSE Short Interest Ratio = NYSE Short Interest Shares / Average Daily Trading Volume NYSE Short Interest Shares represent the monthly number of shares investors have sold short, but have not yet covered or closed out for securities listed on the NYSE, NYSE Arca and NYSE Amex. Short interest shares predict the market by watching whether the majority of investors think the market is likely to fall. When the amount of short interest shares decreases (increases) that indicates the uninformed investors' bullish (bearish) sentiment, the market moves downward (upward). The NYSE Short Interest Ratio is a monthly technical indicator calculated by dividing the NYSE Short Interest Shares over the average daily trading volume over the past 30 days. This ratio indicates how quick it takes to cover the short position in days. A high ratio -that is, heavy short sell of uninformed investors- predicts a bullish market. Seneca (1967) and Kerrigan (1974) find a significant negative relation between the short-interest ratio and future S&P500 returns. However, Woolridge and Dickinson (1994) suggest a positive but insignificant relationship between short interest ratio changes and individual stock prices. Similarly, Brown and Cliff (2004) and Vu and Caster (1987) also find results that do not support the predictive role of the short interest ratio.	Biggs (1966); Gup (1973); Hanna (1976); Lamont & Stein (2004); Mayor (1968); Shiller (2000); Smith (1968).
5. AAII/II Sentiment Indices:			
AAII Bearish Index AAII Bullish Index AAII Neutral Index Investors Intelligence Bearish Percentage Investors Intelligence Bullish Percentage	1989 - 2010 1989 - 2010 1989 - 2010 1987 - 2010 1987 - 2010	Sentiment survey results provide a direct measure of investors' view on the future market. American Association of Individual Investors (AAII) selects a random sample of its members each week to conduct a sentiment survey, and the association gathers each participant's opinion of the market movements in the next six months; up, down, or the same. The percentages of these opinions over the total responses form the bearish, bullish and neutral sentiment indices. One vote per member is accepted for each weekly survey. AAII sentiment indices predict the market contrarily, as they represent the uninformed individual investors' views. Similar to AAII indices, Investors Intelligence indices represent survey results run over more than 130 investment newsletter writers asking for their predictions about the market; the survey answers are classified as bearish, bullish, or neutral. They are also contrarian indicators. Solt and Statman (1988) find no statistically significant relation between the sentiment of investment newsletter writers and subsequent stock returns. Using the same set of data, Clarke and Statman (1998) confirm the results, they also find past returns and market volatility affect sentiment. In contrast, Lee, Jiang and Indro (2001) find the magnitude of bullish (bearish) changes in sentiment leads to downward (upward) revisions on volatility and higher(lower) future excess returns by using II indices as sentiment proxies. Fisher and Statman (2000) study both the AAII and II indices. They find investor sentiment differ across groups, AAII indices predict the stock returns contrarily while II indices play no predictive role. De Bondt (1993) also finds AAII indices predict future returns.	Han (2008); Sanders, Irwin & Leuthold (1997); Wang, Keswani & Taylor (2005).
6. Confidence Index			
Barron's Confidence Index	1932 - 2010	$\text{Barron's Confidence Index} = \frac{\text{average yield on 10 Barron's top grade corporate bonds}}{\text{average yield on 10 Barron's intermediate grade corporate bonds}}$ Barron's-a leading American financial magazine-uses information from the bond market to calculate a sentiment index each week, and the index is referred to as the Barron's Confidence Index. As one of the most historically extensive sentiment indicators, it dates back to 1932. Barron's confidence index measures the discrepancy between the yields of high and low risk bonds that are largely held by institutional investors (Gaumnitz & Salabar, 1969). These informed investors are willing to accept a lower premium in yield for high risk bonds when they have more confidence with the economy, indicating a rising index value. And the exact opposite holds as well. Ring(1974) supports the view that the smart money will move from speculative to quality bonds during bearish market, and back during bullish market, and he documents that the index is a better forecaster of tops than bottoms. In contrast, Branch (1976) does not support Barron's Confidence Index as a stable market predictor in different sample frequencies, neither do Gaumnitz and Salabar (1969).	Malek (2000); Tabell & Tabell (1964).

7. Exchange Seat Prices:			
AMEX Seat Prices NYSE Annual Seat Price	1921 – 1993 1820 - 2003	Exchange seat prices capture professional investors' sentiment. It rises when market activities and stock prices rise, reflecting the prosperity of the brokerage industry, which provides professional services to the capital markets (Schwert, 1977). The AMEX seat prices are available monthly and the NYSE seat prices are available annually. They focus on long term forecasting, while most other sentiment indicators capture relatively short term variation. NYSE seat prices is the only annual sentiment indicator I examined, and it also has the longest sample period across all of my sentiment indicators-it starts in 1820 which means nearly 200 years of data. Keim and Madhavan (2000) document supportive evidence to the view that NYSE seat prices capture market sentiment, although Schwert (1977) finds no evidence that the seat returns predict market returns.	Chiang, Gay & Kolb (1987); You & Holder (2008).
8. Volatility Indices:			
CBOE S&P 500 Volatility Index CBOE NASDAQ Volatility Index CBOE S&P 100 Volatility Index AMEX NYSE Arca NASDAQ 100 Volatility Index CBOE DJIA Volatility Index	1986 – 2011 2001 – 2011 1986 – 2011 2001 – 2011 2005 - 2011	Volatility index, sometimes called the "fear index", measures the implied volatility for a group of near-term put and call options related to a specific market index; that is, it represents investors' expected risk of the market over the next 30 days. An increase (decrease) in the volatility index represents bearish (bullish) sentiment of the market. For example, the S&P 500 volatility index hits its historic high of 89.53 on October 24, 2008, reflecting investors' serious concern during the financial crisis period. I view the volatility indices as primarily a measure of institutional sentiment because of institutions' large presence in the derivative markets (Brown & Cliff, 2004). I study 5 different volatility indices that track investors' sentiment for different stock indices. These include 4 CBOE published volatility indices for the S&P500, the NASDAQ, the DJIA and the S&P100, respectively, and the last volatility index is published by the AMEX to track the sentiment on the NASDAQ 100. Previous literature largely focuses on the S&P500 volatility index only. Whaley(1993) describes the construction of the S&P 500 volatility index in detail. The volatility index firstly measures the implied volatility using prices of only 8 S&P100 at-the-money put and call options, and later the input expanded to options based on the broader S&P 500 index (Investopedia). Whaley (2000) documents the S&P100 volatility index as a reliable "investors fear" gauge, higher levels of the index coincide with high degrees of market turmoil. Giot (2003) also shows a negative and statistically significant relationship between the returns of stock and implied volatility indices on the S&P100 and NASDAQ 100 indices. However Brown and Cliff (2004) document results that do not support the volatility index as a reliable predictor of future stock returns.	Feldman (2010); Fleming, Ostdiek & Whaley (1996); Low (2004); Simon & Wiggins (2001).
9. Margin Account Balances:			
NYSE Margin Debt NYSE Free Credit Balances NYSE Free Credit Balances on Cash Accounts NYSE Free Cash Balances in Margin Accounts	1918 – 2010 1931 – 2010 1971 – 2010 1971 - 2010	To put it simply, trading on margin means borrowing money from brokers to invest. I use market aggregate margin trading statistics to gauge investors' sentiment. Margin debt measures the total dollar amount of borrowing from brokers. Free credit balances represent the amount of money in investors' margin accounts that are free to withdraw. Furthermore, balance in a cash account reflects the money left after all purchases, while balance in a margin account includes cash, as well as proceeds from short sales, along with money used to meet margin requirements, and excess margin and buying power (Investopedia). Investors trade on margin when they forecast a bullish market, therefore, the margin debt rises and the free credit balance decreases as investors fully invest all their available funds. In contrast, during bearish sentiment periods, the margin debt declines and the free credit balance increases, reflecting less active trading. I use monthly released margin account statistics that monitor the overall margin trading within the NYSE. There is controversy on if margin account statistics are contrarian indicators or not. Brown and Cliff (2004) view margin borrowing as a bullish indicator that move in the same direction as the market, and they find that the percentage changes of margin borrowing does not predict the market. Chen and Gu (2009) also document that margin debt borrowers' trading activities follow stock market trends rather than lead the market trends. In contrast, Hirose, Kato and Bremer (2008) report that information about margin buying helps predict future stock returns, especially for small-firm stocks at short horizons in Japanese stock market where margin trading is dominated by individual investors.	Fortune (2000); Glushkov (2006); Kim & Ha (2010).

10. Mutual Fund Balances:			
USA Mutual Fund Equity Funds Total Net Assets USA Mutual Fund Equity Funds Cash Percentage USA Mutual Fund Equity Funds Cash Percentage USA Mutual Fund Equity Funds New Sales USA Mutual Fund Equity and Bond Fund Net Assets USA Mutual Fund Equity and Bond Fund Net Assets USA Mutual Fund Equity and Bond Fund Net Assets USA Mutual Fund Equity and Bond Fund Redemptions USA Mutual Fund Equity and Bond Fund Redemptions	1984 – 2010 1968 – 2010 1984 – 2010 1984 – 2010 1954 – 2010 1954 – 2010 1954 – 2010 1954 – 2010 1954 – 2010	Investment fund statistics can reflect both informed and uninformed investors’ sentiment, as it connects these two groups of market players (the uninformed fund participants and the sophisticated fund managers). Theoretically, individual investors invest when they are confident with the market growth. Hence, the money inflows (outflows) measured by new sales (redemptions) of investment funds represent individual investors’ bullish (bearish) sentiment. They contrarily predict the market. However, the investment fund cash percent and liquid assets represent the level of cash, or cash equivalents that fund managers keep for redemptions after investments. Thus, a higher cash percent represents savvy investors’ bearish sentiment, indicating a market drop. I study the monthly aggregate statistics of mutual funds that invest in the equity market only, and then examine those for mutual funds that invest in both equity and bond markets. Using data from 1933 to 1993, Neal and Wheatley (1998) find evidence that fund net redemptions predict the size premiums. However Brown and Cliff (2004) find that the net redemptions do not predict market returns, neither the cash percentage by using monthly data from 1965 to 1998. Branch (1976) also examines the cash percentages, and the author documents that some mutual funds reduce cash position before price increases while other do such during and after price increase. So that mutual funds influence stock prices but they in turn are also influenced by stock price changes. Some studies examine the predictive ability of fund flows between different funds, like Frazzini and Lamont (2008), Ben-Rephael, Kandel and Wohl (2012) and Hendricks, Patel and Zeckhauser(1993). I, instead, focus on the aggregate mutual fund trading statistics.	Branch (1976); Edward & Zhang (1998); Fant (1999); Friesen & Sapp (2007); Randall, Suk & Tully (2003); Warther (1995).
11. Market Aggregate Number of Dividend News:			
Moody's Monthly Decreased Dividends Moody's Monthly Extra Dividends Declared Moody's Monthly Increased Dividends Declared Moody's Monthly Omitted Dividends Moody's Monthly Resumed Dividends	1956 – 2011 1956 – 2011 1956 – 2011 1956 – 2011 1956 - 2011	Researchers have extensively tested the fundamental information (for example, earnings information) contained in dividend announcements at individual stock level (for example, Nissim & Ziv, 2001; Benartzi, Michaely & Thaler, 1997), as well as the sentiment information contained at this level. Baker and Wurgler (2006), for example, argue that non-dividend paying stocks are likely to be disproportionately sensitive to broad waves of investor sentiment. At the aggregate market level, previous studies like Denis and Osobov (2008) use the aggregate dollar amount of dividend to predict future returns. I, instead, look at if the aggregate number of dividend announcements predicts the aggregate market returns. Since dividend policies largely represent managers' forecast on future returns (Baker & Wurgler, 2004), I view them as institutional sentiment gauges. Positive dividend news includes increased, resumed, or extra, dividends, while negative dividend news means decreased, or omitted, dividends. The simple rationale states that if more stocks declare positive news, a bullish market is more likely and vice versa. These data are reported in S&P's and Moody's Annual Dividend Records, and to my best knowledge, they have not been studied in previous literature.	Deshmukh, Goel & Howe (2013); Michaely, Thaler & Womack (1995).
		Panel B: Market Strength Indicators	
1. Volume Indicators			
NYSE Total Volume *Total Volume Turnovers:* NYSE Share Volume Turnover* NYSE Annual Share Value Turnover*	1928 - 2011 1925 - 2010 1934 - 2010	NYSE Volume Turnover = Total Volume / Average Number of Shares Outstanding NYSE Value Turnover = Total Volume in $USD / Total Market Capitalisation Technical analysis widely uses volume information to capture market liquidity and market price movements. Baker and Stein (2004), for example, note that irrational investors are more likely to trade, which will add liquidity to the market, when they are optimistic and betting on rising stocks rather than when they are pessimistic and betting on falling stocks. Also, Lo, Mamaysky and Wang (2000) document that high volume accompanying a positive price trend suggests that there may be more information content in the trend, e.g., broader participation among investors. Moreover, Blume, Easley and O'hara (1994) provide evidence that volume may provide insights regarding the quality of trader's information that cannot be obtained from price statistics. Scheinkman and Xiong (2003) examine the volume turnover, and find volume reveals underlying differences of opinion, which are in turn related to valuation levels when short selling is difficult.	Baker & Wurgler (2007);

		I study the raw NYSE total volume as well as two transformed volume turnovers. The turnovers adjust the total volume to the average number of shares outstanding in the same period (note that this number may not remain constant on a daily basis) to reflect the change on investors' trading activities more precisely by eliminating the possibility that increased (decreased) volumes result from more(less) shares (in terms of volume) becoming available for trade, but not from investors' real expectations on the market.	
Short-term Trading Indices:			
NYSE Short-term Trading Index* NASDAQ Short-term Trading Index*	1965-2011 1972-2011	Short Term Trading Index = (No. of Advancing Issues / No. of Declining Issues) /(Up Volume / Down Volume) Short-term trading index studies total volumes of uptrending and downtrending stocks in a market separately. It is sometimes referred to as the Arms Index or TRIN as first introduced by Richard W. Arms, Jr. in 1967. The short-term trading index incorporates two sorts of information; the market breadth information and the volume information. The formula shows that a high short-term trading index results from current lifts in the number of advancing issues alongside drops of the up volume-the current market follows a weak uptrend with diverged volume movements-and this signals a future downward market. Conversely, a low short-term index occurs when the number of declining issues increases, with no associated downward market volume, so that the energy driving the downward movement is weak and a market reversal will follow. Brown and Cliff (2004) find no merit of the index in predicting future stock returns; Wang, Keswani and Taylor (2005) find similar results. Whereas Simon and Wiggins (2001) find opposite results in the futures market where the index successfully gauges investors' bearish sentiment and predicts future returns.	
2. Daily Total Market Advances & Declines:			
NYSE Advances NYSE Declines NYSE Net Advances* NYSE AD Line* NYSE Percentage Net Advances* NASDAQ Advances NASDAQ Declines NASDAQ Net Advances* NASDAQ AD Line* NASDAQ Percentage Net Advances* Alternext Advances Alternext Declines Alternext Net Advances* Alternext AD Line* Alternext Percentage Net Advances* *Weekly Total Market Advances & Declines:* NYSE Weekly Advances NYSE Weekly Declines NYSE Net Advances* NYSE AD Line*	1928 - 2011 1928 - 2011 1928 - 2011 1928 - 2011 1928 - 2011 1972 - 2011 1972 - 2011 1972 - 2011 1972 - 2011 1972 - 2011 1959 - 2011 1959 - 2011 1959 - 2011 1959 - 2011 1959 - 2011 1940 - 2010 1940 - 2010 1940 - 2010 1940 - 2010	$\text{Net Advances}_t = \text{Advances}_t - \text{Declines}_t$ $\text{Advance} - \text{Decline Line (AD Line)}_t = \text{Net Advances}_t + \text{AD Line}_{t-1}$ (The first value of AD Line simply takes the value of the same period net advances) $\text{Percentage Net Advances}_t = \frac{\text{Net Advances}_t}{\text{Total Number of Stocks}_t}$ This group of indicators uses the total advances/declines information to measure the strength of the underlying trend. They are often called market breadth indicators. Total advances/declines represent the number of stocks that experiences stock price advances/declines during a specific period. If more stocks experience price advances, a bullish market is more likely, and vice versa. Previous literature studies two forms of the breadth information mainly. Zakon and Pennypacker (1968) study the advance-decline line and they find it is worthless as a leading indicator of the stock market. Brown and Cliff (2004) study the advance/decline ratio and find it worthless in predicting the return either. I study the raw advances/declines information of three major stock exchanges, the NYSE, the NASDAQ, and the Alternext. For the NYSE I also study these indicators in both daily and weekly frequencies to investigate whether their forecast ability differs over different horizons. I also study three popular transformations of the above raw information- the net advances, the advance-decline line, and the percentage net advances. Each of the transformed indicators has unique features. The net advances use the spread between advances and declines to identify the strength of the underlying trend, so that a strong trend not only causes an increased number of advances, but this number should also exceed the number of declines. The advance-decline line takes the historical advance and decline information into account. If an underlying stock market rise is fueled only by a few stocks, and the majority of stocks either decline, or are unchanged, the rise will not last for very long. The percentage net advances adjust the net advances for the total number of stocks in the market. More stocks being available for trade gives larger potential for the differences between advances and declines (the breadth) to expand. With the development of financial markets, not surprisingly I now have a lot more issues trading within any particular stock exchange. For instance,	Feldman (2010)

during the 40 years from 1960 to 2000, the NYSE Issues Traded doubled from 1,528 to 3,083. Thus, market breadth indicators may become more accurate when adjusted for changes in total stock issues within the market, so that the breadth information does not purely result from the market itself, but the investors' real views.

3. Daily Total Market New Highs & New Lows:		
NYSE New Highs	1928 - 2011	$\text{Net New Highs}_t = \text{New Highs}_t - \text{New Lows}_t$
NYSE New Lows	1928 - 2011	
NYSE Net New Highs*	1932 - 2011	$\text{Cumulative New Highs}_t = \text{Net New Highs}_t + \text{Cumulative New Highs}_{t-1}$ (The first value of cumulative new highs simply takes the value of the same period net new highs)
NYSE Cumulative Highs*	1932 - 2011	
NYSE Percentage Net New Highs*	1932 - 2011	$\text{Percentage Net New Highs}_t = \frac{\text{Net New Highs}_t}{\text{Total Number of Stocks}_t}$
NASDAQ New Highs	1974 - 2011	
NASDAQ New Lows	1974 - 2011	This group of market strength indicators generally follows the same rationale to the advances/declines indicators. New highs (lows) measure the number of advancing (declining) stocks reaching their 52-week periodic highs (lows). If there are more issues reaching their periodic highs than issues reaching their periodic lows, it means that a future uptrend is more likely, and vice versa. Again, similarly to the advances/declines indicators, I also include three transformed indicators to measure the market strength-the underlying uptrend improves when the values of the net new highs, the cumulative highs, and the percentage net new highs increase. Brown and Cliff (2004) find that the high/low ratio does not predict future stock returns.
NASDAQ Net New Highs*	1974 - 2011	
NASDAQ Cumulative Highs*	1974 - 2011	
NASDAQ Percentage Net New Highs*	1974 - 2011	
Alternext New Highs	1962 - 2011	
Alternext New Lows	1962 - 2011	
Alternext Net New Highs*	1962 - 2011	
Alternext Cumulative Highs*	1962 - 2011	
Alternext Percentage Net New Highs*	1963 - 2011	
Weekly Total Market New Highs & New Lows:		
NYSE Weekly New Highs	1937 - 2010	
NYSE Weekly New Lows	1937 - 2010	
NYSE Net New Highs*	1937 - 2010	
NYSE Cumulative Highs*	1937 - 2010	

* Transformed Technical Market Indicators

3.2.1 Market Sentiment Indicators

Sentiment is defined by Kirkpatrick and Dahlquist (2010, p. 90) as

> The net amount of any group of market players' optimism or pessimism reflected in any asset or market price at a particular time. When a stock or commodity is trading at a price considerably above or below its intrinsic value, something we will not know until considerably later, the difference or deviation from that value often will be accounted for by sentiment.

Following this definition, I have 50 sentiment indicators in total and I further categorize them into 11 sub-groups based on the type of raw information they use. Sentiment indicators can incorporate various information that past prices cannot reveal. Some use direct sentiment poll results, such as the American Association of Individual Investors (AAII) and Investors Intelligence (II) sentiment indices, while others use data from the underlying derivative markets but not the stock market directly. For instance, I use put or call option volumes and volatility indices. In addition, a number of sentiment indicators use the statistics of different trading activities, such as odd-lot trading statistics, short sales statistics, mutual fund statistics, and margin account balances. Lastly, the rest of indicators include Barron's confidence index, American Stock Exchange (AMEX) seat prices, and Moody's or S&P 500's aggregate number of positive/negative dividend news.

Technical theories impose different signs on the way that the indicators predict the market, since they view different investors' sentiment differently. A key issue is to distinguish between two major groups of market player sentiment: the uninformed and informed traders. Uninformed traders are passive and trade for liquidity (Wang, 2002). De Long, Shleifer, Summers, and Waldmann (1989, 1990a, 1990b) argue that uninformed traders tend to act strategically on noisy signals and therefore their trading can affect prices in a systematic way that deviates asset prices from fundamental values. According to Kirkpatrick and Dahlquist (2010), this group of investors largely consists of individual traders. They lack sufficient financial knowledge when making their investment decisions and their behavior is that of a crowd; in other words, they make decisions in line with everybody else, regardless of the true financial facts. Thus, the theory refers them as uninformed investors and views their decisions as always wrong, such that trading against them will result in significant gains. So-called contrarian indicators measure this group of investors' sentiments. Examples of my contrarian indicators include odd-lot trading statistics, short sales of general public investors, and survey sentiment indices. In contrast, informed traders, who are sophisticated investors that have adequate financial knowledge, build their decisions on precise analysis of the market. Theory views their decisions as always true and accurate. Professional speculators, position traders, hedge fund managers, professional arbitrageurs, and insiders are considered to be in this category (Kirkpatrick & Dahlquist, 2010). Typical sentiment indicators for this group of investors include volatility indices, option trading volumes, and specialists' short sales.

These sentiment indicators have been receiving growing attention. In the academic fields, especially behavioral finance, many sentiment indicators used overlap with those I examine, those used by technical analysis. Since we have many indicators, I review the previous evidence by group in Table 3.1. In brief, the previous evidence is mixed, even when using the same sentiment proxies. For example, Seneca (1967) finds that the short interest ratio predicts monthly S&P 500 returns negatively from 1946 to 1965. Brown and Cliff (2004), however, suggest that the short interest ratio does not predict S&P 500 returns from 1965 to 1998. This raises the concern of data snooping and calls for using a long sample period to safeguard against the data-snooping issue and to update the results. Moreover, many studies in this field largely employ just one or a few indicators as sentiment proxies to predict the market, which can also lead to the data-snooping problem, since so many indicators are proposed and some receive relatively more attention than others.[12] My wide range of indicators also avoids such risk.

3.2.2 Market Strength Indicators

While market sentiment indicators anticipate how investor behavior shifts market movements, market strength indicators measure the internal strength of these movements. The fundamental goal of technical analysis is to make a profit from tracking these movements, which requires accurate analysis of the timing of trends, addressing such questions as when does the market reach a bottom or a peak and can it reach lower lows or higher highs? Market strength indicators answer these questions by confirming the underlying trend when the trend is strong enough so that a rising or declining market may improve, even reaching higher highs or lower lows, or by disagreeing with the trend

[12] While some of the indicators in the database are discussed heavily in the literature, such as sentiment poll results and volatility indices, others receive much less attention. In particular, two groups of my indicators—exchange seat prices and the market aggregate number of dividend announcements—have not been studied in the previous literature to the best of my knowledge. While I find closely related studies that can help explain these indicators (as discussed in Table 4.1), I have not found their exact application by technical analysts on my best effort; however, I include these indicators in my study for completeness.

when the trend is weak and will deteriorate and, thus, becomes more likely to reverse. Market strength is measured based on whether the majority of individual stocks within the stock exchange participate in the uptrend or the downtrend. I have 43 strength indicators, which mainly use three kinds of information.

1. Volume information. One of the earliest technical theories, the Dow theory, documented the importance of volume: "Bull markets terminate in a period of excessive activity and begin with comparatively light transactions" (Rhea, 1932). Indicators such as the NYSE total volume and total volume turnovers directly measure overall market trading activities. Moving one step further, the short-term trading indices use directional up/down volumes that track the trading volumes of advancing or declining issues separately. A strong trend is normally accompanied by an increasing volume in the same direction (Kirkpatrick & Dahlquist, 2010).

2. The total number of advancing/declining stocks. A trend fueled by only a small number of stocks usually does not last long. One can use raw advance/decline information directly to measure market strength. Therefore I include such raw information for the NYSE, NASDAQ, and Alternext. Alternatively one can calculate the relative strength of the up/down trend through many different mathematical transformations. I include the three most common transformations: the net advances, the advance/decline line, and the percentage net advance for the three markets above. I formulate the transformation used in Table 3.1. Moreover, for the NYSE I have raw and transformed indicators data for both daily and weekly intervals.

3. The total number of stocks that reach their periodic highs or lows. The underlying uptrend strengthens when more stocks advance to their periodic highs and vice versa. I also include the raw new highs/lows for the NYSE, NASDAQ, and Alternext and three common transformations of the raw information (net new highs, cumulative highs, and percentage net new highs). The data for the NYSE are again available at daily and weekly intervals.

3.3 Data and Methodology

3.3.1 Sample and Data

I evaluate the technical indicators' forecastability on the S&P 500, which proxies for the overall U.S. stock market. The returns are calculated as the log differences of current prices and prices from one period ahead. The S&P 500 contains the 500 most actively traded large-cap common stocks in the U.S. stock market. As one of the most historically extensive indices, the S&P 500 became available at daily, weekly and monthly frequencies in 1938, 1918, and 1791, respectively.

I study the S&P 500 for several reasons. First, the long data series naturally shield against the potential data-snooping problem as studied in Chapter 2. Second, I have a wide range of technical indicators with sufficiently long data series designed specifically for the sophisticated U.S. market. The 500 stocks are listed on either the NYSE or the NASDAQ, the two largest American stock exchanges. This means that the S&P 500 index correlates highly with the NYSE and NASDAQ indices, which enables me to study technical indicators that contain information from both of these markets. Third, public investors hold the majority of the stocks in the U.S. market. Such heavy involvement of public investors satisfies the essential theoretical condition for many of the sentiment indicators, that uninformed investor sentiment becomes so influential that it can shift market movements. Last, the S&P 500 provides me with a sufficient number of stocks to ensure considerable market breadth when examining the market strength indicators.

I obtain the return and indicator data from Global Financial Data.[13] My sample frequencies vary across the 93 indicators, with one annual indicator, 28 monthly indicators, 18 weekly indicators, and 46 daily indicators that anticipate different terms of market trends. I use the longest samples available for each of the indicators; the annual indicator starts in 1820 and the oldest monthly, weekly, and daily indicators start in 1918, 1932, and 1938, respectively.[14] Most of my sample periods end in 2010 or 2011, subject to data availability. That is, the oldest market indicator (NYSE seat prices) has nearly 200 years of history and the 93 indicators have an average sample length of 54 years.

As discussed in the previous section, I have several different indicator types: ratios (e.g., the NYSE short interest ratio), index numbers (e.g., the AAII bullish index), dollar units (e.g., AMEX seat prices), or simply unit numbers (such as option volumes, or the number of dividend news announcements). I report the mean, standard deviation, minimum, and maximum values of their periodic changes in Appendix 1.

In addition, to test the robustness of my results, I perform sub-sample analyses for each of my indicators. Since the sample periods vary greatly across indicators, I do not define

[13] See www.globalfinancialdata.com.
[14] The data on market sentiment indicators II bearish percentage and II bullish percentage are available from 1963, at the II website www.investorsintelligence.com. I use the longest sample period from Global Financial Data, which starts in 1987.

universal sub-sample periods. Instead, I split each indicator's full sample into two equal sub-samples. I also study state dependent predictability. I use two sources to define business cycles independently, following Jacobsen, Marshall, and Visaltanachoti (2010): NBER data[15] and CFNAI[16] data. The NBER business cycle data start in 1854, with a monthly frequency, and I classify a year as in expansion (contraction) if over seven months of the year are in expanding (contracting) periods. I define each week/day as expanding (contracting) if the month of the week/day falls within an expanding (contracting) month. The CFNAI data start in 1967. I classify a period as a contraction period when the CFNAI-MA3 is less than -0.7 and an expansion period when the CFNAI-MA3 is greater than -0.7. Unlike the NBER data, the CFNAI data are published in real time and are thus free of hindsight bias. I use these data to double-check my NBER results.

For the sentiment regimes, I use Baker and Wurgler's (2006)[17] sentiment index, following Yu and Yuan (2011), to define high-/low-sentiment regimes. I classify a year as a high-sentiment (low-sentiment) year if the prior year has a positive (negative) value of the index. Baker and Wurgler (2006) calculate the index as the first principle component of six measures of investor sentiment, which are the closed-end fund discount, the NYSE share turnover, the number of IPOs, the average first-day return of IPOs, the equity share in new issues, and the dividend premium. The first principle calculation eliminates noise and captures the common component of the different sentiment measures. Furthermore, the authors first regress the six sentiment measures on a set of

[15] See http://www.nber.org/cycles.html.
[16] See http://www.chicagofed.org/webpages/publications/cfnai/.
[17] See http://people.stern.nyu.edu/jwurgler/.

macroeconomic variables to remove business cycle information and then use the residuals as input for first principle component analysis. Therefore my sentiment time varying analysis does not overlap with the business cycle-varying analysis.

3.3.2 Methodology

I run standard OLS regression to test the predictability of each of the 93 technical indicators:

$$R_t = \alpha_t + \beta I_{t-1} + \varepsilon_t \tag{1}$$

where

- R_t represents the daily/weekly/monthly/annual log returns of the S&P 500 index,
- I_{t-1} represents periodic percentage changes of the technical indicators from one period ahead, and
- ε_t represents the residual term.

The methodology simply tests whether periodic variations of the technical indicators anticipate the next period's stock market returns. The parameter β captures the relation between market returns and the technical indicator. I use a conservative 10% significance level.

I also run the following regression for state-dependent predictability, following Jacobsen, Marshall, and Visaltanachoti (2010):

$$R_t = \alpha_t + \beta_1 D_{t-1} I_{t-1} + \beta_2 (1-D_{t-1}) I_{t-1} + \varepsilon_t \tag{2}$$

where

- R_t represents the periodic return on the S&P 500 at time t,
- I_{t-1} represents the percentage change of the technical indicator one period ahead,
- D_{t-1} represents a dummy variable that equals one (zero) during expansions (contractions) for business cycle analysis and one (zero) during high-sentiment (low-sentiment) periods for sentiment cycle analysis,
- and ε_t represents the residual term.

The parameters β_1 and β_2 from equation (2) measure the predictability of the market indicators in expansion and contraction periods for business cycle analysis, respectively, or the predictability in high- and low-sentiment periods for sentiment cycle analysis, respectively. I further perform an F-test to test the statistical differences between β_1 and $\beta_{2.}$ I use a conservative 10% significance level and apply White's standard error corrections on all t-statistics and χ-statistics to counter heteroskedasticity issues.

3.4 Empirical Results

3.4.1 Main OLS Results

Table 3.2 presents my main OLS results for the full sample in the first three columns, followed by the OLS results for two equal-fold sub-samples. For each sample, I report the sample periods, β estimates, and White standard error-corrected t-statistics. Panels A and B present the results for the market sentiment and market strength indicators, respectively.

Table 3.2: OLS Results

	Full Sample			Sub-sample 1			Sub-sample 2		
Market Indicators	**Period**	**β (*10^{-3})**	**t-stats**	**Period 1**	**β (*10^{-3})**	**t-stats**	**Period 2**	**β (*10^{-3})**	**t-stats**
				Panel A: Market Sentiment Indicators					
Option Volumes:									
CBOE Calls Volume	1989 - 2011	-0.41	-1.17	1989-1999	-0.85	-1.55	2000-2011	-0.23	-0.55
CBOE Puts Volume	1989 - 2011	-0.01	-0.12	1989-1999	-0.02	-0.52	2000-2011	0.07	0.20
OEX Calls Volume	1989 - 2011	0.00	-1.26	1989-1999	0.00	-1.51	2000-2011	0.00	-1.29
OEX Puts Volume	1989 - 2011	0.00	0.25	1989-1999	0.00	0.16	2000-2011	0.00	0.34
CBOE Ratio of Traded Value of Puts to Calls	1986 - 2011	0.63	0.77	1986-1998	-0.07	-0.04	1999-2011	1.11	1.36
Odd-lots Volumes:									
NYSE Odd Lot Purchases	1970 - 2011	0.00	**-4.90**	1970-1990	1.07	1.38	1991-2011	0.00	**-4.05**
NYSE Odd Lot Sales	1970 - 2011	0.11	0.27	1970-1990	0.78	1.25	1991-2011	-0.05	-0.10
NYSE Odd Lot Shorts	1970 - 2011	0.00	1.14	1970-1990	-0.04	-0.48	1991-2011	0.00	1.18
Short Sales Volumes:									
NYSE Short Sales-Members	1940 - 2008	6.68	**7.15**	1940-1974	6.76	**4.85**	1975-2008	6.64	**5.26**
NYSE Short Sales-General Public	1940 - 2008	2.63	**2.58**	1940-1974	0.93	0.97	1975-2008	7.18	**3.06**
NYSE Short Sales-Specialists	1940 - 2008	5.90	**5.82**	1940-1974	6.99	**4.93**	1975-2008	5.30	**3.77**
NYSE Short Sales-Total	1940 - 2008	6.80	**5.59**	1940-1974	5.74	**4.04**	1975-2008	7.88	**4.27**
Short Interests:									
NYSE Short Interest Ratio	1931 - 2010	-23.19	**-2.22**	1931-1970	-23.16	**-2.22**	1971-2010	-23.19	**-2.22**
NYSE Short Interest Shares	1931 - 2010	-2.93	-0.12	1931-1970	-2.92	-0.12	1971-2010	-2.93	-0.12
AAII/II Sentiment Indices:									
AAII Bearish Index	1989 - 2010	0.02	0.01	1989-1999	-1.02	-0.38	2000-2010	0.77	0.31
AAII Bullish Index	1989 - 2010	6.39	**2.26**	1989-1999	5.17	1.55	2000-2010	7.50	**1.66**
AAII Neutral Index	1989 - 2010	-8.70	**-2.83**	1989-1999	-3.05	-0.92	2000-2010	-10.75	**-2.65**
Investors Intelligence Bearish Percentage	1987 - 2010	-1.04	-0.11	1987-1998	-5.17	-0.44	1999-2010	1.19	0.09
Investors Intelligence Bullish Percentage	1987 - 2010	-0.36	-0.03	1987-1998	8.19	0.74	1999-2010	-9.74	-0.50
Confidence Index:									
Barron's Confidence Index	1932 - 2010	36.44	0.78	1932-1970	43.62	0.73	1971-2010	25.05	0.33
Exchange Seat Prices:									
AMEX Seat Prices	1921 - 1993	3.38	0.48	1921-1958	12.74	0.82	1959-1993	-3.32	-0.76
Volatility Indices:									
CBOE S&P 500 Volatility Index	1986 - 2011	7.01	**1.74**	1986-1998	3.54	0.50	1999-2011	13.10	**3.04**
CBOE NASDAQ Volatility Index	2001 - 2011	13.28	**2.10**	2001-2005	5.21	0.74	2006-2011	17.22	**1.99**
CBOE S&P 100 Volatility Index	1986 - 2011	7.33	**1.96**	1986-1998	4.09	0.60	1999-2011	12.16	**3.14**
AMEX NYSE Arca NASDAQ 100 Volatility Index	2001 - 2011	4.00	0.61	2001-2005	0.11	0.02	2006-2011	5.61	0.62
CBOE DJIA Volatility Index	2005 - 2011	13.39	**1.90**	2005-2007	11.24	**2.52**	2008-2011	15.75	1.13
Margin Account Balances:									
NYSE Margin Debt	1918 - 2010	-0.72	-0.02	1918-1963	2.05	0.05	1964-2010	-12.29	-0.24
NYSE Free Credit Balances	1931 - 2010	80.49	**2.11**	1931-1970	120.88	**2.07**	1971-2010	48.63	0.95
NYSE Free Credit Balances on Cash Accounts	1971 - 2010	22.34	0.63	1971-1990	-5.56	-0.11	1991-2010	57.21	1.06
NYSE Free Cash Balances in Margin Accounts	1971 - 2010	1.66	0.04	1971-1990	-30.90	-1.00	1991-2010	88.08	1.12
Mutual Fund Balances:									
USA Mutual Fund Equity Funds Total Net Assets	1984 - 2010	92.74	1.44	1984-1996	18.63	0.19	1997-2010	129.87	1.41
USA Mutual Fund Equity Funds Cash Percentage	1968 - 2010	-20.76	-0.69	1968-1988	-1.97	-0.06	1989-2010	-59.02	-0.99
USA Mutual Fund Equity Funds Redemptions	1984 - 2010	-4.74	**-2.89**	1984-1996	-5.73	**-5.22**	1997-2010	6.10	0.25
USA Mutual Fund Equity Funds New Sales	1984 - 2010	6.59	0.54	1984-1996	5.99	0.44	1997-2010	4.21	0.17
USA Mutual Fund Equity and Bond Fund Net Assets	1954 - 2010	10.50	**6.14**	1954-1981	91.76	1.32	1982-2010	9.76	**8.05**
USA Mutual Fund Equity and Bond Fund Cash Percent	1954 - 2010	-17.87	-0.78	1954-1981	-2.94	-0.10	1982-2010	-34.84	-0.91
USA Mutual Fund Equity and Bond Fund Liquid Assets	1954 - 2010	13.26	0.51	1954-1981	26.58	0.86	1982-2010	-5.70	-0.13
USA Mutual Fund Equity and Bond Fund Redemptions	1954 - 2010	-10.50	-0.91	1954-1981	-13.13	-0.99	1982-2010	-8.53	-0.46
USA Mutual Fund Equity and Bond Fund New Sales	1954 - 2010	7.89	0.85	1954-1981	7.28	0.68	1982-2010	8.73	0.53
Number of Dividend News:									
Moody's Monthly Decreased Dividends	1956 - 2011	40.61	1.57	1956-1984	90.97	**3.22**	1985-2011	-35.03	-0.73
Moody's Monthly Extra Dividends Declared	1956 - 2011	-63.32	-1.38	1956-1984	-161.23	**-1.91**	1985-2011	-41.05	-0.80
Moody's Monthly Increased Dividends Declared	1956 - 2011	-97.86	**-1.97**	1956-1984	-125.17	**-2.17**	1985-2011	-57.17	-0.66
Moody's Monthly Omitted Dividends	1956 - 2011	7.60	0.24	1956-1984	35.53	0.99	1985-2011	-40.49	-0.72
Moody's Monthly Resumed Dividends	1956 - 2011	15.28	0.81	1956-1984	73.86	**2.09**	1985-2011	-1.88	-0.07
S&P Monthly Dividend Decreases Declared	1955 - 2010	0.43	0.45	1955-1982	1.37	**1.70**	1983-2010	-1.09	-0.53
S&P Monthly Extra Dividends Declared	1955 - 2010	4.48	**2.17**	1955-1982	5.27	**2.23**	1983-2010	3.60	0.99
S&P Monthly Increased Dividends Declared	1955 - 2010	2.11	0.57	1955-1982	8.39	1.39	1983-2010	-0.79	-0.20
S&P Monthly Omitted Dividends Declared	1955 - 2010	0.88	0.68	1955-1982	0.22	0.10	1983-2010	1.25	0.91
S&P Monthly Resumed Dividends Declared	1955 - 2010	2.85	**1.89**	1955-1982	3.29	**2.18**	1983-2010	2.39	1.02

Table 3.2 Continued

Market Indicators	Full Sample Period	Full Sample β (*10^{-3})	Full Sample t-stats	Sub-sample 1 Period 1	Sub-sample 1 β (*10^{-3})	Sub-sample 1 t-stats	Sub-sample 2 Period 2	Sub-sample 2 β (*10^{-3})	Sub-sample 2 t-stats
Panel B: Market Strength Indicators									
Total Volume:									
NYSE Total Volume	1928 - 2011	0.09	0.83	1928-1969	0.07	0.71	1970-2011	0.65	**3.48**
Total Volume Turnovers:									
NYSE Share Volume Turnover	1925 - 2010	5.39	0.13	1925-1967	84.20	**1.72**	1968-2010	-70.03	-1.27
NYSE Annual Share Value Turnover	1934 - 2010	28.23	0.64	1934-1971	40.38	0.85	1972-2010	-43.56	-0.37
Short-term Trading Indices:									
NYSE Short-term Trading Index	1965-2011	-0.49	**-2.15**	1965-1987	-1.12	**-2.94**	1988-2011	0.07	0.24
NASDAQ Short-term Trading Index	1972-2011	-0.01	-1.16	1972-1991	-0.18	-1.18	1992-2011	-0.01	-1.15
Daily Total Market Advances & Declines:									
NYSE Advances	1928 - 2011	0.51	**2.98**	1928-1969	0.43	**2.12**	1970-2011	0.77	**2.44**
NYSE Declines	1928 - 2011	-0.72	**-3.65**	1928-1969	-0.53	**-2.36**	1970-2011	-1.18	**-3.19**
NYSE Net Advances	1928 - 2011	0.00	0.49	1928-1969	0.00	-0.33	1970-2011	0.00	0.99
NYSE AD Line	1928 - 2011	0.00	-0.35	1928-1969	0.00	-0.41	1970-2011	0.00	-0.12
NYSE Percentage Net Advances	1940 - 2011	0.00	0.36	1928-1969	0.00	-0.51	1970-2011	0.00	0.99
NASDAQ Advances	1972 - 2011	0.23	1.48	1972-1991	0.35	**2.34**	1992-2011	0.00	-0.01
NASDAQ Declines	1972 - 2011	-0.10	**-3.41**	1972-1991	-0.09	**-4.65**	1992-2011	-0.76	-1.09
NASDAQ Net Advances	1972 - 2011	0.00	-0.50	1972-1991	0.01	0.55	1992-2011	0.00	-0.97
NASDAQ AD Line	1972 - 2011	0.00	-0.22	1972-1991	0.00	-0.53	1992-2011	0.00	0.16
NASDAQ Percentage Net Advances	1972 - 2011	0.00	-0.51	1972-1991	0.01	0.55	1992-2011	0.00	-0.97
Alternext Advances	1959 - 2011	1.18	**4.02**	1959-1984	1.53	**5.38**	1985-2011	0.47	0.65
Alternext Declines	1959 - 2011	-1.04	**-2.46**	1959-1984	-1.06	**-1.85**	1985-2011	-0.98	**-2.03**
Alternext Net Advances	1959 - 2011	0.01	0.80	1959-1984	0.00	0.74	1985-2011	0.01	0.50
Alternext AD Line	1959 - 2011	0.00	-0.03	1959-1984	0.00	-0.14	1985-2011	0.00	0.07
Alternext Percentage Net Advances	1959 - 2011	0.01	0.60	1963-1986	0.00	-0.31	1987-2011	0.01	0.87
Weekly Total Market Advances & Declines:									
NYSE Weekly Advances	1940 - 2010	-1.49	**-3.33**	1940-1974	-1.14	-1.50	1975-2010	-1.69	**-3.38**
NYSE Weekly Declines	1940 - 2010	0.65	1.21	1940-1974	-0.28	-0.39	1975-2010	1.75	**2.05**
NYSE Net Advances	1940 - 2010	0.00	0.22	1940-1974	0.00	-0.17	1975-2010	0.00	0.35
NYSE AD Line	1940 - 2010	-1.20	-0.52	1940-1974	-1.16	-0.49	1975-2010	-47.20	-0.85
Daily Total Market New Highs & New Lows:									
NYSE New Highs	1928 - 2011	0.14	**3.61**	1932-1971	0.71	**4.86**	1972-2011	0.10	**9.80**
NYSE New Lows	1932 - 2011	-0.13	-1.50	1932-1971	-0.12	-1.23	1972-2011	-0.15	-0.93
NYSE Net New Highs	1932 - 2011	0.04	**1.77**	1932-1971	0.05	1.44	1972-2011	0.03	1.37
NYSE Cumulative Highs	1932 - 2011	-0.01	-0.34	1932-1971	0.00	-0.09	1972-2011	-0.01	-0.30
NYSE Percentage Net New Highs	1932 - 2011	0.04	1.60	1932-1971	0.05	1.04	1972-2011	0.03	1.37
NASDAQ New Highs	1974 - 2011	-0.16	-0.43	1974-1992	0.63	**1.67**	1993-2011	-0.71	-1.20
NASDAQ New Lows	1974 - 2011	0.25	1.26	1974-1992	-0.24	-1.01	1993-2011	0.67	**2.23**
NASDAQ Net New Highs	1974 - 2011	-0.01	-0.21	1974-1992	-0.03	-0.54	1993-2011	0.01	0.21
NASDAQ Cumulative Highs	1974 - 2011	0.03	0.98	1974-1992	0.01	0.21	1993-2011	0.04	1.20
NASDAQ Percentage Net New Highs	1974 - 2011	-0.01	-0.22	1974-1992	-0.03	-0.55	1993-2011	0.01	0.19
Alternext New Highs	1962 - 2011	0.20	**2.23**	1962-1986	0.14	**2.40**	1987-2011	0.40	**1.69**
Alternext New Lows	1962 - 2011	-0.06	-0.89	1962-1986	-0.27	**-2.31**	1987-2011	0.01	0.09
Alternext Net New Highs	1962 - 2011	0.00	0.11	1962-1986	-0.05	-0.98	1987-2011	0.04	0.79
Alternext Cumulative Highs	1962 - 2011	-0.03	-0.88	1962-1986	-0.03	-0.67	1987-2011	-0.04	-0.70
Alternext Percentage Net New Highs	1962 - 2011	0.01	0.30	1963-1986	-0.03	-0.54	1987-2011	0.04	0.71
Weekly Total Maket New Highs & New Lows:									
NYSE Weekly New Highs	1937 - 2010	0.11	0.26	1937-1973	0.17	0.32	1974-2010	0.05	0.07
NYSE Weekly New Lows	1937 - 2010	-0.30	-0.74	1937-1973	-0.33	-0.76	1974-2010	-0.09	-0.08
NYSE Net New Highs	1937 - 2010	0.11	**1.88**	1937-1973	0.12	**1.78**	1974-2010	0.10	1.32
NYSE Cumulative Highs	1937 - 2010	-0.01	**-3.62**	1937-1973	0.54	**2.19**	1974-2010	-0.01	**-3.55**

This table reports the OLS results of the regression model $R_t = \alpha_t + \beta I_{t-1} + \varepsilon_t$ for full samples and two equal length sub-samples . R_t represents S&P 500 periodic returns calculated as log differences of the S&P 500 Index values, I_{t-1} represents periodic percentage changes of market indicators. I obtain all data from the Global Financial Data. The *t*-statistics reported are White standard errors corrected and marked in bold if significant at 10% significance level. Panel A and Panel B report results for market sentiment and market strength indicators respectively.

The full-sample results show that 30 out of the total 93 market indicators predict the market at the 10% significance level. This includes 18 market sentiment indicators and 12 market strength indicators. In regard to the different underlying information, five groups of indicators (option volumes, Barron's confidence index, exchange seat prices, total volumes, and total volume turnovers) exhibit no predictability at all. On the other hand, short sales volumes, volatility indices, and raw total market advance/decline indicators seem to perform better than the other indicators at first glance; all of them show (marginal) significance in predicting the market, except the NASDAQ 100 volatility index.

Although 30 indicators show some preliminary predictability, I also need to consider an important and relevant question: Do they work in the way that technical theory expects? In other words, can one really make a profit from following the technical textbook? My results provide a mixed answer to this question, with 10 of the 30 market indicators showing significant predictability, but with signs opposite from the expected. Eight sentiment indicators predict the market differently from what theory implies. Typical contrarian indicators such as the NYSE short interest ratio, the AAII bullish index, and U.S. mutual fund equity fund redemptions do not actually exhibit a contrarian nature. Instead, they capture the correct market direction. Hence, the traditional market wisdom that trading against uninformed investors no longer seems to hold here. In contrast, indicators on savvy investors, such as NYSE members/specialists, who are supposed to be correct, are also unreliable. For example, the increase in savvy short sales should predict a downward market. However, my results show that it is actually associated with a future market rise. Similarly, two market strength indicators, weekly NYSE advances and weekly NYSE cumulative highs, which should predict the market positively, actually have negative signs. Such results imply that, even though these market indicators show a significant relation with future returns, trading on them in the way indicated by theory will incur losses.

In addition, the predictability of the same market strength information varies with the way it is used. First, the predictability depends on whether raw or transformed information is used. Interestingly, at both daily and weekly frequencies, all eight raw advance/decline indicators (marginally) predict the market, in contrast with none of the transformed indicators. Hence, transformation of advance/decline information does not provide any further insight into market trends; it even appears to cause information loss. Furthermore, different underlying predictive horizons can incur variations in a particular indicator’s predictability. At daily frequencies, raw advances predict the market positively and raw declines predict the market negatively, which is in line with theory. However, such relations reverse at weekly frequencies. In addition, the new highs/new lows indicators work better in their raw forms at daily frequencies, whereas they only work in their transformed forms at weekly frequencies.

The mixed full-sample results make it difficult to conclude yet whether the market indicators are useful or not, with 30 out of the 93 indictors showing some preliminary predictability, especially considering that they provide different indications than expected by the underlying theory and the predictability can differ with the method of using the information. I then further test the general stability of the indication by splitting the full samples into two sub-samples of equal length. Note that since the original full-sample lengths vary across indicators, the two sub-samples also have different lengths for different indicators.

My sub-sample results cast further doubt on the predictive power of the market indicators. Only 10 market indicators remain predictive in both of the sub-samples: three different types of investors' short-sales volumes, the NYSE short interest ratio, daily NYSE advances and declines, daily Alternext declines, daily new highs of the NYSE and Alternext, and weekly NYSE cumulative highs. I highlight the 10 predictive market indicators in boxes. If I further group these indicators by their underlying information, only some short sales statistics and market advances/declines or new highs/lows information may still contain some predictive value.

The sub-sample results have several additional implications. First, Branch (1976) suggests that the predictability of technical indicators may disappear over time, since they will attract more investors to exploit their predictability after they are found to work. In this case, I should find more efficient technical indicators in the first sub-sample. However, I discover similar numbers of efficient technical indicators in the first and second sub-samples, with only 10 indicators actually showing statistical significance in the latter half of the sample period. Nevertheless, most market indicators (52 out of 93) show no predictability in either sub-sample; it appears that these 52 indicators have never worked across their full history, which can be as long as 193 years (the sample of NYSE seat prices starts in 1820). It seems that the argument that predictability is gradually exploited over time does not hold.

Second, one may argue that the development of financial markets enabled some trading methods that masked the true informational content of some historically useful technical indicators and led to the loss of their predictability. For example, Kirkpatrick and Dahlquist (2010) argue that margin debt, which was previously a very reliable indicator, is no longer an accurate gauge of investor sentiment because investors can, through using derivatives, hold positions outside the Federal Reserve requirements for margins. My results, however, do not appear to support such an argument, since margin debt does not work in the first sub-sample before 1963, when stock index derivatives were not as widely used by the public as they are now. I actually also find no predictability for the rest of the margin account statistics indicators. This further supports the view that predictability does not seem to decrease over time but, rather, probably to a large extent never existed.

Of my 93 market indicators, only 10 survive the sub-sample analysis. It should be noted that the weekly NYSE cumulative highs predict the market differently in the two sub-sample periods, positively in the first sub-sample and negatively in the second. This raises an intriguing question: Even though the 10 market indicators are overall predictors of the market in the long run, do the indications they supply remain the same over time? How stable is the parameter β? I perform rolling window regressions to answer these questions.

3.4.2 Rolling Window Regressions

I run a 10-year[18] rolling window regression on the 10 indicators that survive the sub-sample test. For each indicator, I first run the original OLS regression on the first 10 years of the sample and then move the sample one month forward by replacing the observations in the first month of the previous 10 years with those of the latest one month and repeat the OLS regression. Thus, the new regression window remains 10 years but rolls one month forward. I repeat this process until the last observation in the full sample is included in the last regression. The observed β should maintain at a relatively stable level if the indicator predicts the market consistently over time.

Figure 3.1 plots the rolling OLS β values in solid lines and their 90% confidence bounds in dotted lines over time. On average, all three of the NYSE short sales–members/specialists/total maintain reasonable consistency in predicting the market, except for the short period in 2001, when the market was closed because of the 911 attack. Surprisingly, members' and specialists' short sales are persistently positively related to the market over time. That is, when the informed NYSE members, or the specialists, increase their short positions to hedge against a market fall, the market actually rises. Besides, I discover an intriguing pattern for the short interest ratio: The sign of β keeps switching between positive and negative over time. This casts strong doubts on its predictability, since it seems difficult to follow the varying indication it provides from

[18] One could argue that a regression window of 10 years is not adequate. For example, Jacobsen and Dannenburg (2003) suggest that, for monthly observations, 50 years of data are required to produce reliable GARCH estimates. However, in my case I use the longest sample available for each indicator and some of these indicators have a full history of only around 50 years (e.g., Alternext new highs). My primary focus also lies in the stability of predictability across time and not the exact magnitude of the β value; a 10-year window for my rolling window regressions should serve such a goal.

Figure 3.1: 10-year Rolling Window OLS Regressions

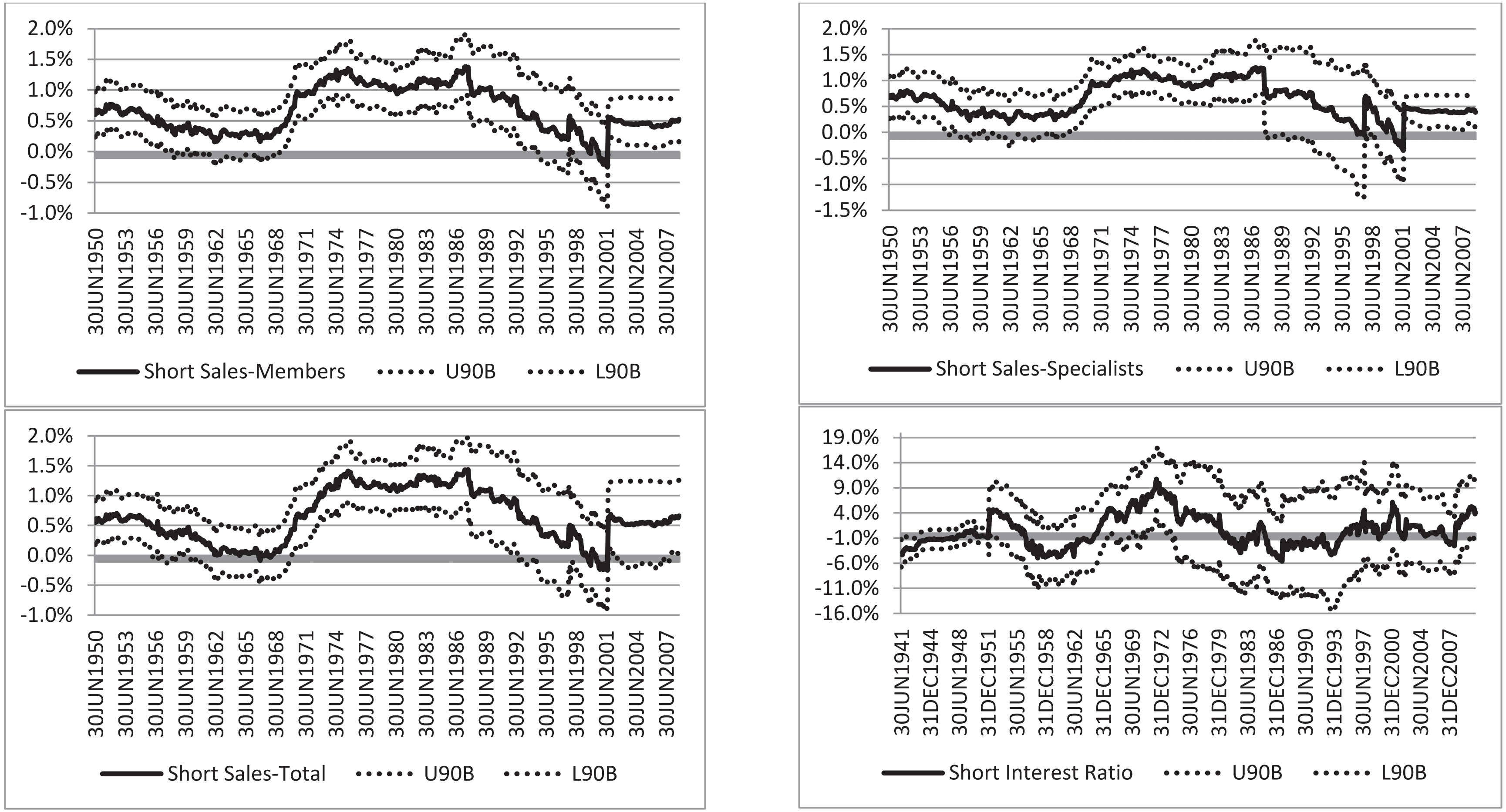


Figure 3.1 Continued

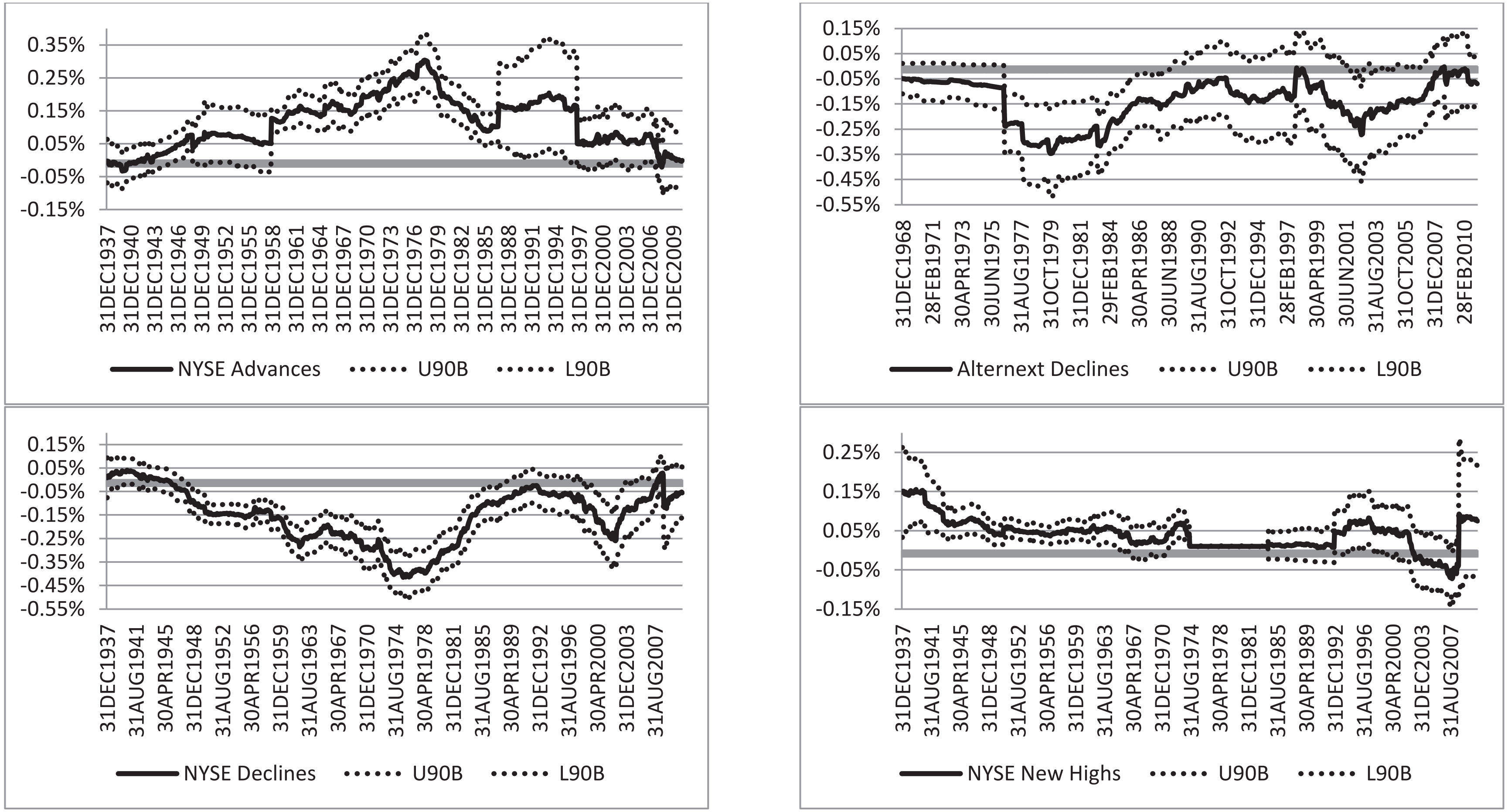
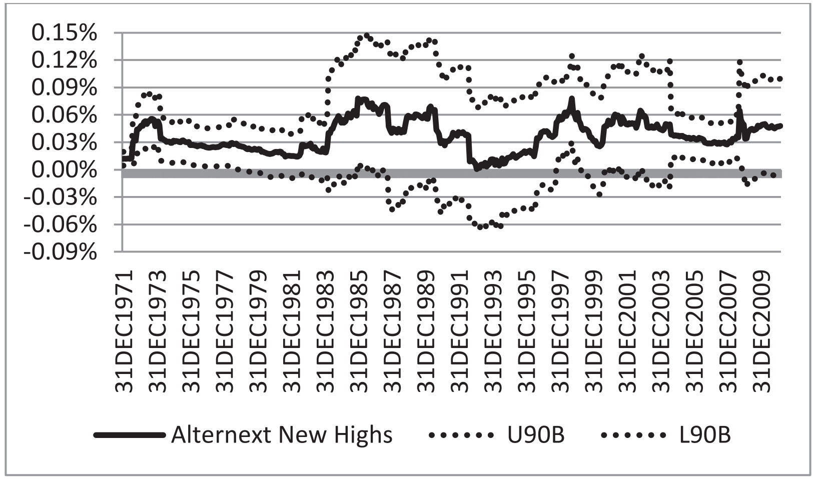


Figure 3.1 Continued



time to time. In addition, the wide confidence bounds make it even harder to rely on such predictability.

For the market strength indicators, the five raw indicators (NYSE advances/declines/new highs and Alternext declines/new highs) generally predict the market consistently over time, although at the same time, except for NYSE declines, the market indicators often experience periods with relatively wide confidence bounds for the β estimates. For example, NYSE advances have a wider confidence bound from late 1947 to late 1958 and from early 1987 to late 1997. The same is also the case for NYSE new highs after the 2008 financial crisis period. In contrast, the large fluctuation of β largely eliminates the NYSE weekly cumulative highs as reliable market predictors. The rolling window regression shows that for NYSE weekly cumulative highs, β is positive before 1974 (positive and close to zero from 1947 to 1953), when it switches sign and remains negative and close to zero for the following 10 years to 1984. Then its sign switches again to be positive until 1997, whereafter it becomes almost always negative. This probably explains why, in the sub-sample test, NYSE weekly cumulative highs predict the market differently in the two sub-samples.

The rolling window regression results warn me about the danger of using short interest ratios and NYSE cumulative highs as market predictors, even though they all exhibit statistical significance in the full sample and sub-samples on first examination. This again emphasizes the importance of using a long sample period. The other eight indicators generally present relatively stable predictability, although to some degree they are exposed to the problem of wide confidence bounds. I perform several robustness checks to address this problem in Section 6 and the results remain largely the same.

3.4.3 Economic Significance

My last step takes into account transaction costs and examines the risk-adjusted returns of investing on the eight indicators that provide relatively reliable indication over time. I use the methodology of Driesprong, Jacobsen, and Maat (2008) to test the economic significance of the market indicators. For each of the eight market indicators, I calculate my portfolio return by using OLS estimates, as follows:

- I first split the sample into two equal lengths and I estimate the OLS model parameters α_t and β_t using the first half of my sample.
- At time t + 1, I use α_t, β_t, and the last market indicator change I_t to calculate the expected return $E(R_{t+1})$. Then I compare $E(R_{t+1})$ with the same period's risk-free rate r^f_{t+1}.[19] I fully invest in the market if $E(R_{t+1})$ is higher than r^f_{t+1} , so that the portfolio return $r^P_{t+1} = r^m_{t+1}$, and I fully invest in risk-free assets if $E(R_{t+1})$ is lower than r^f_{t+1}; thus $r^P_{t+1} = r^f_{t+1}$.
- I re-estimate my model every period to update the model whenever a new observation becomes available and then calculate my portfolio returns.
- Similarly to Driesprong, Jacobsen, and Maat (2008), I assume a switching cost of 0.10% between the market and risk-free assets, in accordance with Solnik (1993).

I then compare the risk and return pattern of my portfolio with that of a naive buy and hold portfolio; I document the results in Table 2.3. I first report the mean, standard deviation, and Sharpe ratio for the buy and hold strategy and columns 7 to 9 report those of the technical strategy. I calculate the Sharpe ratio as

[19] I source my risk-free rate data from Global Financial Data using three-month U.S. Treasury bill rates.

$$\text{Sharpe ratio} = (r_t^p - r_t^f)/\sigma_t^p$$

where r_t^p represents the returns of the technical trading strategies; r_t^f represents the risk-free rate, which equals the U.S. three-month Treasury bill rates; and σ^p represents the standard deviation of r_t^p. The next column reports the *t*-values, testing the null hypothesis that the Sharpe ratio of the buy and hold strategy equals that of the technical strategy. The significance test is performed according to the methodology proposed by Lo (2002) and de Roon, Eiling, Gerard, and Hillion (2011), which assumes that the excess returns $r_t^p - r_t^f$ are independent and identically distributed normal.

The last four columns report the α and β estimates and their associated *t*-values for Jensen's α estimation. I estimate Jensen's α using the regression

$$r_t^p - r_t^f = \alpha + \beta\,(r_t^m - r_t^f) + \varepsilon_t$$

where r_t^p, r_t^f, and r_t^m represent the returns of the technical trading strategies, risk-free rate, and market returns, respectively. The term α then captures the excess return on a given systematic risk level β of the technical trading strategy by using the buy and hold strategy as the benchmark.

Compared with the buy and hold strategy, the technical strategies generally have both lower returns and lower risks. Three technical strategies (NYSE advances, declines, and new highs) even have negative returns, on average, before considering risks, which suggests investing on risk-free assets will be more mean–variance efficient. Furthermore, in terms of the Sharpe ratio that measures the price for each unit of risk, none of the technical strategies significantly outperforms the buy and hold strategy. In fact, most technical strategies have negative Sharpe ratios that underperform investing on risk-free

Table 3.3: OLS Economic Significance Test

Market Indicators	Frequency	N	Buy & Hold Strategy: Mean ($*10^{-3}$)	Buy & Hold Strategy: Std. Dev. ($*10^{-2}$)	Buy & Hold Strategy: Sharpe Ratio ($*10^{-2}$)	Technical Strategy: Mean ($*10^{-3}$)	Technical Strategy: Std. Dev. ($*10^{-2}$)	Technical Strategy: Sharpe Ratio ($*10^{-2}$)	t-stats	α ($*10^{-3}$)	t-stats	β	t-stats
Panel A: Market Sentiment Indicators													
NYSE Short Sales-Members	Weekly	1743	1.28	2.27	0.84	0.93	1.70	-0.97	1.06	-0.27	-0.97	0.57	**16.34**
NYSE Short Sales-Specialists	Weekly	1742	1.28	2.27	0.84	1.03	1.62	-0.42	0.69	-0.16	-0.57	0.51	**13.69**
NYSE Short Sales-Total	Weekly	1742	1.28	2.27	0.84	1.13	1.69	0.18	0.38	-0.06	-0.23	0.56	**15.76**
Panel B: Market Strength Indicators													
NYSE Advances	Daily	11024	0.24	1.06	0.85	-0.08	0.69	-3.35	**5.15**	-0.28	**-5.51**	0.40	**17.23**
NYSE Declines	Daily	11024	0.24	1.06	0.85	-0.05	0.84	-2.36	**5.13**	-0.26	**-5.25**	0.62	**20.14**
Alternext Declines	Daily	6608	0.30	1.18	1.57	-0.07	0.99	-1.87	**4.79**	-0.32	**-4.45**	0.69	**15.48**
NYSE New Highs	Daily	10307	0.26	1.07	1.07	0.15	0.98	-0.02	**2.52**	-0.10	**-2.38**	0.82	**62.32**
Alternext New Highs	Daily	6109	0.26	1.20	1.24	0.14	1.15	0.26	**2.78**	-0.11	**-2.67**	0.93	**62.96**

This table compares risk and return characteristics of buy and hold strategies with strategies based on market indicators that show significant predictability in both sub-samples under the OLS regressions. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, then I report *t*-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated *t*-statistics testing their differences from zero for α and β values. All *t*-statistics are White standard errors corrected and marked in bold if significant at 10% significance level.

assets. The results of Jensen's α estimation provide more or less similar implications. Although all the β estimates are significantly below one, indicating lower risk levels, none of the technical trading strategies produce a more positive excess return, captured by α, than the buy and hold strategy at this level of risk. Overall, my OLS results indicate none of the 93 market indicators generate returns outperforming the market.

3.5 Time-Varying Predictability

My conclusion may be too restrictive yet if return predictability is state dependent. Prior literature has shown that some return predictability models' effectiveness varies across business cycles (Dangl & Halling, 2009; Henkel, Martin, & Nardari, 2010; Jacobsen, Marshall, & Visaltanachoti, 2010) or across sentiment regimes (Stambaugh, Yu, & Yuan, 2011). Several of my market indicators exhibit sign-switching predictability across time, for example, the short interest ratio and weekly NYSE cumulative highs. If some of the technical market indicators have time-varying or state-dependent predictability, it remains possible that they have not been picked out by my full-sample and sub-sample tests. Hence, in this section, I implicitly investigate the time variation and state dependency of the 93 indicators.

3.5.1 Business Cycle-Varying Predictability

Han, Yang, and Zhou (2013) find that the moving average trading strategies generate much higher abnormal returns in recessions. Chordia and Shivakumar (2002) discover similar evidence for momentum strategies, which generate positive returns only during expansions. On the other hand, Griffin, Ji, and Martin (2003) claim profitable momentum strategies in both good and bad economic states. All these studies provide evidence for business cycle-related predictability but do not pay attention to the market indicators. I seek to fill the gap here for the effect of market indicators on business cycle-varying predictability, if any.

I use the monthly NBER business cycle data[1] that start in 1854 to define expansion and contraction periods.[2] I report the regression results in Table 3.4. The first two columns repeat my full-sample results again for comparison. Columns 3 to 6 report β_1 and β_2, which measure the predictability of the market indicators in expansions and contractions, with White standard error-corrected *t*-statistics. The last column reports the *F*-test results, testing the statistical differences between β_1 and β_2.

Generally, market indicators' predictability does not seem to strengthen under different business states. I have 26 predictive indicators in expansions and 21 in contractions, suggesting overall market indicators do not seem to work better in one business state. In addition, compared with the 30 significant results discovered under the full sample, my results seem to suggest that predictability is not strengthened even if I allow it to be time varying across business cycles. The F-test results give a similar message, that the predictability of most market indicators (74 out of the total 93) in contractions is not statistically different from that in expansions. This largely eliminates the possibility that

[1] See http://www.nber.org/cycles.html.

[2] My indicators have different frequencies and I define expansions and contractions as follows: The only annual indicator, NYSE seat prices, starts in 1820, whereas, due to data availability on business cycles, my time-varying evaluation on the annual indicator starts in 1854. I classify a year as in expansion (contraction) if over seven months of the year are in expanding (contracting) periods. I define each week/day as in expansion (contraction) if the month it falls in is expanding (contracting).

Table 3.4: NBER Business Cycle Time-Varying Results

Market Indicators	Full Sample		Expansions		Contractions		Chi-statistic
	β (*10^{-3})	t-stats	$\beta1$ (*10^{-3})	t-stats	$\beta2$ (*10^{-3})	t-stats	
Panel A: Market Sentiment Indicators							
Option Volumes:							
CBOE Calls Volume	0.00	1.15	-0.31	-0.88	-3.22	-0.90	0.65
CBOE Puts Volume	-0.01	-0.12	0.01	0.18	-0.77	-0.25	0.06
OEX Calls Volume	0.00	-1.26	0.00	-1.17	-1.72	-1.31	1.73
OEX Puts Volume	0.00	0.25	0.00	0.27	1.55	1.18	1.40
CBOE Ratio of Traded Value of Puts to Calls	0.63	0.77	0.72	0.78	4.19	1.23	0.97
Odd-lots Volumes:							
NYSE Odd Lot Purchases	0.00	**-4.90**	0.00	**-5.89**	-0.23	-0.16	0.20
NYSE Odd Lot Sales	0.11	0.27	0.30	0.59	-0.02	-0.02	0.06
NYSE Odd Lot Shorts	0.00	1.14	0.00	1.11	0.01	1.53	1.26
Short Sales Volumes:							
NYSE Short Sales-Members	6.68	**7.15**	5.20	**4.63**	9.65	**4.81**	**3.74**
NYSE Short Sales-General Public	2.63	**2.58**	1.53	**1.67**	7.84	**2.64**	**4.13**
NYSE Short Sales-Specialists	5.90	**5.82**	4.92	**3.46**	7.41	**4.67**	1.36
NYSE Short Sales-Total	6.80	**5.59**	5.13	**4.22**	11.57	**4.94**	**5.94**
Short Interests:							
NYSE Short Interest Ratio	-23.19	**-2.22**	-20.54	**-2.01**	-45.56	-1.48	0.60
NYSE Short Interest Shares	-2.93	-0.12	-3.87	-0.16	-2.32	-0.04	0.00
AAII/II Sentiment Indices:							
AAII Bearish Index	0.02	0.01	1.19	0.65	-3.43	-0.45	0.35
AAII Bullish Index	6.39	**2.26**	2.09	0.76	19.05	**2.22**	**3.53**
AAII Neutral Index	-8.70	**-2.83**	-5.89	**-1.85**	-24.61	**-2.79**	**4.03**
Investors Intelligence Bearish Percentage	-1.04	-0.11	7.12	0.75	-56.87	-1.27	1.96
Investors Intelligence Bullish Percentage	-0.36	-0.03	-8.97	-0.92	28.17	0.74	0.89
Confidence Index:							
Barron's Confidence Index	36.44	0.78	-54.55	-1.13	182.58	**1.82**	**4.54**
Exchange Seat Prices:							
AMEX Seat Prices	3.38	0.48	3.95	0.69	-0.25	-0.01	0.01
NYSE Annual Seat Price	-16.55	-0.73	-31.32	-0.91	-33.93	-0.37	0.00
Volatility Indices:							
CBOE S&P 500 Volatility Index	7.01	**1.74**	5.56	1.13	176.30	1.47	0.86
CBOE NASDAQ Volatility Index	13.28	**2.10**	17.01	**3.21**	15.40	0.53	0.10
CBOE S&P 100 Volatility Index	7.33	**1.96**	6.19	1.36	12.57	1.11	0.27
AMEX NYSE Arca NASDAQ 100 Volatility Index	4.00	0.61	10.92	**2.67**	-5.71	-0.38	1.11
CBOE DJIA Volatility Index	13.39	**1.90**	9.81	**2.24**	22.21	0.97	0.28
Margin Account Balances:							
NYSE Margin Debt	-0.72	-0.02	-17.78	-0.42	35.82	0.41	0.30
NYSE Free Credit Balances	80.49	**2.11**	56.75	1.62	176.92	1.45	0.90
NYSE Free Credit Balances on Cash Accounts	22.34	0.63	32.78	0.96	-64.18	-0.42	0.39
NYSE Free Cash Balances in Margin Accounts	1.66	0.04	-22.78	-0.70	69.74	0.81	1.02
Mutual Fund Balances:							
USA Mutual Fund Equity Funds Total Net Assets	92.74	1.44	-6.10	-0.08	376.29	**3.05**	**7.25**
USA Mutual Fund Equity Funds Cash Percentage	-20.76	-0.69	25.89	0.88	-288.05	**-2.68**	**7.91**
USA Mutual Fund Equity Funds Redemptions	-4.74	**-2.89**	-4.53	**-3.08**	-2.93	-0.05	0.00
USA Mutual Fund Equity Funds New Sales	6.59	0.54	1.20	0.10	56.28	1.05	1.00
USA Mutual Fund Equity and Bond Fund Net Assets	10.50	**6.14**	6.24	1.26	269.91	**2.33**	**2.80**
USA Mutual Fund Equity and Bond Fund Cash Percent	-17.87	-0.78	10.37	0.47	-240.46	**-2.57**	**6.80**
USA Mutual Fund Equity and Bond Fund Liquid Assets	13.26	0.51	26.46	1.03	-72.82	-0.73	0.94
USA Mutual Fund Equity and Bond Fund Redemptions	-10.50	-0.91	-8.75	-0.76	-15.27	-0.37	0.02
USA Mutual Fund Equity and Bond Fund New Sales	7.89	0.85	3.31	0.37	27.69	0.97	0.66
Number of Dividend News:							
Moody's Monthly Decreased Dividends	40.61	1.57	66.23	**2.80**	4.40	0.07	0.79
Moody's Monthly Extra Dividends Declared	-63.32	-1.38	-30.23	-0.68	-413.47	**-2.01**	**3.31**
Moody's Monthly Increased Dividends Declared	-97.86	**-1.97**	-93.18	**-1.85**	-75.62	-0.47	0.01
Moody's Monthly Omitted Dividends	7.60	0.24	39.20	1.26	-98.80	-1.14	2.23
Moody's Monthly Resumed Dividends	15.28	0.81	32.23	**1.93**	10.13	0.13	0.08
S&P Monthly Dividend Decreases Declared	0.43	0.45	0.60	0.62	3.34	0.60	0.23
S&P Monthly Extra Dividends Declared	4.48	**2.17**	7.31	**3.79**	-12.79	-1.64	**6.26**
S&P Monthly Increased Dividends Declared	2.11	0.57	7.93	1.43	-2.87	-0.75	2.63
S&P Monthly Omitted Dividends Declared	0.88	0.68	1.21	0.89	-2.23	-0.46	0.46
S&P Monthly Resumed Dividends Declared	2.85	**1.89**	4.72	**3.75**	-3.18	-0.67	2.66

Table 3.4 Continued

Market Indicators	Full Sample β (*10⁻³)	t-stats	Expansions β1 (*10⁻³)	t-stats	Contractions β2 (*10⁻³)	t-stats	Chi-statistic
Panel B: Market Strength Indicators							
Total Volume:							
NYSE Total Volume	0.09	0.83	0.05	0.67	1.59	**1.84**	**3.14**
Total Volume Turnovers:							
NYSE Share Volume Turnover	5.39	0.13	34.14	1.08	16.04	0.14	0.02
NYSE Annual Share Value Turnover	28.23	0.64	35.07	0.84	18.58	0.05	0.00
Short-term Trading Indices:							
NYSE Short-term Trading Index	-0.49	**-2.15**	-0.33	-1.25	-1.39	**-2.12**	2.30
NASDAQ Short-term Trading Index	-0.01	-1.16	0.00	0.58	-0.02	-0.93	1.02
Daily Total Market Advances & Declines:							
NYSE Advances	0.51	**2.98**	0.84	**5.15**	-0.15	-0.38	**5.40**
NYSE Declines	-0.72	**-3.65**	-0.80	**-4.53**	-0.62	-1.31	0.12
NYSE Net Advances	0.00	0.49	0.00	0.22	0.00	0.24	0.02
NYSE AD Line	0.00	-0.35	0.00	-0.96	0.00	0.70	0.92
NYSE Percentage Net Advances	0.00	0.36	0.00	0.08	0.00	0.19	0.02
NASDAQ Advances	0.23	1.48	0.36	1.06	0.22	1.17	0.14
NASDAQ Declines	-0.10	**-3.41**	-0.08	**-5.74**	-1.68	-1.45	1.90
NASDAQ Net Advances	0.00	-0.50	0.00	-0.59	0.02	1.05	1.29
NASDAQ AD Line	0.00	-0.22	0.00	0.36	-0.01	-0.76	0.70
NASDAQ Percentage Net Advances	0.00	-0.51	0.00	-0.60	0.02	1.05	1.29
Alternext Advances	1.18	**4.02**	1.18	**3.22**	1.20	**2.42**	0.00
Alternext Declines	-1.04	**-2.46**	-0.80	**-2.05**	-2.66	**-2.29**	2.31
Alternext Net Advances	0.01	0.80	0.00	0.07	0.02	0.75	0.52
Alternext AD Line	0.00	-0.03	-0.01	-0.96	0.01	0.47	0.49
Alternext Percentage Net Advances	0.01	0.60	0.00	-0.07	0.03	0.79	0.62
Weekly Total Market Advances & Declines:							
NYSE Weekly Advances	-1.49	**-3.33**	-0.44	-0.77	-2.35	**-4.08**	**5.61**
NYSE Weekly Declines	0.65	1.21	0.71	1.31	0.79	0.55	0.00
NYSE Net Advances	0.00	0.22	0.00	0.27	-0.03	-0.19	0.04
NYSE AD Line	-1.20	-0.52	-1.24	-0.53	1.54	0.02	0.00
Daily Total Maket New Highs & New Lows:							
NYSE New Highs	0.14	**3.61**	0.52	**3.89**	0.11	**7.73**	**9.38**
NYSE New Lows	-0.13	-1.50	-0.16	-1.58	0.01	0.07	0.63
NYSE Net New Highs	0.04	**1.77**	0.05	**2.34**	-0.06	-1.24	**4.76**
NYSE Cumulative Highs	-0.01	-0.34	0.00	0.18	-0.02	-0.50	0.28
NYSE Percentage Net New Highs	0.04	1.60	0.05	**2.08**	-0.06	-1.30	**4.55**
NASDAQ New Highs	-0.16	-0.43	0.24	0.73	-0.99	-1.03	1.47
NASDAQ New Lows	0.25	1.26	0.02	0.08	1.10	**1.65**	2.40
NASDAQ Net New Highs	-0.01	-0.21	-0.01	-0.40	-0.01	-0.11	0.02
NASDAQ Cumulative Highs	0.03	0.98	0.03	0.89	0.04	0.26	0.01
NASDAQ Percentage Net New Highs	-0.01	-0.22	-0.01	-0.41	-0.01	-0.12	0.02
Alternext New Highs	0.20	**2.23**	0.17	**2.41**	0.36	0.97	0.25
Alternext New Lows	-0.06	-0.89	-0.16	-0.13	0.20	0.35	0.13
Alternext Net New Highs	0.00	0.11	-0.03	-0.59	0.07	1.16	1.60
Alternext Cumulative Highs	-0.03	-0.88	-0.05	-1.16	-0.10	-1.32	0.42
Alternext Percentage Net New Highs	0.01	0.30	-0.02	-0.49	0.07	1.18	1.51
Weekly Total Maket New Highs & New Lows:							
NYSE Weekly New Highs	0.11	0.26	0.29	0.62	-0.21	-0.23	0.23
NYSE Weekly New Lows	-0.30	-0.74	-0.45	-1.02	0.07	0.09	0.29
NYSE Net New Highs	0.11	**1.88**	0.08	1.43	0.31	**2.24**	2.32
NYSE Cumulative Highs	-0.01	**-3.62**	-0.01	**-7.07**	-6.04	**-4.57**	**20.82**

This table reports the OLS results of the regression model $R_t = \alpha_t + \beta_1 D_{t-1} I_{t-1} + \beta_2(1-D_{t-1})I_{t-1} + \varepsilon_t$. R_t represents S&P 500 periodic returns calculated as log differences of the S&P 500 Index values, I_{t-1} represents periodic percentage changes of market indicators. D_{t-1} is a dummy variable that equals 1(0) during NBER business cycle expansions(contractions). Therefore β_1 and β_2 measure the predictability of a market indicator during expansions and contractions respectively. I replicate the full sample OLS results for comparison in the first two columns, then I report β_1 and β_2 with associated *t*-statistics, and the last column reports *chi*-statistics testing the null hypothesis that β_1 and β_2 are equal. I obtain all data from the Global Financial Data. The *t*-statistics and *chi*-statistics reported are White standard errors corrected and marked in bold if significant at 10% significance level. Panel A and Panel B report results for market sentiment and market strength indicators respectively.

these indicators work better in one business state and not the other, offsetting overall predictability.

To allow the maximum benefit of the doubt, I perform economic significance tests for indicators that exhibit significant predictability in any of the expansion or contraction periods and I tabulate the results in Tables 3.5 and 3.6, respectively. Generally, the technical trading strategies have lower risk levels than the buy and hold strategies in both business states, although they largely do not beat the buy and hold strategies in returns for each unit of risk as measured by the Sharpe ratio. Jensen's α results largely tell the same story: The technical trading strategies usually have low β levels, which means low systematic risk, but they do not generate excess returns to the market at the risk level β either. I have two exceptions in the expansion periods. Equity fund redemptions have a Sharpe ratio significantly higher than the market's and a marginally significant Jensen's α and NYSE net new highs have a significant positive Jensen's α and a marginally significantly higher Sharpe ratio. These two indicators may show some predictability during expansion periods only; however, this finding does not alter my main conclusions.

Table 3.5: NBER Expansions Economic Significance Test

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Odd Lot Purchases	Daily	5202	0.25	1.17	1.30	0.31	0.85	2.49	1.16	0.13	1.61	0.54	**22.54**
NYSE Short Sales-Members	Weekly	1760	1.28	2.27	0.85	1.27	1.47	1.19	0.17	0.11	0.40	0.43	**11.74**
NYSE Short Sales-General Public	Weekly	1738	1.28	2.27	0.85	1.61	1.63	3.21	1.34	0.43	1.55	0.52	**13.56**
NYSE Short Sales-Specialists	Weekly	1758	1.28	2.27	0.85	1.49	1.45	2.74	0.95	0.33	1.23	0.42	**11.44**
NYSE Short Sales-Total	Weekly	1756	1.28	2.27	0.85	1.46	1.50	2.45	0.83	0.30	1.09	0.45	**12.11**
NYSE Short Interest Ratio	Monthly	458	5.29	4.51	1.34	6.55	3.48	5.34	1.27	1.17	1.10	0.60	**10.96**
AAII Neutral Index	Weekly	563	-0.21	2.66	-2.43	0.23	1.33	-1.58	0.20	-0.06	-0.13	0.25	**5.96**
CBOE NASDAQ Volatility Index	Daily	1254	0.01	1.57	-0.29	-0.01	0.35	-1.93	0.47	-0.05	-0.57	0.05	**5.62**
AMEX NYSE Arca NASDAQ 100 Volatility Index	Daily	1253	0.01	1.57	-0.30	-0.05	0.35	-2.94	0.75	-0.09	-0.95	0.05	**5.61**
CBOE DJIA Volatility Index	Daily	732	-0.03	1.88	-0.20	0.01	0.00	0.00	0.04	0.00	**N/A**	0.00	**N/A**
USA Mutual Fund Equity Funds Redemptions	Monthly	144	1.29	4.87	-3.16	4.91	3.94	5.27	**1.71**	2.06	1.12	0.69	**7.28**
Moody's Monthly Decreased Dividends	Monthly	310	6.16	4.57	5.76	5.24	3.56	4.81	0.25	-0.53	-0.39	0.61	**9.02**
Moody's Monthly Increased Dividends Declared	Monthly	310	6.16	4.57	5.76	5.65	3.61	5.89	0.04	-0.16	-0.12	0.63	**9.26**
Moody's Monthly Resumed Dividends	Monthly	310	6.16	4.57	5.76	5.66	3.46	6.16	0.10	1.11	0.81	0.52	**6.73**
S&P Monthly Extra Dividends Declared	Monthly	317	6.36	4.54	5.03	6.38	2.99	7.71	0.58	0.82	0.61	0.44	**6.37**
S&P Monthly Resumed Dividends Declared	Monthly	312	7.30	4.43	7.01	7.23	3.28	9.25	0.55	0.01	0.01	0.58	**8.33**
Panel B: Market Strength Indicators													
NYSE Advances	Daily	10975	0.24	1.06	0.86	0.00	0.67	-2.24	**3.71**	-0.19	**-3.88**	0.39	**17.56**
NYSE Declines	Daily	10975	0.24	1.06	0.86	0.09	0.76	-0.83	**2.33**	-0.12	**-2.28**	0.51	**19.56**
NASDAQ Declines	Daily	4955	0.25	1.18	1.33	0.30	0.87	2.44	1.08	0.13	1.50	0.55	**22.04**
Alternext Advances	Daily	6573	0.30	1.18	1.59	-0.08	0.47	-4.15	**4.13**	-0.22	**-4.27**	0.14	**8.22**
Alternext Declines	Daily	6573	0.30	1.18	1.59	-0.28	0.62	-6.34	**6.49**	-0.46	**-6.90**	0.27	**11.51**
NYSE New Highs	Daily	10260	0.26	1.07	1.07	0.14	0.14	-0.83	1.39	-0.02	**-2.22**	0.00	**5.08**
NYSE Net New Highs	Daily	10093	0.31	1.08	1.51	0.35	0.83	2.39	1.29	0.10	**1.84**	0.60	**26.43**
NYSE Percentage Net New Highs	Daily	10091	0.26	1.08	1.01	0.30	0.82	1.86	1.24	0.09	1.64	0.59	**23.05**
Alternext New Highs	Daily	6076	0.26	1.20	1.25	0.27	0.94	1.74	0.58	0.07	0.88	0.62	**19.22**
NYSE Cumulative Highs	Weekly	1937	1.64	2.32	2.63	1.74	1.63	4.34	0.98	0.40	1.52	0.49	**15.56**

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability during NBER expansion periods. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, then I report *t*-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated *t*-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level. The estimations are based on the OLS regression results.

Table 3.6: NBER Contractions Economic Significance Test

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Short Sales-Members	Weekly	1780	1.26	2.26	0.76	1.18	0.82	1.10	0.13	0.07	0.39	0.14	**2.98**
NYSE Short Sales-General Public	Weekly	1783	1.26	2.26	0.76	1.11	0.66	0.26	0.18	0.00	0.03	0.09	**2.01**
NYSE Short Sales-Specialists	Weekly	1781	1.26	2.26	0.76	1.09	0.77	0.01	0.28	-0.02	-0.10	0.12	**2.72**
NYSE Short Sales-Total	Weekly	1782	1.26	2.26	0.76	1.12	0.77	0.39	0.14	0.01	0.07	0.12	**2.69**
AAII Bullish Index	Weekly	563	-0.21	2.66	-2.43	0.36	0.87	-0.86	0.32	-0.01	-0.04	0.11	**2.54**
AAII Neutral Index	Weekly	563	-0.21	2.66	-2.43	0.56	1.22	1.02	0.79	0.25	0.57	0.21	**2.44**
Barron's Confidence Index	Weekly	2063	1.24	2.31	0.92	0.99	0.54	-0.81	0.63	-0.06	-0.49	0.06	**3.69**
USA Mutual Fund Equity Funds Total Net Assets	Monthly	321	6.46	4.54	5.22	3.39	1.47	-4.74	1.42	-0.03	-0.06	0.05	**2.20**
USA Mutual Fund Equity Funds Cash Percentage	Monthly	321	6.46	4.54	5.22	3.32	1.96	-3.94	1.44	-0.37	-0.39	0.14	**2.33**
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	147	1.75	4.89	-2.22	1.41	1.92	-7.44	0.51	0.14	0.14	0.07	**1.82**
USA Mutual Fund Equity and Bond Fund Cash Percent	Monthly	241	4.92	4.36	3.44	2.92	1.59	-3.18	0.83	0.26	0.38	0.06	**2.21**
Moody's Monthly Extra Dividends Declared	Monthly	310	6.16	4.57	5.76	2.06	1.74	-8.42	**2.10**	-1.12	-1.22	0.10	**1.72**
Panel B: Market Strength Indicators													
NYSE Total Volume	Daily	10844	0.24	1.06	0.84	0.15	0.17	0.00	0.64	-0.01	-0.85	0.01	**2.63**
NYSE Short-term Trading Index	Daily	5725	0.28	1.14	1.51	-0.02	0.47	-2.70	**2.88**	-0.16	**-2.90**	0.15	**7.97**
Alternext Advances	Daily	6472	0.30	1.18	1.59	0.01	0.32	-3.22	**3.13**	-0.12	**-3.40**	0.06	**6.07**
Alternext Declines	Daily	6472	0.30	1.18	1.59	-0.01	0.43	-2.94	**3.16**	-0.15	**-3.15**	0.11	**7.32**
NYSE Weekly Advances	Weekly	1841	1.47	2.26	2.01	0.93	0.94	-0.94	1.17	-0.17	-0.83	0.17	**3.98**
NYSE New Highs	Daily	10130	0.26	1.07	1.07	0.16	0.16	0.77	0.22	0.00	0.42	0.01	**3.28**
NASDAQ New Lows	Daily	4534	0.24	1.21	1.26	0.02	0.50	-1.32	1.57	-0.10	-1.50	0.15	**7.48**
NYSE Net New Highs	Weekly	1927	1.61	2.32	2.52	0.90	0.51	-2.52	**1.77**	-0.16	-1.22	0.05	1.48
NYSE Cumulative Highs	Weekly	1937	1.64	2.32	2.63	0.88	1.23	-1.26	**1.77**	-0.33	-1.36	0.28	**7.48**

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability during NBER contraction periods. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, then I report *t*-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated *t*-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level. The estimations are based on the OLS regression results.

3.5.2 Sentiment Regime-Varying Predictability

I also test a second set of possible predictability regimes: the sentiment regimes introduced by Yu and Yuan (2011). These authors find a significantly positive mean–variance relationship during low-sentiment periods but no relation during high-sentiment periods in which sentiment shifts price away from its fundamental values. Stambaugh, Yu, and Yuan (2012) also document that a set of asset pricing anomalies becomes stronger during high-sentiment periods. Their finding could have an impact on the predictability of market indicators. Many market indicators work on the basis of measuring investor sentiment, which technical analysis believes is the force that drives prices from their fundamental values (Kirkpatrick & Dahlquist, 2010). I therefore wonder whether these market indicators show stronger predictability during high-sentiment periods in which such forces become stronger. If this is the case, the full-sample analysis can miss such predictability.

Following Yu and Yuan (2011), I use the annual Baker and Wurgler (2006) sentiment index to define sentiment periods. Baker and Wurgler calculate a composite sentiment index as the first principle component of six measures of investor sentiment, namely, the closed-end fund discount, the NYSE share turnover, the number of IPOs, the average first-day return of IPOs, the equity share in new issues, and the dividend premium. The first principle calculation eliminates noise and captures the common component of the different sentiment measures. Furthermore, the authors first regress the six sentiment measures on a set of macroeconomic variables to remove business cycle information and they then use the residuals as input for first principle component analysis. Therefore, my sentiment time-varying analysis does not overlap with the business cycle-varying analysis above. I then classify a year as a high-sentiment year if the prior year has a positive Baker and Wurgler (2006) index value. I use the same regime-switching methodology as above and define the dummy variable as equal to one (zero) during high-sentiment (low-sentiment) periods.

I present the sentiment regime-varying results in Table 3.7.[1] Again, I first recall the full-sample results in the first two columns and then subsequently present the results during high- and low-sentiment periods; lastly, I present the *F*-test results, testing the differences between high- and low-sentiment periods.

I find a total of 21 and 25 market indicators predicting the market during high- and low-sentiment periods, respectively. Contrary to what was expected, I do not discover more predictive indicators during high-sentiment periods, when sentiment becomes more important in driving prices. Instead, I even have a few more predictive indicators during the low-sentiment period. Moreover, both numbers of significant predictors are less than the 30 found under the full-sample periods. Moreover, the *F*-test results also show that, statistically, 83 out of the 93 indicators do not predict the market differently in two regimes. This finding contributes to the view that separate high- and low-sentiment regimes does not seem to increase the predictability of the market indicators.

To further check if any of the single-state predictive indicators show true predictive value, I also perform similar economic significance tests as that above and document the results

[1] Notice that the full-sample results are for the longest sample available for each of the indicators, while the sentiment regime varying results are for the period from 1967 to 2011 where the sentiment index is available. This may cause some unusual effect during comparison. For example, the NYSE Total Volume predicts returns in both regimes but not the full-sample. However this would not affect my main conclusion since I perform further analysis for the best benefit of doubt, also those indicators whose sample starts after 1967 would not suffer from this problem.

Table 3.7: Sentiment Cycle Time-Varying Results

Market Indicators	Full Sample β (*10⁻³)	t-stats	High Sentiment β1 (*10⁻³)	t-stats	Low Sentiment β2 (*10⁻³)	t-stats	Chi-statistic
Panel A: Market Sentiment Indicators							
Option Volumes:							
CBOE Calls Volume	0.00	1.15	-0.19	-0.45	-0.65	-1.10	0.40
CBOE Puts Volume	-0.01	-0.12	0.01	0.38	-0.24	-0.48	0.26
OEX Calls Volume	0.00	-1.26	0.00	-1.21	-0.31	-1.40	1.95
OEX Puts Volume	0.00	0.25	0.00	0.25	0.18	0.55	0.30
CBOE Ratio of Traded Value of Puts to Calls	0.63	0.77	0.59	0.50	0.82	0.74	0.02
Odd-lots Volumes:							
NYSE Odd Lot Purchases	0.00	**-4.90**	-0.14	-0.21	0.00	**-6.68**	0.04
NYSE Odd Lot Sales	0.11	0.27	0.61	1.17	-0.16	-0.24	0.87
NYSE Odd Lot Shorts	0.00	1.14	0.01	1.46	0.00	0.29	1.61
Short Sales Volumes:							
NYSE Short Sales-Members	6.68	**7.15**	7.39	**4.92**	7.63	**4.43**	0.01
NYSE Short Sales-General Public	2.63	**2.58**	6.79	**2.25**	4.70	**2.16**	0.32
NYSE Short Sales-Specialists	5.90	**5.82**	5.93	**3.63**	6.51	**3.64**	0.06
NYSE Short Sales-Total	6.80	**5.59**	8.62	**3.62**	8.45	**4.30**	0.00
Short Interests:							
NYSE Short Interest Ratio	-23.19	**-2.22**	-9.58	-0.32	67.65	**2.19**	**3.33**
NYSE Short Interest Shares	-2.93	-0.12	43.55	0.86	11.86	0.29	0.25
AAII/II Sentiment Indices:							
AAII Bearish Index	0.02	0.01	1.82	0.68	-2.05	-0.75	1.05
AAII Bullish Index	6.39	**2.26**	4.98	1.32	7.87	**1.92**	0.27
AAII Neutral Index	-8.70	**-2.83**	-10.55	**-2.44**	-6.71	-1.55	0.40
Investors Intelligence Bearish Percentage	-1.04	-0.11	14.85	1.12	-18.18	-1.39	**3.14**
Investors Intelligence Bullish Percentage	-0.36	-0.03	-7.94	-0.56	5.39	0.34	0.39
Confidence Index:							
Barron's Confidence Index	36.44	0.78	-95.13	-1.20	38.75	0.46	1.33
Exchange Seat Prices:							
AMEX Seat Prices	3.38	0.48	4.63	0.28	-2.62	-0.63	0.19
NYSE Annual Seat Price	-16.55	-0.73	31.87	0.30	65.06	0.55	0.05
Volatility Indices:							
CBOE S&P 500 Volatility Index	7.01	**1.74**	4.71	0.77	12.19	**2.44**	0.90
CBOE NASDAQ Volatility Index	13.28	**2.10**	3.00	0.46	18.48	**1.99**	1.86
CBOE S&P 100 Volatility Index	7.33	**1.96**	5.61	1.00	10.80	**2.30**	0.50
AMEX NYSE Arca NASDAQ 100 Volatility Index	4.00	0.61	3.22	0.61	3.96	0.44	0.00
CBOE DJIA Volatility Index	13.39	**1.90**	9.06	**1.93**	15.91	1.37	0.30
Margin Account Balances:							
NYSE Margin Debt	-0.72	-0.02	-55.63	-0.83	35.59	0.47	0.85
NYSE Free Credit Balances	80.49	**2.11**	2.42	0.04	67.13	1.08	0.60
NYSE Free Credit Balances on Cash Accounts	22.34	0.63	58.72	1.11	-7.45	-0.16	0.87
NYSE Free Cash Balances in Margin Accounts	1.66	0.04	-38.28	-1.03	50.08	0.95	1.91
Mutual Fund Balances:							
USA Mutual Fund Equity Funds Total Net Assets	92.74	1.44	49.93	0.65	142.33	1.50	0.66
USA Mutual Fund Equity Funds Cash Percentage	-20.76	-0.69	-74.82	-1.65	21.77	0.56	2.60
USA Mutual Fund Equity Funds Redemptions	-4.74	**-2.89**	-5.32	**-4.64**	10.52	0.35	0.28
USA Mutual Fund Equity Funds New Sales	6.59	0.54	2.44	0.18	16.16	0.60	0.21
USA Mutual Fund Equity and Bond Fund Net Assets	10.50	**6.14**	127.09	**2.09**	9.66	**11.91**	**3.74**
USA Mutual Fund Equity and Bond Fund Cash Percent	-17.87	-0.78	-61.17	-1.42	6.46	0.20	1.59
USA Mutual Fund Equity and Bond Fund Liquid Assets	13.26	0.51	-7.66	-0.19	-190.00	0.63	0.34
USA Mutual Fund Equity and Bond Fund Redemptions	-10.50	-0.91	-18.90	-0.99	-5.32	-0.28	0.25
USA Mutual Fund Equity and Bond Fund New Sales	7.89	0.85	15.15	0.99	5.21	0.39	0.24
Number of Dividend News:							
Moody's Monthly Decreased Dividends	40.61	1.57	40.15	0.92	28.67	0.63	0.03
Moody's Monthly Extra Dividends Declared	-63.32	-1.38	-49.04	-0.81	-72.71	-0.96	0.06
Moody's Monthly Increased Dividends Declared	-97.86	**-1.97**	-29.62	-0.32	-159.24	**-1.93**	1.07
Moody's Monthly Omitted Dividends	7.60	0.24	23.30	0.46	-19.25	-0.36	0.32
Moody's Monthly Resumed Dividends	15.28	0.81	39.00	**2.02**	-14.91	-0.46	2.05
S&P Monthly Dividend Decreases Declared	0.43	0.45	0.34	0.13	0.58	0.72	0.01
S&P Monthly Extra Dividends Declared	4.48	**2.17**	5.04	1.46	3.07	0.91	0.17
S&P Monthly Increased Dividends Declared	2.11	0.57	-0.93	-0.26	7.81	1.08	1.19
S&P Monthly Omitted Dividends Declared	0.88	0.68	1.10	0.73	-0.07	-0.03	0.19
S&P Monthly Resumed Dividends Declared	2.85	**1.89**	7.01	**3.16**	0.71	0.35	**4.72**

Table 3.7 Continued

Market Indicators	Full Sample β (*10⁻³)	Full Sample t-stats	High Sentiment β1 (*10⁻³)	High Sentiment t-stats	Low Sentiment β2 (*10⁻³)	Low Sentiment t-stats	Chi-statistic
Panel B: Market Strength Indicators							
Total Volume:							
NYSE Total Volume	0.09	0.83	0.61	**2.24**	0.54	**1.74**	0.03
Total Volume Turnovers:							
NYSE Share Volume Turnover	5.39	0.13	23.08	0.57	-113.88	**-1.69**	**3.05**
NYSE Annual Share Value Turnover	28.23	0.64	194.47	1.43	-207.02	-1.47	**4.28**
Short-term Trading Indices:							
NYSE Short-term Trading Index	-0.49	**-2.15**	-0.49	-1.11	-0.49	**-2.01**	0.00
NASDAQ Short-term Trading Index	-0.01	-1.16	0.00	0.85	-0.02	-1.28	2.02
Daily Total Market Advances & Declines:							
NYSE Advances	0.51	**2.98**	1.18	**2.39**	0.66	**1.88**	0.74
NYSE Declines	-0.72	**-3.65**	-1.13	**-3.47**	-1.31	**-2.57**	0.08
NYSE Net Advances	0.00	0.49	0.00	0.79	0.00	0.75	0.11
NYSE AD Line	0.00	-0.35	0.00	0.19	-0.01	-0.71	0.53
NYSE Percentage Net Advances	0.00	0.36	0.00	0.79	0.00	0.76	0.11
NASDAQ Advances	0.23	1.48	-0.13	-0.28	0.28	1.65	0.65
NASDAQ Declines	-0.10	**-3.41**	-0.07	**-11.09**	-1.27	**-2.46**	**5.35**
NASDAQ Net Advances	0.00	-0.50	0.00	0.43	0.00	-0.94	0.54
NASDAQ AD Line	0.00	-0.22	0.00	0.44	0.00	-0.46	0.41
NASDAQ Percentage Net Advances	0.00	-0.51	0.00	0.41	0.00	-0.94	0.51
Alternext Advances	1.18	**4.02**	1.32	**1.87**	1.01	**3.54**	0.16
Alternext Declines	-1.04	**-2.46**	-1.16	**-2.06**	-0.87	**-1.95**	0.16
Alternext Net Advances	0.01	0.80	-0.01	-0.35	0.01	1.04	0.80
Alternext AD Line	0.00	-0.03	0.00	0.31	0.00	0.08	0.04
Alternext Percentage Net Advances	0.01	0.60	0.00	0.00	0.01	1.06	0.83
Weekly Total Market Advances & Declines:							
NYSE Weekly Advances	-1.49	**-3.33**	0.47	0.47	-2.24	**-5.14**	**6.16**
NYSE Weekly Declines	0.65	1.21	1.64	1.46	0.41	0.40	0.64
NYSE Net Advances	0.00	0.22	0.01	0.75	-0.01	-0.36	0.58
NYSE AD Line	-1.20	-0.52	-3.08	-0.03	-21.32	-0.38	0.03
Daily Total Maket New Highs & New Lows:							
NYSE New Highs	0.14	**3.61**	0.13	0.66	0.11	**8.51**	0.01
NYSE New Lows	-0.13	-1.50	-0.33	-1.19	-0.18	-1.01	0.22
NYSE Net New Highs	0.04	**1.77**	0.03	1.25	0.00	0.10	0.40
NYSE Cumulative Highs	-0.01	-0.34	-0.02	-0.50	0.00	0.13	0.24
NYSE Percentage Net New Highs	0.04	1.60	0.03	1.35	0.00	0.16	0.42
NASDAQ New Highs	-0.16	-0.43	-0.17	-0.43	-0.13	-0.22	0.00
NASDAQ New Lows	0.25	1.26	0.31	0.79	0.21	0.96	0.04
NASDAQ Net New Highs	-0.01	-0.21	-0.03	-0.71	0.04	0.70	0.96
NASDAQ Cumulative Highs	0.03	0.98	0.06	**1.91**	-0.01	-0.25	1.81
NASDAQ Percentage Net New Highs	-0.01	-0.22	-0.03	-0.76	0.04	0.75	1.09
Alternext New Highs	0.20	**2.23**	0.60	**2.39**	0.29	**1.82**	1.07
Alternext New Lows	-0.06	-0.89	-0.03	-0.14	-0.07	-0.82	0.03
Alternext Net New Highs	0.00	0.11	-0.04	-0.64	0.04	0.71	0.89
Alternext Cumulative Highs	-0.03	-0.88	-0.08	-1.59	0.00	0.04	1.16
Alternext Percentage Net New Highs	0.01	0.30	-0.03	-0.58	0.04	0.81	0.95
Weekly Total Maket New Highs & New Lows:							
NYSE Weekly New Highs	0.11	0.26	1.42	**2.26**	-0.24	-0.37	**3.43**
NYSE Weekly New Lows	-0.30	-0.74	0.78	0.52	-0.77	-0.79	0.76
NYSE Net New Highs	0.11	**1.88**	0.66	**2.13**	0.03	0.56	**4.01**
NYSE Cumulative Highs	-0.01	**-3.62**	31.60	0.25	-0.01	**-3.46**	0.06

This table reports the OLS results of the regression model $R_t = \alpha_t + \beta_1 D_{t-1} I_{t-1} + \beta_2(1-D_{t-1})I_{t-1} + \varepsilon_t$. R_t represents S&P 500 periodic returns calculated as log differences of the S&P 500 Index values, I_{t-1} represents periodic percentage changes of market indicators. D_{t-1} is a dummy variable that equals 1(0) during high(low) sentiment periods measured by using the Baker and Wurgler (2006) sentiment index. Therefore β_1 and β_2 measure the predictability of a market indicator during expansions and contractions respectively. I replicate the full sample OLS results for comparison in the first two columns, then I report β_1 and β_2 with associated *t*-statistics, and the last column reports *chi*-statistics testing the null hypothesis that β_1 and β_2 are equal. I obtain all data from the Global Financial Data. The *t*-statistics and *chi*-statistics reported are White standard errors corrected and marked in bold if significant at 10% significance level. Panel A and Panel B report results for market sentiment and market strength indicators respectively.

in Tables 3.8 and 3.9 for the two regimes. However, I find that none of the market indicators outperform the market in terms of the Sharpe ratio or Jensen's α. The results show that predictability does not strengthen under different sentiment regimes and my main conclusion in the full-sample remains robust.

3.6 Robustness Checks

I perform several robustness checks and find my conclusions hold. First, in the previous OLS rolling window regression analysis, quite a few of my market indicators exhibit the widening of the confidence bounds problem. And this may be a sign of volatility clustering. Therefore I used the GARCH (1, 1) instead of the OLS model to replicate my analysis. On the other hand, outliers can be another issue that may cause the instability of indication. To deal with this issue, I also replicate my analysis using robust regressions to control the effect of potential outliers in the dependent variable side. In addition, in previous analysis I only test the economic significance of the market indicators that show significant predictability in both sub-samples under several alternative models. This may be too restrictive. I loosen my criteria; I additionally test the economic significance for the indicators that show significant predictability in the full-sample analysis but not in the sub-sample analysis. After all these checks, I find technical market indicators still show very limited predictive ability.

Moreover, I also use an alternative dataset to define the business cycles - the CFNAI (Chicago Fed National Activity Index)[23] data that starts from 1967. Compare with the

[23] http://www.chicagofed.org/webpages/publications/cfnai/

Table 3.8: High Sentiment Periods Economic Significance Test

Market Indicators	Frequency	N	Buy & Hold Strategy Mean ($*10^{-3}$)	Buy & Hold Strategy Std. Dev. ($*10^{-2}$)	Buy & Hold Strategy Sharpe Ratio ($*10^{-2}$)	Technical Strategy Mean ($*10^{-3}$)	Technical Strategy Std. Dev. ($*10^{-2}$)	Technical Strategy Sharpe Ratio ($*10^{-2}$)	t-stats	α ($*10^{-3}$)	t-stats	β	t-stats
Panel A: Market Sentiment Indicators													
NYSE Short Sales-Members	Weekly	930	0.86	2.36	0.13	0.13	1.03	-6.84	**2.23**	-0.62	**-2.02**	0.20	**5.07**
NYSE Short Sales-General Public	Weekly	970	0.86	2.36	0.13	0.53	1.26	-2.36	0.87	-0.25	-0.70	0.28	**7.01**
NYSE Short Sales-Specialists	Weekly	927	0.86	2.36	0.13	0.58	1.00	-2.45	0.81	-0.21	-0.69	0.18	**5.09**
NYSE Short Sales-Total	Weekly	938	0.86	2.36	0.13	0.24	1.13	-5.19	**1.77**	-0.51	-1.53	0.23	**5.84**
AAII Neutral Index	Weekly	508	-0.14	2.70	-2.19	0.33	1.02	-1.21	0.21	0.02	0.05	0.14	**3.19**
CBOE DJIA Volatility Index	Daily	714	-0.11	1.92	-0.66	0.01	0.00	0.00	0.13	0.00	**N/A**	0.00	**N/A**
USA Mutual Fund Equity Funds Cash Percentage	Monthly	228	4.98	4.40	4.22	5.47	2.55	9.19	0.84	1.55	1.11	0.34	**5.90**
USA Mutual Fund Equity Funds Redemptions	Monthly	145	2.09	4.86	-0.85	2.63	3.29	0.38	0.19	-0.36	-0.18	0.47	**5.41**
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	241	4.78	4.62	3.07	3.80	2.33	1.87	0.20	-0.11	-0.08	0.26	**4.04**
Moody's Monthly Resumed Dividends	Monthly	243	5.77	4.35	5.62	4.46	2.61	4.34	0.23	-0.05	-0.04	0.35	**5.53**
S&P Monthly Resumed Dividends Declared	Monthly	232	6.26	4.51	6.40	4.37	3.09	3.23	0.63	-0.13	-0.08	0.46	**5.14**
Panel B: Market Strength Indicators													
NYSE Total Volume	Daily	5585	0.27	1.14	1.44	0.19	0.70	1.25	0.16	0.04	0.49	0.37	**19.24**
NYSE Advances	Daily	4843	0.27	1.14	1.44	-0.01	0.36	-3.21	**2.99**	-0.11	**-2.23**	0.10	**11.35**
NYSE Declines	Daily	4987	0.27	1.14	1.44	-0.01	0.51	-2.22	**2.61**	-0.12	**-1.88**	0.19	**13.10**
NASDAQ Declines	Daily	4910	0.24	1.18	1.27	0.25	0.75	2.06	0.65	0.09	1.15	0.41	**19.02**
Alternext Advances	Daily	4902	0.27	1.14	1.44	-0.04	0.42	-3.50	**3.30**	-0.14	**-2.58**	0.13	**11.33**
Alternext Declines	Daily	5056	0.27	1.14	1.44	0.01	0.53	-1.83	**2.37**	-0.11	**-1.68**	0.21	**13.89**
NASDAQ Cumulative Highs	Daily	4541	0.23	1.21	1.20	0.26	0.78	2.14	0.75	0.11	1.21	0.42	**18.75**
Alternext New Highs	Daily	4875	0.27	1.15	1.47	0.02	0.49	-1.74	**2.21**	-0.09	-1.37	0.18	**14.00**
NYSE Weekly New Highs	Weekly	1199	1.36	2.34	2.61	0.70	1.27	-0.33	0.32	-0.17	-0.52	0.29	**8.08**
NYSE Net New Highs	Weekly	1151	1.62	2.33	3.78	1.12	1.40	2.72	0.41	0.13	0.40	0.36	**9.97**

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability during high sentiment periods. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, then I report *t*-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated *t*-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level. The estimations are based on the OLS regression results.

Table 3.9: Low Sentiment Periods Economic Significance Test

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Odd Lot Purchases	Daily	5175	0.24	1.17	1.26	0.01	0.89	-0.96	**2.22**	-0.17	**-2.08**	0.56	**25.61**
NYSE Short Sales-Members	Weekly	1002	0.86	2.36	0.13	0.81	0.68	-0.31	0.13	-0.07	-0.34	0.09	**3.32**
NYSE Short Sales-General Public	Weekly	1012	0.86	2.36	0.13	0.83	0.78	-0.05	0.05	-0.05	-0.19	0.12	**4.11**
NYSE Short Sales-Specialists	Weekly	1005	0.86	2.36	0.13	0.76	0.72	-1.00	0.33	-0.14	-0.62	0.10	**3.49**
NYSE Short Sales-Total	Weekly	1009	0.86	2.36	0.13	0.64	0.72	-2.57	0.79	-0.23	-1.01	0.10	**3.66**
NYSE Short Interest Ratio	Weekly	263	4.78	4.62	3.07	2.64	2.74	-2.63	0.96	-0.63	-0.46	0.29	**3.84**
AAII Bullish Index	Weekly	538	-0.14	2.70	-2.19	0.29	1.28	-1.30	0.20	-0.08	-0.16	0.22	**4.70**
CBOE S&P 500 Volatility Index	Daily	2935	0.04	1.36	-0.25	0.05	0.83	-0.26	0.00	-0.08	-0.71	0.39	**14.17**
CBOE NASDAQ Volatility Index	Daily	1069	-0.01	1.58	-0.45	0.20	0.76	1.86	0.79	0.00	-0.02	0.23	**4.98**
CBOE S&P 100 Volatility Index	Daily	2956	0.04	1.36	-0.25	0.14	0.84	0.77	0.66	0.00	0.01	0.39	**14.23**
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	266	4.78	4.62	3.07	2.23	2.71	-4.18	1.23	-1.03	-0.75	0.30	**4.06**
Moody's Monthly Increased Dividends Declared	Monthly	246	5.77	4.35	5.62	3.90	2.61	2.16	0.59	-0.05	-0.04	0.32	**4.31**
Panel B: Market Strength Indicators													
NYSE Total Volume	Daily	5512	0.27	1.14	1.44	0.08	0.81	-0.27	**1.66**	-0.10	-1.27	0.49	**22.07**
NYSE Share Volume Turnover	Daily	258	4.78	4.62	3.07	4.04	2.34	2.93	0.02	1.00	0.84	0.21	**4.08**
NYSE Short-term Trading Index	Daily	4959	0.27	1.14	1.41	-0.13	0.53	-4.38	**4.22**	-0.27	**-4.13**	0.22	**10.60**
NYSE Advances	Daily	4901	0.27	1.14	1.44	-0.11	0.37	-5.77	**4.69**	-0.24	**-4.76**	0.11	**6.67**
NYSE Declines	Daily	4918	0.27	1.14	1.44	-0.09	0.48	-4.01	**3.83**	-0.23	**-3.77**	0.18	**10.07**
NASDAQ Advances	Daily	4403	0.24	1.18	1.27	-0.12	0.52	-4.01	**3.51**	-0.23	**-3.35**	0.20	**10.82**
NASDAQ Declines	Daily	4273	0.24	1.18	1.27	-0.16	0.50	-4.92	**4.04**	-0.28	**-4.02**	0.18	**9.60**
Alternext Advances	Daily	4931	0.27	1.14	1.44	-0.06	0.41	-4.07	**3.66**	-0.19	**-3.62**	0.13	**8.57**
Alternext Declines	Daily	5100	0.27	1.14	1.44	0.07	0.66	-0.54	1.60	-0.13	**-1.72**	0.32	**12.71**
NYSE Weekly Advances	Weekly	1059	1.36	2.34	2.61	0.63	1.36	-0.86	1.32	-0.22	-0.63	0.34	**6.00**
NYSE New Highs	Daily	5556	0.28	1.15	1.51	0.06	0.85	-0.59	**2.16**	-0.11	-1.47	0.54	**24.73**
Alternext New Highs	Daily	5249	0.27	1.15	1.47	-0.01	0.72	-1.59	**2.66**	-0.16	**-2.13**	0.40	**18.38**
NYSE Cumulative Highs	Weekly	1196	1.64	2.33	3.86	0.94	1.62	1.19	1.19	-0.27	-0.80	0.48	**11.25**

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability during low sentiment periods. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, then I report *t*-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated *t*-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level. The estimations are based on the OLS regression results.

NBER data, the CFNAI data is published in real time and thus is free of the hindsight bias. The results stay similar, no indicator predict market significantly under either contractions or expansions. Last but not least, I also check if my results are sensitive to the 2008 financial crisis period, also I remove top and bottom 5% extreme observations from the distribution of each market indicator to control for outliers from the predictive variable direction. My results stay robust. To save space, I present the detailed results on these robustness checks in Appendix 2.

3.7 Conclusion

I review the predictability of a wide range of 93 technical market indicators in predicting the S&P 500 returns. This adds to the literature with evidence from widely used but less examined market indicators, to more conclusively answer the question of whether technical analysis is useful or not. Overall, I do not find the market indicators generate profits that beat the buy and hold strategy. This result does not change if I consider the possibility of regime-switching predictability on business cycles or sentiment cycles. Moreover, my results remain robust if I use a GARCH (1,1) or robust regression method. With previous mixed findings on price-based technical indicators, it is still not easy to provide a simple positive or negative answer to the broad question of whether or not technical analysis is useful. My results, at least, make the answer not inconclusive with evidence from the family of market indicators missing.

Chapter 4 Popularity versus Profitability: Evidence from Bollinger Bands

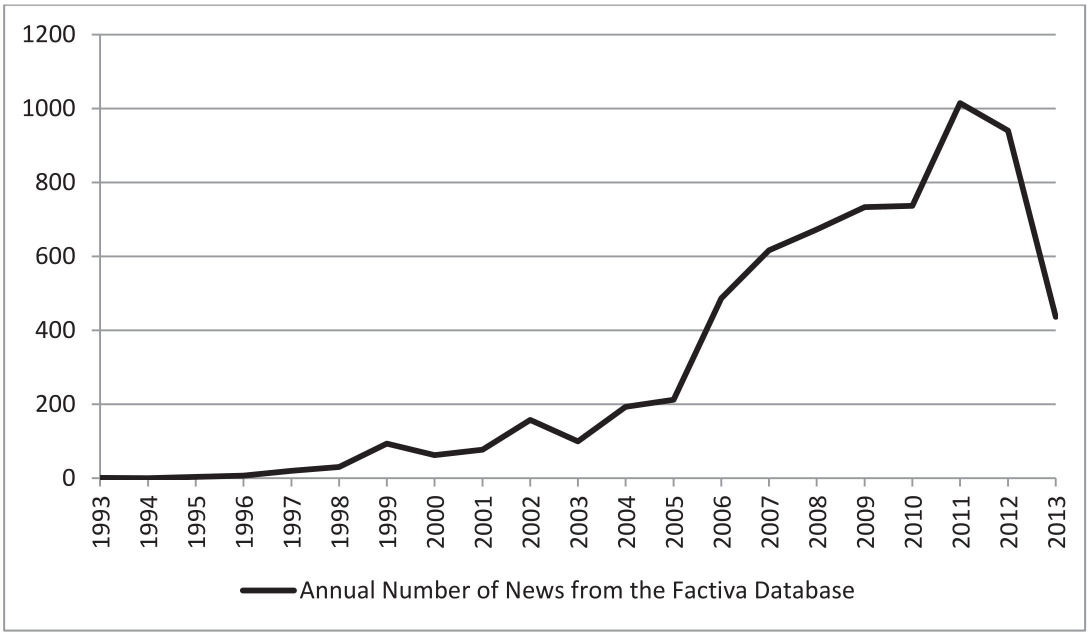
4.1 Introduction

As documented in Chapter 3, despite the ongoing debate in the academic literature on its profitability, technical analysis remains popularly used by practitioners. Among numerous technical indicators, techniques involving Bollinger Bands are some of the most widely used. In 1983, just over 30 years ago, John Bollinger introduced Bollinger Bands on the Financial News Network (which eventually became CNBC), where he was chief market analyst.[24] Ever since, Bollinger Bands gradually gained popularity among investors. In 2001, Bollinger published his influential work on this indicator, *Bollinger on Bollinger Bands*. In four years' time, the English version of the book witnessed seven editions.[25] As of this writing (2014), his book has been translated into 11 languages.[26] Recent survey results suggest Bollinger Bands have become a technical analyst favorite. Abbey and Doukas (2012) find that, over the period 2004–2009, Bollinger Bands were the most favored technical indicator based on a sample of 428 individual currency traders dominating several popular technical indicators, including the relative strength index, moving average convergence divergence, and moving average crossovers. Ciana (2011) documents Bollinger Bands as the third most popular technical indicator worldwide

[24] See http://www.prweb.com/releases/2008/04/prweb814374.htm and http://www.bollingerbands.com/services/bb/rules.php .
[25] See https://st0.forex-mmcis.com/en_US/books/Other_Books/John_Bollinger_-_Bollinger_on_Bollinger_Band.pdf.
[26] The 11 languages include Chinese (simplified and traditional), French, German, Italian, Japanese, Korean, Lithuanian, Russian, Turkish, and Spanish (http://en.wikipedia.org/wiki/John_Bollinger).

among users of the Bloomberg Professional service from 2005 to 2010.[27] Bollinger Bands were trademarked by Bollinger in 2011. Nowadays almost all major financial websites and analytical software providers, such as Yahoo and Bloomberg, incorporate Bollinger Bands. The growing attention to Bollinger Bands becomes apparent when I plot the annual number of news articles on Bollinger Bands published in the United States from the Factiva database.[28] The first news article appears in 1993 and the number of articles rises steadily until 2001, when it reaches 77. It then jumps in 2002 to 157 news articles by year's end, more than double the 77 articles of the preceding year. This seems to be a good indication of the impact of the 2001 *Bollinger on Bollinger Bands* publication. Attention on Bollinger Bands continues to grow and the annual number of articles exceeded a thousand at its peak in 2011.

Figure 4.1: Popularity of Bollinger Bands in the US 1993-2013



[27] The first and the second most popular indicators are the relative strength index and moving average convergence divergence, respectively.

[28] Many previous studies use media coverage to measure investor attention (e.g., Barber & Odean, 2008; Fang & Peress, 2009). Due to data availability, I could only measure investor attention to Bollinger Bands in the United States. I exclude all discontinued sources in Factiva to obtain the total number of news.

Did the increasing popularity affect the potential profits of Bollinger Bands-based trading strategies? This question is particularly interesting if I consider the long-debated "self-destructive" nature of many famous return predictability anomalies that have disappeared over time. By the self-destructiveness, researchers argue that the profitability of an efficient trading strategy can be fully eliminated by its own popularity among investors, because investors compete with each other to arbitrage away all trading opportunities. For example, by using the updated US stock market data that starts earliest in 1831 and ends in 2001, Schwert (2003) demonstrates that a variety of previously documented anomalies, including the size effect, the value effect, the weekend effect, and the dividend yield effect, seem to lose their predictive power after the papers that made them famous were published. In addition, the author finds that the small-firm turn-of-year effect and the predictive ability of variables such as dividend yield and inflation are much weaker. Schwert notes that the anomalies documented that have disappeared are likely to be those were implemented by practitioners into trading strategies, while the less-implemented anomalies became weaker but continued to exist. Similarly, McLean and Pontiff (2014) find that profitable trading studies from academic studies seem to disappear out of sample. Of course, evidence to support this argument is never conclusive, since correlation does not imply causation and some anomalies continue to exist even after they have been reported.[29] Still it is the best indication I may be able to obtain from the data. However, if trading profits reported in academic studies can be traded away, I

[29] A number of studies document that the so-called Halloween/Sell in May effect persists out of sample (for instance, Andrade, Chhaochharia, & Fuerst, 2012; Grimbacher, Swinkels, & van Vliet, 2010; Jacobsen & Visaltanachoti, 2009; Zhang and Jacobsen, 2014). Moreover, as Bouman and Jacobsen (2002) document in their original study, the Sell in May effect was a well-known market wisdom before the start of their sample, but the effect persisted in their sample.

expect that, given the dramatically increased attention and popularity of Bollinger Bands, their profitability should have disappeared almost instantaneously

While examination of the profitability of a favorite technical indicator of practitioners is interesting in itself, the study of Bollinger Bands also provides an ideal opportunity to verify whether and how the popularity of trading strategies affects their profitability. Bollinger Bands, in this respect, seem an interesting natural experiment for the following reasons. First, unlike other popular technical analysis strategies, the trading strategy was not known before 1983. Second, the strategy is easy to implement. Like many technical indicators, Bollinger Bands use only information derived from historical prices to predict future returns. This means investors have easy access to the data. In addition, the strategy itself is relatively easy to implement, since it does not involve sophisticated financial modeling or parameter estimation. Third, based on newspaper articles and other key data, I have a reasonable indication of the increasing popularity over time and large enough data samples to measure profits over time. Lastly, the gradual development of Bollinger Bands in international markets may be of extra interest. Bollinger Bands originated in the US market and *Bollinger on Bollinger Bands* was published first in the United States. So if investors' usage has an impact on the strategy's profitability, I should expect the impact to show up in the United States first and then gradually affect other countries.

My main result is that my evidence is consistent with the often heard hypothesis that potentially profitable trading strategies indeed quickly self-destruct with increasing popularity. To illustrate the main results of my paper, it may be good to compare the profitability of a Bollinger Band-based trading strategy on the Standard & Poor's (S&P) 500 with the popularity of Bollinger Bands from 1993 to 2013 (where I proxy popularity by the number of news articles in the Factiva database on Bollinger Bands, reported in Figure 4.1). I plot the results in Figure 4.2. The black solid line plots the annual returns of the strategy and the black dotted line plots the linear trend of the annual returns. Intriguingly, the returns are mostly negative during this period and such losses even have worsened over time. At the same time, Bollinger Bands have received growing attention from investors (as shown in Figure 4.1). Figure 4.3 shows annual returns before 1993. Bollinger Bands-based trading strategies seem to have worked well before the mid-1980s and the returns are generally positive for nearly 60 years; however, the returns are mostly negative afterward. The trend line indicates apparent downward profitability in this longer sample. Interestingly, the trend line intersects with the *x*-axis around the mid-1980s (i.e., Profit = 0) and this generally coincides with when Bollinger Bands were first introduced. This illustrates the main point of my paper.

More formally, I carry out statistical tests to examine profitability on an international sample. I include 14 major international stock markets: Australia, France, Germany, Hong Kong, Italy, Japan, Korea, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States, with both the Dow Jones Industrial Average (DJIA) and the S&P 500 for the latter. For each market, I use the longest sample available that starts between 1885 (DJIA) and 1971 (Madrid SE General Index) and all samples end in 2014. In addition to the full sample, I use three sub-samples that match the key dates of Bollinger Bands' development—before 1983, from 1983 to 2001, and since 2002—to allow a comparison on the profitability over time. My results generally match with the preliminary check above. In the full sample, Bollinger Bands show strong predictive ability in all 14 markets. Buy (sell) signals produce significantly positive (negative)

Figure 4.2: Annual Returns of Bollinger Bands-based Trading Strategy in the US 1993-2013

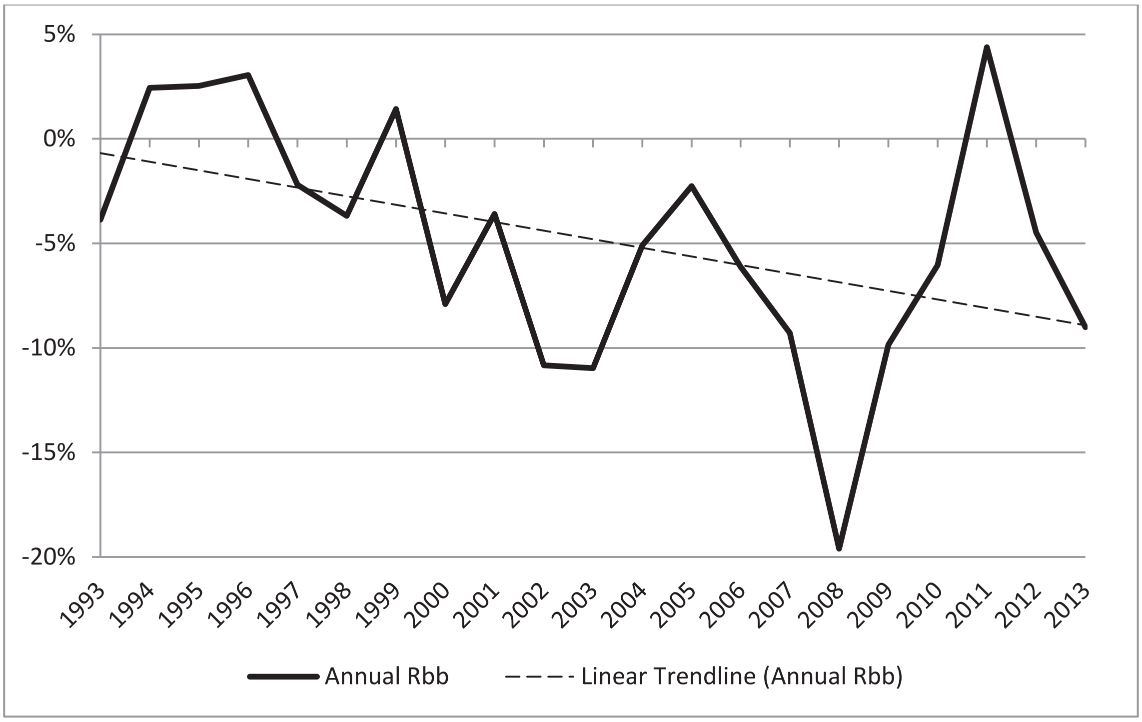
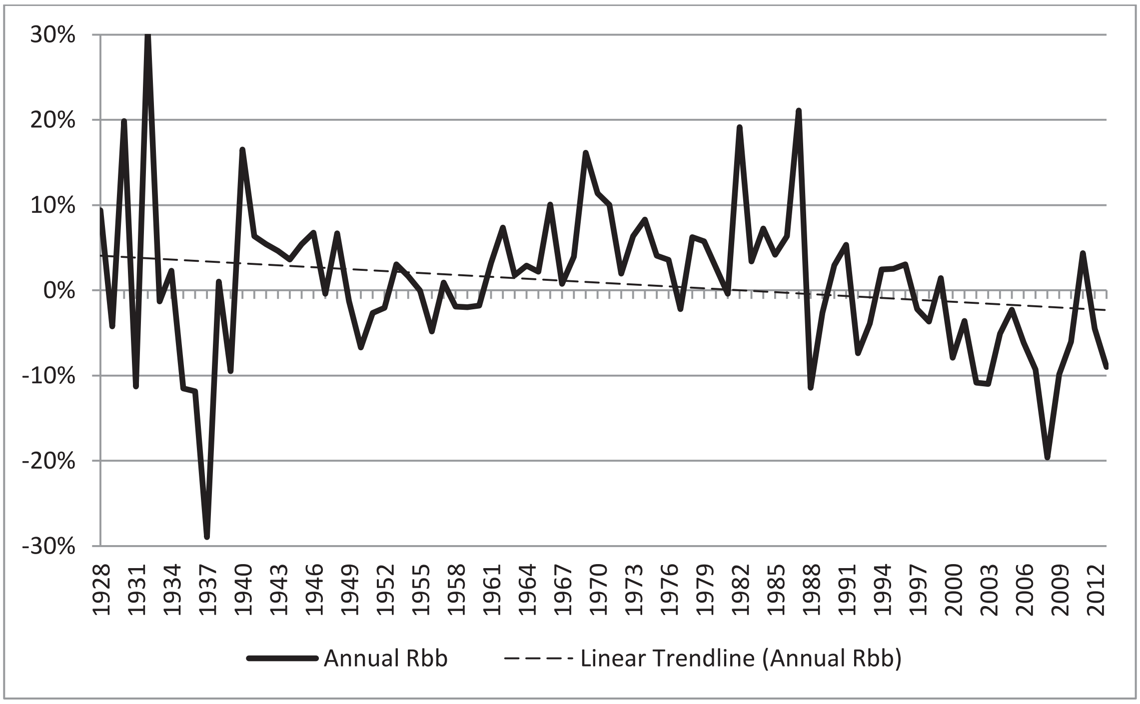


Figure 4.3: Annual Returns of Bollinger Bands-based Trading Strategy in the US 1928-2013



returns that are higher (lower) than the market returns in 14 (12) markets, respectively. Moreover, the average spread between returns conditional on buy and sell signals are statistically positive in all 14 markets. The average spread across 14 markets, 0.294%, is about 10 times higher than the corresponding average market return of 0.026%. I find even stronger profitability in using Bollinger Bands in the first sub-sample before 1983. While Bollinger Bands show strong profitability in all 14 markets as well, the average daily spread between buy and sell signals over 14 markets increases to 0.454%, compared to the average market return of 0.021% in this period. However, in the next sub-sample, from 1983 to 2001, Bollinger Bands' profitability decreases and even disappears in a number of markets. Buy (sell) signals generate higher (lower) returns than the market in 10 (eight) markets only and the average spread between conditional buy and sell returns is significantly positive in 11 markets. Note that Bollinger Bands lose their profitability in two US markets, where they originate, immediately in the period during which they are introduced. Lastly, since 2002, their profitability shrinks further to nearly none. Only in two markets, Italy and New Zealand do Bollinger Bands still show possible predictive ability, although further evidence shows that such predictability is also largely weakened compared with before. More intriguingly, Bollinger Bands even generate significantly lower returns than the market in the S&P 500 market. The results from this sub-sample also confirm the importance of Bolllinger's influential publication, as studied by previous studies. In most international markets, the forecastability of Bollinger Bands disappeared after the 2001 publication.

Further investigation shows that in seven markets, returns of a Bollinger Bands-based strategy are significantly lower during 1983-2001 than those before 1983, with an average decline of -56% across all markets. And in all 14 markets except only Italy, returns are significantly lower after 2002, the average decline is -156%. More importantly, the declines after 2002 in all 14 markets are significantly lower than those during 1983-2001 suggesting an impact of the key publication. If I plot the annual returns, they immediately changed from positive to negative in the US market in 1983; soon after in the Japanese market, around 1990; then in a number of European stock markets, including the UK, Swiss, French, and German stock markets; and, lastly, in Asian-Pacific stock markets, including the Australian, Korean, and Hong Kong markets.

I conduct several additional robustness checks and find the conclusion holds. First, I use a different version of Bollinger Bands, "Squeeze," which Bollinger emphasizes as the best application of Bollinger Bands but that has not yet received any academic attention (Bollinger, 2001, p. 63). Second, to closely monitor profitability over time, I check the average returns per signal by using rolling window regressions and I also track the annual returns of Bollinger Bands-based trading strategies. Third, I take transaction costs into account and measure the economic significance of my findings by calculating both Jensen's α and Sharpe ratios. In addition, while the default version of Bollinger Bands aims to capture relatively medium-term trends, I alter the parameter settings as suggested in *Bollinger on Bollinger Bands* to measure the short- and long-term profitability. I also use GARCH(1,1) or robust regression models to estimate parameters instead of ordinary least squares (OLS) to account for possible heteroskedasticity or outlier problems. My results remain similar.

My results indicate that trading on Bollinger Bands may no longer be profitable (which may also explain why academic studies to date, discussed in detail in Section 3, have produced mixed results[30]). However, I feel the more general conclusion may be of greater interest, since my results suggest that no matter how profitable a trading result has been in the past, future performance may be strongly affected by how well known and popular the trading strategy becomes. In that sense, I feel my results have much wider implications. While it is often assumed that trading will make the profits of anomalies disappear, few studies to date have tried to see whether this actually happens and under what conditions. My results warn about how investor trading can fully destroy such profitability over time. Another interesting implication is that the documentation of anomalies or profitable trading strategies may change the underlying return-generating process itself. Last but not least, although I cannot fully eliminate the possibility of data snooping, I take several measures to best avoid such a risk. I discuss this issue in more detail in the next section.

4.2 Anomalies and Data Snooping

My analysis suggests that a historical profitable trading strategy can use its usefulness over time and this phenomenon may relate closely to the strategy's usage. Such a finding is in line with a strand of literature that suggests that many so-called return predictability anomalies disappear over time. For example, by using different methodologies, Mehdian and Perry (2002) and Gu (2003) reach the same conclusion, that the January effect has disappeared from US stock market indices since 1988. The former uses a sample from 1964 to 1998 and later a sample from 1957 to 2000. In addition, based on up-to-date US

[30] Studies on Bollinger Bands include those of Leung and Chong (2003), Balsara, Chen, and Zheng (2007, 2009), Lento, Gradojevic, and Wright (2007), Lento (2009), Mühlhofer (2009), Butler and Kazakov (2010), Lento and Gradojevic (2011), and Abbey and Doukas (2012).

stock market data, Schwert (2003) comprehensively studies the persistence of a variety of anomalies on samples that start at the earliest in 1831 and end in 2001. The author finds that the size effect, the value effect, the weekend effect and the dividend yield effect seem to lose their predictive power after the papers that made them famous were published. In addition, Schwert finds that the small-firm turn-of-year effect and the predictive ability of variables such as dividend yield or inflation are much weaker. In another comprehensive study, Marquering, Nisser, and Valla (2006) use a sample from 1960 to 2003 to examine the persistence of several well-known stock market calendar anomalies on US stock market indices before and after their publication. The authors provide strong evidence that the weekend effect, the holiday effect, the time-of-the-month effect and the January effect disappeared after these anomalies were published. The turn-of-the-month effect still seems present and the small-firm effect has recently resurrected. The anomalies have disappeared not only in the US market, but also in many international stock markets. In the UK stock market, Dimson and Marsh (1999) study the small-firm effect and conclude that the size effect not only disappeared but even reversed since its publication during their sample from 1955 to 1998. Zhang and Jacobsen (2013) use over 300 years of monthly UK stock market data to examine the persistence of monthly seasonals and conclude that monthly seasonals are largely sample specific. Fountas and Segredakis (2002) conclude that the January effect has largely disappeared for 18 emerging markets from 1987 to 1995. Using a longer sample over more countries, Darrat, Li, Liu, and Su (2011) also suggest that the January effect persists in only three of the 34 international stock markets they examine from 1988 to 2010.[31]

[31] While studies such as those of Sullivan, Timmermann, and White (2001), Schwert (2003), Marquering,

As discussed in Chapter 2, researchers point to the importance of data-snooping bias in explaining the disappeared anomalies. After taking into account possible data-snooping bias by using a bootstrap methodology, Sullivan, Timmermann, and White (2001) find that a number of anomalies no longer hold out of sample on 100 years of US stock market data from 1897 to 1996, including day of the week effects, week of the month effects, month of the year effects, turn of the month effects, turn of the year effects and holiday effects. Other studies reconsider the profitability of historically useful trading strategies by using fresh samples. For example, my results in Chapter 2 find that classic technical indicators such as moving averages and trading range breakouts lose their predictive ability out of sample in the US market, not just in a later period, from 1987 to 2012, but also in an earlier period, from 1885 to 1896. This indicates that the in-sample results are likely to be sample specific.

While data snooping remains a possible explanation for the disappeared anomalies as shown in Chapter 2, a competing explanation is investor overuse, which eliminates all trading opportunities of a true anomaly. This explanation is worth noting, especially if I consider anomalies that persist after accounting for data snooping. For example, Sullivan

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Nisser, and Valla (2006), and Zhang and Jacobsen (2013) provide in-depth overviews of the evidence of various return predictability anomalies, I only briefly describe the anomalies here. The January effect was first noticed by Rozeff and Kinney (1976) on the New York Stock Exchange from 1904 to 1974. It refers to the phenomenon of statistically significant differences in mean returns among months due primarily to large January returns. Lakonishok and Smidt (1988) document persistently anomalous returns around the turn of the week, the turn of the month, and the turn of the year and around holidays on the DJIA from 1896 to 1986. The size effect refers to small-capitalisation firms earning higher average returns than those predicted by the capital asset pricing model, or CAPM (Banz 1981; Reinganum 1983). Keim (1983) and Reinganum (1983) show that much of the abnormal return to small firms (measured relative to the CAPM) occurs during the first two weeks in January. This anomaly became known as the small-firm turn of the year effect. The weekend effect was first documented by French (1980), who documents that the average return to the S&P composite portfolio is reliably negative over weekends in the period 1953–1977. Basu (1977, 1983) notes that firms with high earnings-to-price ratios earn positive abnormal returns relative to the CAPM, which is referred to as the value effect.

Timmermann, and White (1999) utilize a bootstrap methodology to validate the predictive ability of technical indicators, including moving averages and trading range breakouts, found by Brock, Lakonishok, and LeBaron (1992) on the DJIA from 1897 to 1986. While the authors find the positive in-sample results are robust to data-snooping bias, they fail to confirm the positive results out of sample on a 10-year fresh sample from 1987 to 1996. They suggest that one reason could be the markets having become more efficient, which eliminates such arbitrage opportunities. McLean and Pontiff (2014) study the out-of-sample predictability of 95 published characteristics that show to predict cross-sectional stock returns, and they find statistical biases seem to reduce the predictability by 25%, while investors' learning reduces the predictability by 31% after accounting for statistical biases.

Therefore, whether an anomaly persists or not can relate closely to its popularity among investors. Put differently, how fast investors learn about the strategies, whether investors use trading strategies based on the anomaly, and how many investors use the strategies matter. However that may not be the full story as some anomalies seem to persist. For example, a number of studies confirm the out of sample persistence of the Halloween indicator since it was first documented by Bouman and Jacobsen (2002) out of sample (for instance, Andrade, Chhaochharia, & Fuerst, 2012; Grimbacher, Swinkels, & van Vliet, 2010; Jacobsen and Visaltanachoti, 2009; Zhang and Jacobsen, 2014). The persistence may be because investors do not trade on these anomalies; alternatively, an anomaly may become a self-fulfilling prophecy (as opposed to a self-defeating prophecy), which is not likely to last long, or there may be institutional or psychological barriers in place that make the anomalies persist. For example, as Bouman and Jacobsen (2002) suggest, if the Halloween effect is caused by investors taking vacations during the summer, it may persist if that behavior does not change.

Previous studies document additional results that support the argument. Peyer and Vermaelen (2009) suggest the buyback anomaly persists in the US market in a fresh sample from 1991 to 2001 and suggest open market repurchases are a response to market overreactions to bad news. Since a repurchase is a unique event in the life of a company, individual shareholders cannot learn from their mistakes. Moreover, tender offers are too infrequent an event to attract professional arbitrageurs, which may well explain the persistence of this anomaly. As another example, Lev and Nissim (2004) show that the accrual anomaly persists in US stock returns from 1965 to 2002 and they suggest the main reason might be because firms with extreme accruals have characteristics that are unattractive to most institutional investors. Individual investors are unable to profit from trading on accruals information due to the high transaction and information costs associated with implementing a consistently profitable accruals strategy. In an international context, Pincus, Rajgopal, and Venkatachalam (2007) re-examine the accrual anomaly in 20 countries from 1994 to 2002 and find it persists in Canada, Australia, the United Kingdom, and the United States. They also conclude that the anomaly is more likely to occur in countries with a common law tradition, which allow the extensive use of accrual accounting, or with a lower concentration of share ownership and these factors reveal earnings management and barriers to arbitrage. Baker, Bradley, and Wurgler (2010) show that the low volatility anomaly has even strengthened in the US market over the 41 years between 1968 and 2008 and this is due to investors' preference for risk and the typical institutional investor's mandate to maximize the ratio of excess returns and tracking error relative to a fixed benchmark without resorting to leverage. In addition, such activity discourages arbitrage activity in high-alpha, low-beta stocks and low-alpha, high-beta stocks.[32]

In my case of Bollinger Bands, although I cannot fully eliminate the possibility that the gradually decreasing profitability of Bollinger Bands is simply a result of data snooping, previous studies show that data-driven results are likely to change immediately out of sample (e.g., my results in Chapter 2), instead of my finding of gradual elimination. Moreover, my results are best safeguarded against data snooping throughout several measures. First, I use the longest sample available for each country. Second, the Bollinger Bands themselves are less examined in the literature compared to classical technical indicators, such as moving averages and trading range breakouts; I also use the original default settings of the Bollinger Bands instead of searching for other trading strategies to fit the sample. Third, my sample is international and I include all countries for which I am able to obtain at least 10 years of daily data for each sub-sample.

4.3 Bollinger Bands

I discuss parameter settings and existing evidence of Bollinger Bands in more detail in this section. While Bollinger Bands are developed 30 years ago, Bollinger suggests that it

[32] Bouman and Jacobsen (2002) document that returns from November to April are significantly higher than returns from May to October in 19 stock markets from 1970 to 1998. This is referred to as the Halloween effect or the sell in May effect. Ikenberry, Lakonishok, and Vermaelen (1995) investigate the stock price performance of firms that announced an open market share repurchase between 1980 and 1990 and they find average abnormal buy-and-hold returns of 12.1% over the four years following the announcement. This is referred to as the buyback anomaly. Sloan (1996) pioneered the documentation of the accruals anomaly. The author finds a negative association between accounting accruals (the non-cash component of earnings) and subsequent stock returns in a sample of US stocks from 1962 to 1991. Finally, the low volatility anomaly refers to high-volatility and high-beta stocks substantially underperforming low-volatility and low-beta stocks in US markets, as first noticed by Black (1972), Black, Jensen, and Scholes (1972), and Haugen and Heins (1975).

is still a valid strategy in today's market.[33] The continuously growing attention from investors even after 30 years is probably also a good indication of their applicability. Bollinger also clearly specifies in his book the best parameter settings for Bollinger Bands. Therefore in this study, I strictly follow the suggested parameter settings so that the results are meaningful to investors; this also avoids potential data-snooping bias from mining different parameter settings for favorable results. Bollinger Bands generally include three parameters, with the following default settings (Bollinger, 2001, p. 23):

- A middle band = 20-day moving averages of the underlying prices,
- An upper band = middle band + 2*standard deviations of the underlying prices, and
- A lower band = middle band – 2*standard deviations of the underlying prices.

I write Bollinger Bands with the default settings as (20,2), where the first and the second numbers represent the number of days used to form the middle band and the number of standard deviations used to form the upper and lower bands, respectively. Bollinger (2001, p. 53) suggests that a window of 20 days capture reasonable intermediate-term price fluctuations and, in statistical terms, the ±2 standard deviations should contain about 95% of the price variations. This means that the price falling outside the bands signals a potential market change.

In more statistical terms, one may argue that the effectiveness of Bollinger Bands is dependent on whether stock returns follow a normal distribution, so that the ±2 standard deviations could eliminate most noises in price changes. While stock returns have an

[33] http://www.bollingerbands.com/services/bb/

unknown distribution, many researchers document evidence that returns are somewhat predictable, the distribution of returns has fat tails and the prices themselves are serially correlated. By using real market data, Grime (2012) finds that instead of finding exact 95% price changes within the bands by definition, about 85% to 90% of price changes are within the bands. Also, the idea of using moving standard deviations in Bollinger Bands adjusts for the serial correlation. Therefore, the statistical properties of Bollinger Bands allow a reasonable approximation of underlying price changes.

The basic application of Bollinger Bands, namely, the volatility breakout method, generates a buy (sell) signal when the underlying price closes outside the upper (lower) band: "Perhaps the most elegant direct application of Bollinger Bands is a volatility-breakout system" (Bollinger, 2001, p. 127).

Other than the breakout method, Bollinger (2001, p. 119) specifically recommends another method of using Bollinger Bands: the Squeeze: "The Squeeze … is without doubt the most popular Bollinger Bands topic." This version of Bollinger Bands introduces another parameter, called the BandWidth (Bollinger, 2001, p. 63):

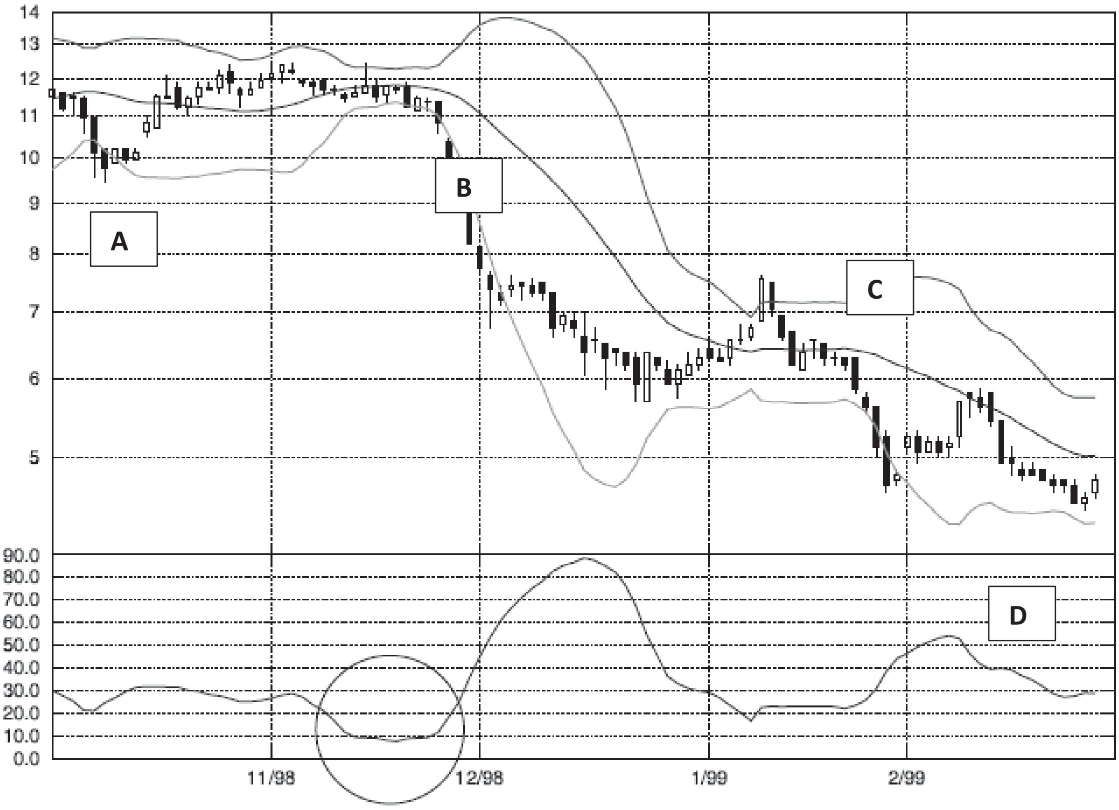
$$\text{BandWidth} = (\text{Upper BB} - \text{Lower BB})/\text{Middle BB}$$

BandWidth shows how wide the Bollinger Bands are by depicting volatility as a function of its average. The intuition is that when the volatility falls to historical lows, the market is likely to experience a major change. The standard version of the Squeeze will generate a buy (sell) signal under two conditions: (1) The price breaks the upper (lower) band and (2) BandWidth drops to its six-month minimum. So, in fact, using BandWidth filters the signals of the volatility breakout method. In addition, Bollinger (2001, p. 24) also recommends several alternative parameter settings, such as (10, 1.9) and (50, 2.1), to capture relatively short- and long-term price variations.

I use an example from *Bollinger on Bollinger Bands* to illustrate. The black bar charts in the upper panel of the graph in Figure 4.4 plot the underlying stock prices and the gray lines plot the upper, middle, and lower Bollinger Bands of the prices. The lower panel of the graph plots the associated BandWidth readings. By using the volatility breakout method, trading signals will be generated at points A through D on the graph. Meanwhile, the Squeeze method only generates a signal at point B, when BandWidth reaches its six-month minimum (as highlighted in the circle in Figure 4.4).

Current academic evidence on Bollinger Bands is generally mixed. I provide a brief review here on current empirical evidence. Several papers document evidence on aggregate stock markets. Balsara, Chen, and Zheng (2009) find that using Bollinger Bands underperforms the market between 1990 and 2007 for three major US stock market indices (the DJIA, the NASDAQ, and the S&P 500), although significant positive returns are observed for a contrarian version of Bollinger Bands. Butler and Kazakov (2010), in contrast, claim positive results when using Bollinger Bands on the DJIA from 1990 to 2009. Instead of using the default parameter settings, the authors use a computer algorithm to optimize the parameters of Bollinger Bands. Leung and Chong (2003) find that the use of Bollinger Bands outperforms the use of moving average envelopes in the G7 and the four Asian Tiger countries from the period 1985 to 2000. The only authors who examine the profitability of Bollinger Bands on individual stocks, Balsara, Chen, and Zheng (2007) observe significant positive returns on buy trades generated by a contrarian version of Bollinger Bands from 1990 to 2005 in the Chinese stock market.

Figure 4.4: The Bollinger Bands – An Example



(Source: Bollinger, 2001, p. 130, Figure 16.3)

The use of Bollinger Bands is also examined in other financial markets. Lento, Gradojevic, and Wright (2007) and Lento and Gradojevic (2011) study the profitability of Bollinger Bands in several US and Canadian aggregate stock markets, as well as forex markets, for the period 1995 to 2004. They conclude that Bollinger Bands do not beat the market anywhere, although profitability may improve for a contrarian version of Bollinger Bands or a combined signal approach with other technical indicators such as trading range breakouts, moving averages, or filter rules. Lento (2009) extends tests on Bollinger Bands to several Asian-Pacific stock and forex markets in various sample periods ranging from 1987 to 2005, including the countries Australia, India, Indonesia, Korea, Japan, Hong Kong, Singapore, and Taiwan. The author finds that the contrarian version of Bollinger Bands can generate profit in these countries. Additionally, in the forex market, Abbey and Doukas (2012) test the profitability of Bollinger Bands in individual currency trading and find that technical currency traders who use the Bollinger Bands underperform relative to their peers who do not use it. Lastly, in the real estate market, Mühlhofer (2009) applies Bollinger Bands on the US National Property Index from 1978 to 2010 and documents results that support their predictability.

4.4 Data and Methodology

My study includes 14 major stock market indices from 13 countries: Australia, France, Germany, Hong Kong, Italy, Japan, Korea, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States. A number of seminal works find that technical trading strategies generate superior returns on the DJIA (e.g., Alexander 1961; Brock, Lakonishok, & LeBaron 1992) and that the S&P 500 proxies for the overall US stock market performance. Therefore I study both the DJIA and the S&P 500 for the United States. My sample includes all countries that have daily stock market data available before 1973, allowing for at least 10 years for the first sub-sample. For each market I use the longest available daily data from the Global Financial Data[34] database. The DJIA has the longest sample, starting in 1885, with Spain having the shortest sample, starting in 1971. All of my samples end in March 2014. This provides me sample periods ranging from 44 years to 130 years for the different markets. I study the predictive ability of Bollinger Bands for the full sample and three sub-samples: before 1983, from 1983 to

[34] See www.globalfinancialdata.com.

2001, and after 2002. I best avoid data-snooping bias in my results by using the longest samples and as many markets as I can. The methodology here is similar to that used in Chapter 2, I follow the methodology of Brock, Lakonishok, and LeBaron (1992) and specifically test the following two null hypotheses:

H1: $R_{buy} - R_{sell} = 0$.

H2: $R_{buy/sell} = R_m$.

I run the following OLS regression for each country to test the null hypothesis H1 that the average returns conditional on Bollinger Bands buy and sell signals are equal. If the Bollinger Bands do not produce useful trading signals, the buy and sell signals should not generate statistically different returns. Therefore, β should not be statistically different from zero in the following regression:

$$R_t = \alpha + \beta D_{t-1} + \varepsilon_t \qquad (1)$$

where

- R_t represents the daily log-returns of a market index,
- D_{t-1} is a dummy variable that equals one (zero) when a buy (sell) signal is generated, and
- ε_t represents the residual term.

I further study the buy and sell signals separately by H2. I use *t*-tests to determine whether the average buy/sell returns are significantly different from the same period market returns. If Bollinger Bands produce useful trading signals, the conditional buy (sell) returns should be higher (lower) than the market returns. I use White standard errors to correct for the potential heteroskedasticity problem and a conservative 10% significance level.

4.5 Main Results

4.5.1 H1

I report my main results from using the Bollinger Bands default settings (20, 2) in Table 4.1. The first three columns report the market index and the sample period used for each country. I then report my results for the full sample and the three sub-sample periods. For each sample period, I report the market returns R_m, the average spread between conditional buy and sell returns $R_{buy} - R_{sell}$, and the t-statistics testing H1, that $R_{buy} - R_{sell}$ is not different from zero. Moreover, I report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively.

Table 4.1: International Results on Bollinger Bands (20, 2)

This table reports the international results on the predictability of Bollinger bands (20, 2). The first three columns report the market index and the sample period used for each country. I then report my results for the full sample and the three sub-sample periods. For each sample period, I report the market returns R_m, the average spread between conditional buy and sell returns $R_{buy} - R_{sell}$, and the t-statistics testing H1, that $R_{buy} - R_{sell}$ is not different from zero. Moreover, I report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. I use a 10% significance level and White standard error corrected t-statistics.

			Full Sample			Before 1983			1983-2001			Since 2002		
Country	**Index**	**Period**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**
				Panel A: Breakout Method (20,2)										
Australia	ASX All-Ordinaries	Jan 1958 - Mar 2014	0.26	3.48	**7.36**	0.21	5.04	**9.95**	0.40	3.25	**3.03**	0.15	0.03	0.02
France	CAC All-Tradable Index	Sep 1968 - Mar 2014	0.27	1.90	**3.22**	0.11	4.11	**5.67**	0.53	2.39	**2.54**	0.04	-2.46	**-1.65**
Germany	CDAX Composite Index	Jan 1970 - Mar 2014	0.18	2.74	**5.08**	0.00	4.25	**9.16**	0.34	3.43	**3.91**	0.12	-0.50	-0.34
Hong Kong	Hang Seng Composite Index	Nov 1969 - Mar 2014	0.45	4.33	**3.65**	0.50	8.17	**3.69**	0.57	4.18	**2.04**	0.21	-0.07	-0.04
Italy	Banca Commerciale Italiana Index	Dec 1956 - Mar 2014	0.19	3.96	**7.14**	0.12	3.70	**4.51**	0.45	4.19	**4.17**	-0.07	3.86	**3.53**
Japan	Nikkei 225 Stock Average	May 1949 - Mar 2014	0.25	1.57	**2.97**	0.39	2.50	**4.05**	0.06	-0.31	-0.30	0.10	1.55	0.95
Korea	Korea SE Stock Price Index	Jan 1962 - Mar 2014	0.44	2.65	**3.05**	0.62	3.41	**2.24**	0.31	2.02	**1.78**	0.34	1.40	0.92
New Zealand	New Zealand SE All-Share Capital Index	Jan 1970 - Mar 2014	0.20	3.91	**8.03**	0.18	4.65	**9.75**	0.26	4.72	**4.74**	0.12	1.77	**2.30**
Singapore	Singapore FTSE Straits-Times Index	Jul 1965 - Mar 2014	0.33	5.79	**8.08**	0.53	7.03	**7.94**	0.22	7.19	**5.09**	0.21	0.92	0.77
Spain	Madrid SE General Index	Aug 1971 - Mar 2014	0.26	4.30	**6.48**	-0.26	8.25	**9.96**	0.63	4.78	**4.64**	0.07	-0.23	-0.16
Switzerland	Switzerland Price Index	Jan 1969 - Mar 2014	0.19	2.01	**3.71**	-0.02	3.60	**5.17**	0.40	2.04	**2.12**	0.10	-0.49	-0.41
UK	FTSE All-Share Index	Dec 1968 - Mar 2014	0.27	2.19	**3.75**	0.24	5.31	**4.81**	0.39	2.09	**2.63**	0.11	-1.66	-1.34
US	S&P 500 Composite Price Index	Jan 1928 - Mar 2014	0.20	1.14	**2.54**	0.14	1.95	**3.74**	0.44	0.46	0.40	0.16	-2.28	**-1.69**
US	Dow Jones Industrials Average	Jan 1885 - Mar 2014	0.18	1.22	**3.78**	0.13	1.57	**4.56**	0.47	0.99	0.76	0.16	-1.57	-1.34
Average			*0.26*	*2.94*		*0.21*	*4.54*		*0.39*	*2.96*		*0.13*	*0.02*	
				Panel B: Squeeze Method (20,2)										
Australia	ASX All-Ordinaries	Jan 1958 - Mar 2014	0.26	3.08	**2.32**	0.21	4.95	**2.57**	0.40	3.02	1.07	0.15	-0.16	-0.06
France	CAC All-Tradable Index	Sep 1968 - Mar 2014	0.27	0.65	0.25	0.11	2.90	0.84	0.53	0.06	0.01	0.04	-1.58	-0.33
Germany	CDAX Composite Index	Jan 1970 - Mar 2014	0.18	4.58	**1.79**	0.00	4.32	**2.43**	0.34	13.01	**3.00**	0.12	-3.88	-0.89
Hong Kong	Hang Seng Composite Index	Nov 1969 - Mar 2014	0.45	1.87	0.42	0.50	12.71	**1.71**	0.57	-6.17	-1.09	0.21	-6.31	-0.89
Italy	Banca Commerciale Italiana Index	Dec 1956 - Mar 2014	0.19	6.55	**3.36**	0.12	6.10	**2.37**	0.45	7.45	**2.29**	-0.07	4.98	1.01
Japan	Nikkei 225 Stock Average	May 1949 - Mar 2014	0.25	4.96	**2.55**	0.39	6.75	**2.95**	0.06	-6.02	-1.40	0.10	11.48	**3.32**
Korea	Korea SE Stock Price Index	Jan 1962 - Mar 2014	0.44	13.52	1.13	0.62	14.41	0.70	0.31	16.56	**2.49**	0.34	-0.08	-0.02
New Zealand	New Zealand SE All-Share Capital Index	Jan 1970 - Mar 2014	0.20	3.33	1.41	0.18	5.31	1.55	0.26	5.17	1.04	0.12	-8.10	**-9.14**
Singapore	Singapore FTSE Straits-Times Index	Jul 1965 - Mar 2014	0.33	5.44	**2.39**	0.53	1.47	0.48	0.22	9.80	**2.40**	0.21	3.21	0.89
Spain	Madrid SE General Index	Aug 1971 - Mar 2014	0.26	6.92	**2.90**	-0.26	7.75	**2.57**	0.63	9.84	**2.51**	0.07	-0.72	-0.17
Switzerland	Switzerland Price Index	Jan 1969 - Mar 2014	0.19	3.71	**1.92**	-0.02	5.86	**4.03**	0.40	8.39	**3.74**	0.10	-2.39	-0.63
UK	FTSE All-Share Index	Dec 1968 - Mar 2014	0.27	4.08	**2.22**	0.24	3.90	0.87	0.39	5.84	**2.07**	0.11	1.40	0.63
US	S&P 500 Composite Price Index	Jan 1928 - Mar 2014	0.20	1.91	1.43	0.14	3.50	**2.21**	0.44	-0.35	-0.20	0.16	-2.47	-0.57
US	Dow Jones Industrials Average	Jan 1885 - Mar 2014	0.18	2.94	**2.68**	0.13	4.54	**3.45**	0.47	-1.17	-0.50	0.16	-5.61	**-4.25**
Average			*0.26*	*4.54*		*0.21*	*6.03*		*0.39*	*4.67*		*0.13*	*-0.73*	

In the full sample, the breakout method generates a significantly positive R_{buy} - R_{sell} in all 14 stock markets and these returns are all significantly higher than the average market returns. The average return of the breakout method is 0.294% across the 14 countries, compared to the same period average market return of 0.026%. The results from the first sub-sample before 1983 indicate the even stronger predictive power of Bollinger Bands. Again, in all 14 markets, R_{buy} - R_{sell} is significantly positive, indicating that Bollinger Bands generate useful buy and sell signals. The average R_{buy} - R_{sell} across the 14 markets (0.454%) is higher than the average market return (0.021%); it is also higher than the full-sample average R_{buy} - R_{sell} (0.294%), indicating stronger predictive power in the first sub-sample than in the full sample.

Bollinger Bands seem to initially show strong predictive power, but the power starts decreasing after 1983. From 1983 to 2001, investors start hearing about Bollinger Bands and begin putting them into practice, although the seminal book *Bollinger on Bollinger Bands* was not yet published. While remaining profitable in most markets (11 out of 14), Bollinger Bands no longer produced significant positive R_{buy} - R_{sell} in Japan or the United States. It is worth noting that Bollinger Bands' profitability disappears instantly in the two major US stock markets (the S&P 500 and the DJIA) since 1983, when Bollinger Bands were first introduced. Moreover, the predictive power of Bollinger Bands drops more dramatically after 2001, with its increasing fame from *Bollinger on Bollinger Bands*. R_{buy} - R_{sell} is only significantly positive in Italy and New Zealand but not the other 12 markets. Moreover, R_{buy}-R_{sell} is even significantly negative in the French stock market and in the S&P 500 market. During the last sub-sample period, the average R_{buy} - R_{sell}

drops dramatically to 0.002%, compared to 0.454% before the introduction of Bollinger Bands in 1983 and 0.296% before the publication of *Bollinger on Bollinger Bands*.

The gradually decreasing predictive power is consistent with the use of the Squeeze method. The Squeeze method generates significant positive returns in nine markets in both the full sample and the first sub-sample before 1983, the number of markets reducing to seven after 1983 and falling to only one after 2001. Nevertheless, it may be interesting to note that the Squeeze method does not seem to beat the volatility breakout method in terms of the number of international markets in which it shows predictive ability, although it is stated to be “the best method” by Bollinger (2001, p. 119).

4.5.2 H2

More explicitly, the buy or sell signals may possibly still work well separately, on their own. I then test H2 and present the results for the breakout method and Squeeze method in Tables 4.2 and 4.3, respectively. The two tables have the same layouts. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference.

Table 4.2: Results on Bollinger Bands (20, 2) Breakout Method Buy/Sell Signals

This table reports the international results on Bollinger bands (20, 2) breakout method. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. I use a 10% significance level and White standard error corrected t-statistics.

Country	$R_m(*10^{-3})$	N(buy)	$R_{buy}(*10^{-3})$	t-stats	N(sell)	$R_{sell}(*10^{-3})$	t-stats	R_{buy}-$R_{sell}(*10^{-3})$	t-stats
Full Sample (20,2)									
Australia	0.26	1610	1.98	**7.30**	1168	-1.50	**-6.44**	3.48	**7.36**
France	0.27	1191	1.30	**2.96**	900	-0.60	**-2.18**	1.90	**3.22**
Germany	0.18	1211	1.37	**3.70**	920	-1.37	**-4.26**	2.74	**5.08**
Hong Kong	0.45	1301	2.75	**4.22**	812	-1.57	**-2.97**	4.33	**3.65**
Italy	0.19	1541	3.14	**8.86**	1259	-0.82	**-2.78**	3.96	**7.14**
Japan	0.25	1844	1.65	**4.89**	1362	0.08	-0.51	1.57	**2.97**
Korea	0.44	1633	3.32	**5.60**	1142	0.67	0.38	2.65	**3.05**
New Zealand	0.20	1307	2.45	**9.26**	903	-1.46	**-5.77**	3.91	**8.03**
Singapore	0.33	1457	3.15	**8.16**	1025	-2.64	**-7.32**	5.79	**8.08**
Spain	0.26	1066	2.49	**5.66**	875	-1.81	**-4.80**	4.30	**6.48**
Switzerland	0.19	1116	1.09	**2.96**	937	-0.92	**-3.33**	2.01	**3.71**
UK	0.27	1154	1.05	**2.35**	951	-1.15	**-3.92**	2.19	**3.75**
S&P 500	0.20	2203	0.78	**2.24**	1804	-0.36	**-2.00**	1.14	**2.54**
DJIA	0.18	3579	0.99	**4.35**	2985	-0.23	**-2.04**	1.22	**3.78**
Before 1983 (20, 2)									
Australia	0.21	756	2.72	**8.67**	566	-2.32	**-7.64**	5.04	**9.95**
France	0.11	365	2.07	**3.80**	330	-2.04	**-4.00**	4.11	**5.67**
Germany	0.00	347	2.06	**6.38**	322	-2.19	**-6.57**	4.25	**9.16**
Hong Kong	0.50	444	4.08	**3.26**	247	-4.10	**-3.20**	8.17	**3.69**
Italy	0.12	698	3.33	**6.56**	580	-0.37	-0.93	3.70	**4.51**
Japan	0.39	1066	2.18	**5.97**	726	-0.32	**-2.02**	2.50	**4.05**
Korea	0.62	779	4.55	**4.27**	420	1.15	0.43	3.41	**2.24**
New Zealand	0.18	381	2.61	**7.90**	297	-2.04	**-6.44**	4.65	**9.75**
Singapore	0.53	673	4.12	**8.41**	351	-2.91	**-6.00**	7.03	**7.94**
Spain	-0.26	241	3.90	**7.25**	249	-4.35	**-7.20**	8.25	**9.96**
Switzerland	-0.02	327	1.67	**3.67**	337	-1.93	**-4.20**	3.60	**5.17**
UK	0.24	350	2.39	**3.31**	333	-2.93	**-4.76**	5.31	**4.81**
S&P 500	0.14	1463	1.07	**2.93**	1257	-0.88	**-2.99**	1.95	**3.74**
DJIA	0.13	2770	1.22	**5.21**	2450	-0.35	**-2.21**	1.57	**4.56**
1983 - 2001 (20, 2)									
Australia	0.40	546	2.01	**3.61**	374	-1.24	**-3.11**	3.25	**3.03**
France	0.53	574	1.96	**2.99**	329	-0.43	-1.57	2.39	**2.54**
Germany	0.34	590	1.76	**3.21**	354	-1.67	**-3.60**	3.43	**3.91**
Hong Kong	0.57	575	2.61	**2.50**	327	-1.57	**-2.02**	4.18	**2.04**
Italy	0.45	548	3.70	**5.56**	395	-0.49	-1.39	4.19	**4.17**
Japan	0.06	489	0.86	1.28	395	1.17	1.61	-0.31	-0.30
Korea	0.31	580	2.94	**3.77**	501	0.92	0.82	2.02	**1.78**
New Zealand	0.26	560	3.36	**6.61**	376	-1.36	**-2.89**	4.72	**4.74**
Singapore	0.22	478	3.33	**4.41**	425	-3.86	**-5.48**	7.19	**5.09**
Spain	0.63	565	2.81	**4.13**	352	-1.97	**-3.98**	4.78	**4.64**
Switzerland	0.40	553	1.44	**2.42**	337	-0.60	**-1.84**	2.04	**2.12**
UK	0.39	532	0.95	1.38	363	-1.14	**-3.15**	2.09	**2.63**
S&P 500	0.44	491	0.65	0.42	304	0.19	-0.41	0.46	0.40
DJIA	0.47	528	0.48	0.02	288	-0.51	-1.52	0.99	0.76
Since 2002 (20, 2)									
Australia	0.15	308	0.14	-0.02	228	0.11	-0.06	0.03	0.02
France	0.04	252	-1.31	-1.45	241	1.14	1.17	-2.46	-1.65
Germany	0.12	274	-0.36	-0.51	244	0.14	0.03	-0.50	-0.34
Hong Kong	0.21	282	0.97	0.80	238	1.04	0.81	-0.07	-0.04
Italy	-0.07	295	1.65	**2.39**	284	-2.21	**-2.92**	3.86	**3.53**
Japan	0.10	289	1.07	1.01	241	-0.48	-0.55	1.55	0.95
Korea	0.34	274	0.61	0.29	221	-0.79	-1.08	1.40	0.92
New Zealand	0.12	366	0.90	**2.11**	230	-0.88	**-2.18**	1.77	**2.30**
Singapore	0.21	306	0.73	0.75	249	-0.19	-0.51	0.92	0.77
Spain	0.07	260	0.47	0.41	274	0.69	0.67	-0.23	-0.16
Switzerland	0.10	236	-0.52	-0.78	263	-0.03	-0.18	-0.49	-0.41
UK	0.11	272	-0.50	-0.80	255	1.16	1.33	-1.66	-1.34
S&P 500	0.16	249	-0.64	-0.93	243	1.64	**1.71**	-2.28	**-1.69**
DJIA	0.16	281	-0.28	-0.58	247	1.29	1.42	-1.57	-1.34

Table 4.3: Results on Bollinger Bands (20, 2) Squeeze Method Buy/Sell Signals

This table reports the international results on Bollinger bands (20, 2) Squeeze method. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. I use a 10% significance level and White standard error corrected t-statistics.

Country	$R_m(*10^{-3})$	N(buy)	$R_{buy}(*10^{-3})$	t-stats	N(sell)	$R_{sell}(*10^{-3})$	t-stats	$R_{buy}-R_{sell}(*10^{-3})$	t-stats
Full Sample (20,2)									
Australia	0.26	33	2.16	1.21	24	-0.92	-0.65	3.08	**2.32**
France	0.27	27	1.83	0.71	17	1.18	0.33	0.65	0.25
Germany	0.18	36	0.51	0.19	19	-4.07	**-1.74**	4.58	**1.79**
Hong Kong	0.45	28	5.37	1.39	18	3.50	0.69	1.87	0.42
Italy	0.19	39	4.59	**2.21**	26	-1.96	-0.89	6.55	**3.36**
Japan	0.25	38	1.69	0.76	31	-3.27	**-1.67**	4.96	**2.55**
Korea	0.44	37	12.23	**3.64**	34	-1.29	-0.51	13.52	1.13
New Zealand	0.20	23	1.82	0.94	24	-1.51	-1.00	3.33	1.41
Singapore	0.33	29	4.43	**1.76**	32	-1.01	-0.61	5.44	**2.39**
Spain	0.26	22	5.74	**2.10**	20	-1.18	-0.53	6.92	**2.90**
Switzerland	0.19	19	3.59	1.52	27	-0.11	-0.16	3.71	**1.92**
UK	0.27	34	1.78	0.83	26	-2.30	-1.22	4.08	**2.22**
S&P 500	0.20	62	1.66	0.99	49	-0.25	-0.28	1.91	1.43
DJIA	0.18	99	2.64	**2.29**	81	-0.30	-0.41	2.94	**2.68**
Before 1983 (20, 2)									
Australia	0.21	16	4.18	**2.11**	7	-0.76	-0.34	4.95	**2.57**
France	0.11	7	0.70	0.17	6	-2.20	-0.60	2.90	0.84
Germany	0.00	9	-1.52	-0.80	5	-5.84	**-2.28**	4.32	**2.43**
Hong Kong	0.50	10	5.72	0.76	7	-6.99	-0.91	12.71	**1.71**
Italy	0.12	20	5.07	**1.80**	11	-1.03	-0.31	6.10	**2.37**
Japan	0.39	27	2.40	1.13	20	-4.35	**-2.29**	6.75	**2.95**
Korea	0.62	21	18.47	**3.37**	16	4.06	0.57	14.41	0.70
New Zealand	0.18	5	-0.23	-0.16	7	-5.54	**-2.66**	5.31	1.55
Singapore	0.53	11	3.01	0.79	10	1.53	0.31	1.47	0.48
Spain	-0.26	6	3.53	1.10	7	-4.22	-1.23	7.75	**2.57**
Switzerland	-0.02	4	4.73	1.19	14	-1.14	-0.52	5.86	**4.03**
UK	0.24	7	0.98	0.17	6	-2.93	-0.67	3.90	0.87
S&P 500	0.14	37	2.65	1.32	37	-0.85	-0.52	3.50	**2.21**
DJIA	0.13	68	3.43	**2.60**	67	-1.11	-0.97	4.54	**3.45**
1983 - 2001 (20, 2)									
Australia	0.40	8	2.22	0.52	11	-0.80	-0.41	3.02	1.07
France	0.53	9	2.99	0.68	7	2.93	0.59	0.06	0.01
Germany	0.34	11	5.32	1.62	8	-7.69	**-2.23**	13.01	**3.00**
Hong Kong	0.57	12	7.15	1.23	5	13.32	1.54	-6.17	-1.09
Italy	0.45	13	5.85	1.50	10	-1.60	-0.50	7.45	**2.29**
Japan	0.06	7	-2.85	-0.58	6	3.18	0.58	-6.02	-1.40
Korea	0.31	7	7.70	1.22	13	-8.86	**-2.07**	16.56	**2.49**
New Zealand	0.26	5	4.03	0.80	15	-1.14	-0.52	5.17	1.04
Singapore	0.22	13	6.33	1.50	12	-3.46	-0.87	9.80	**2.40**
Spain	0.63	10	9.20	**2.28**	9	-0.64	-0.32	9.84	**2.51**
Switzerland	0.40	6	6.00	1.43	6	-2.38	-0.71	8.39	**3.74**
UK	0.39	15	1.57	0.51	12	-4.27	**-1.81**	5.84	**2.07**
S&P 500	0.44	13	0.47	0.01	6	0.83	0.09	-0.35	-0.20
DJIA	0.47	15	0.56	0.03	9	1.73	0.35	-1.17	-0.50
Since 2002 (20, 2)									
Australia	0.15	9	-1.50	-0.49	6	-1.34	-0.36	-0.16	-0.06
France	0.04	11	1.60	0.36	4	3.18	0.44	-1.58	-0.33
Germany	0.12	16	-1.64	-0.48	6	2.23	0.35	-3.88	-0.89
Hong Kong	0.21	6	1.24	0.17	6	7.55	1.18	-6.31	-0.89
Italy	-0.07	6	0.24	0.06	5	-4.74	-0.88	4.98	1.01
Japan	0.10	4	4.82	0.60	5	-6.67	-0.97	11.48	**3.32**
Korea	0.34	9	1.19	0.17	5	1.27	0.14	-0.08	-0.02
New Zealand	0.12	13	1.77	0.89	2	9.86	**2.07**	-8.10	**-9.14**
Singapore	0.21	5	2.60	0.46	10	-0.61	-0.22	3.21	0.89
Spain	0.07	6	2.18	0.35	4	2.91	0.38	-0.72	-0.17
Switzerland	0.10	9	1.48	0.35	7	3.87	0.85	-2.39	-0.63
UK	0.11	12	2.52	0.69	8	1.12	0.24	1.40	0.63
S&P 500	0.16	12	-0.13	-0.08	6	2.35	0.41	-2.47	-0.57
DJIA	0.16	16	1.22	0.35	5	6.83	1.24	-5.61	**-4.25**

Table 4.2 shows that, generally, the Bollinger Band breakout method generates more buy signals than sell signals, which is consistent with the overall uptrend of the stock markets. Moreover, the buy (sell) signals produce significant positive (negative) returns that are significantly higher (lower) than the market returns in 12 markets in the full sample and in the first sub-sample. This result indicates that using buy signals or sell signals alone generates superior returns before 1983. However, since 1983, using buy signals or sell signals only seems to show decreased profitability. During 1983 to 2001, the buy signals generate higher returns than the markets in only 10 markets and the sell signals generate lower returns than the markets in only eight markets. Like the results of testing H1, since 2002, both buy and sell signals generate useful signals only in Italy and New Zealand markets and the sell signals alone even generate significantly higher returns than the market in the S&P 500.

The results for the Squeeze method in Table 4.3 are similar. Note that the Squeeze method produces much fewer signals then the breakout method due to the precondition set by BandWidth. To illustrate, the breakout method produces 3579 buy signals and 2985 sell signals on the DJIA across the full sample from 1885 to 2014, which results in an annual average of 51.69 signals. In contrast, the Squeeze method produces only 99 buy signals and 81 sell signals during the same period, that is, 1.42 signals per year. Due to this limited number of trading signals, even during periods when Bollinger Bands have predictive power, the breakout method performs better than the Squeeze method, although the Squeeze method is stated as the best approach in *Bollinger on Bollinger Bands*.

Therefore, my evidence from buy or sell signals alone is consistent with those from H1. Bollinger Bands indeed generate useful signals before 1983, but not afterward. Performance worsens over time. Bollinger Bands first lose their predictive ability in the United States, immediately after 1983, and then in other countries. Bollinger Bands generally show very limited predictive power since 2002.

4.5.3 Rolling Window Regressions

To check the stability of my results and to more closely monitor what happens to predictability over time, I conduct rolling window regressions for the above OLS estimation of H1 for the Bollinger Band breakout method.[35] The rolling samples are 10 years long and roll ahead one month each time. I perform the task for each of my sample markets and plot the results in Figure 4.5.

The solid black lines plot the average $R_{buy} – R_{sell}$ over time and the black dotted lines plots the 90% confidence bounds. The plots uncover a clearly decreasing profitability in most of the sample markets, including the Australian, German, French, Hong Kong, New Zealand, Singapore, Swiss, UK, and US stock markets. Note that, in Table 4.1, although the Bollinger Bands still generate positive returns in New Zealand since 2002, profitability also shows a significant downward trend. In countries such as Germany, Hong Kong, Japan, Korea, and Switzerland, the problem of widening confidence bounds—especially in the later stage of the sample periods—can also lead to unstable

[35] Due to the limited number of trading signals, I do not present the results for the Squeeze method.

Figure 4.5: 10-year Rolling Window Regressions of the Bollinger Bands (20,2) Breakout Method

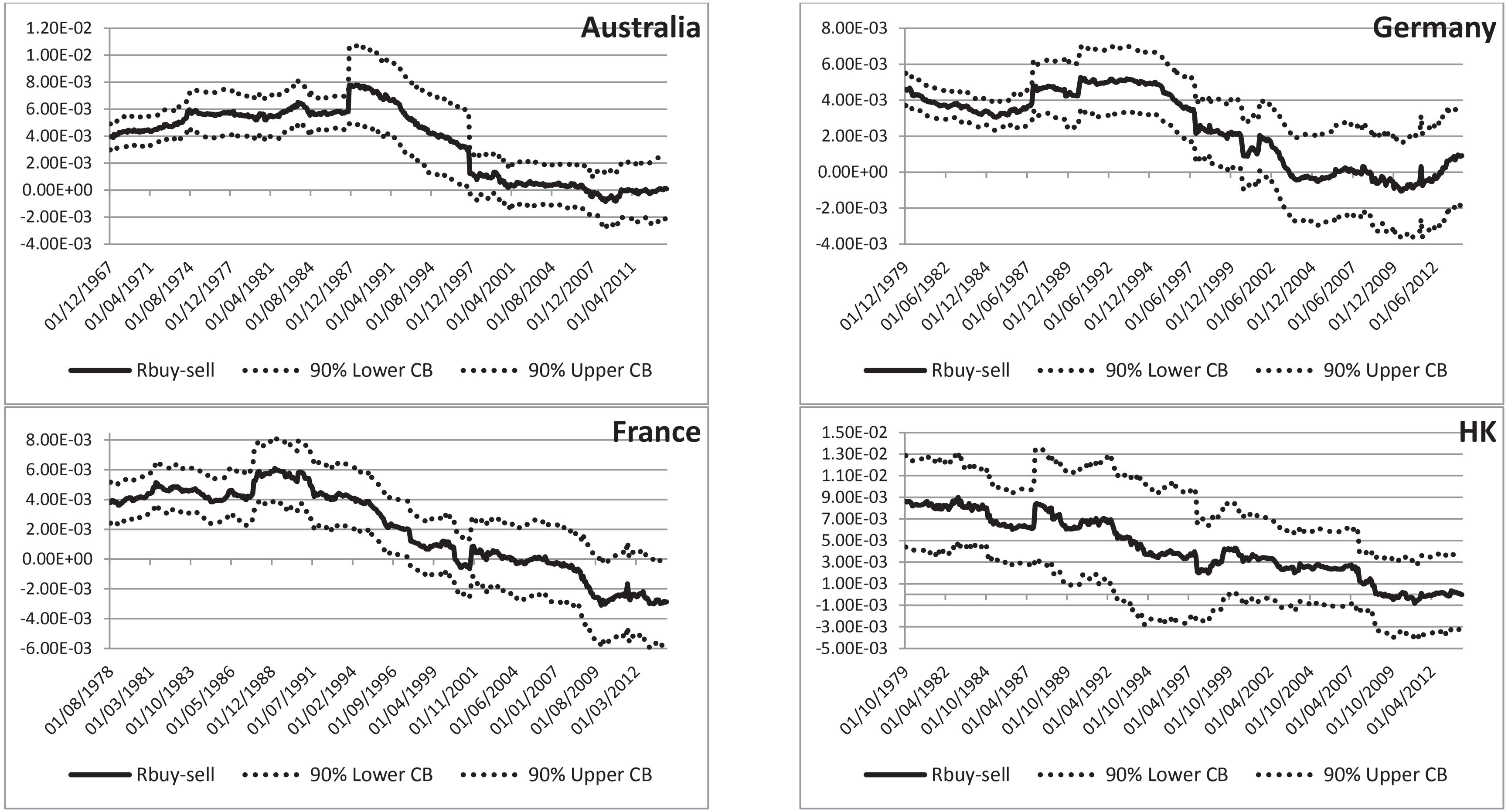


Figure 4.5 Continued

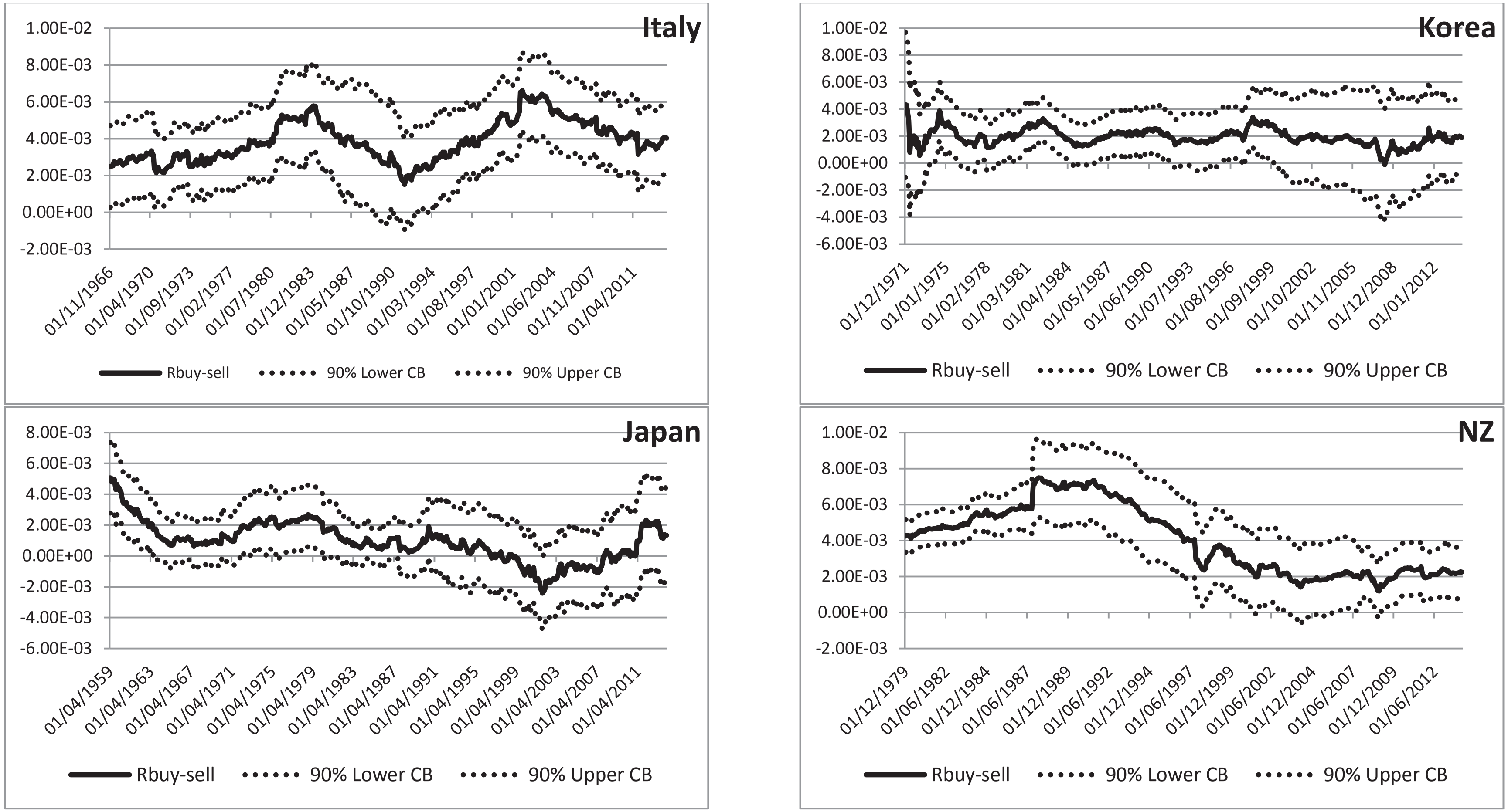
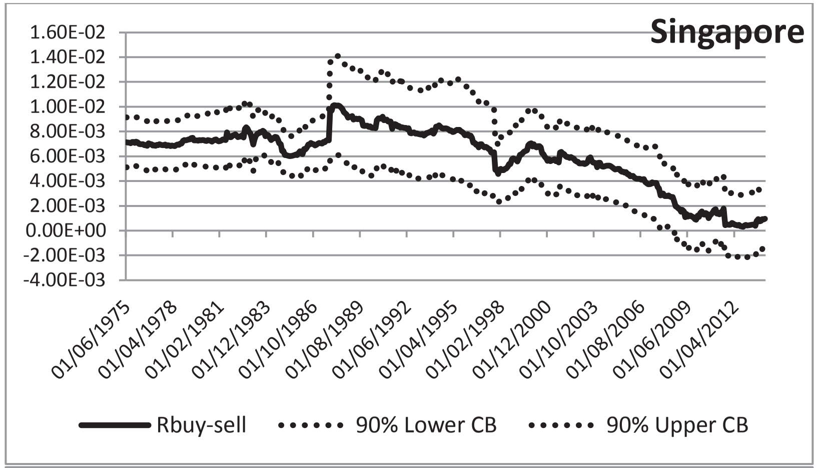
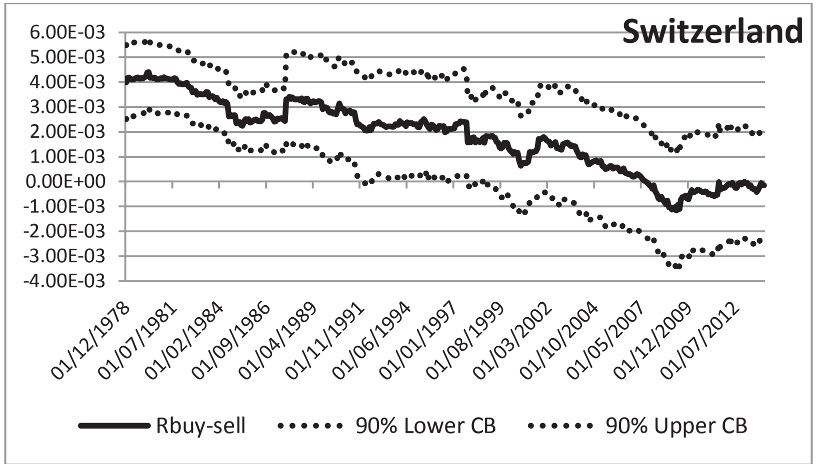
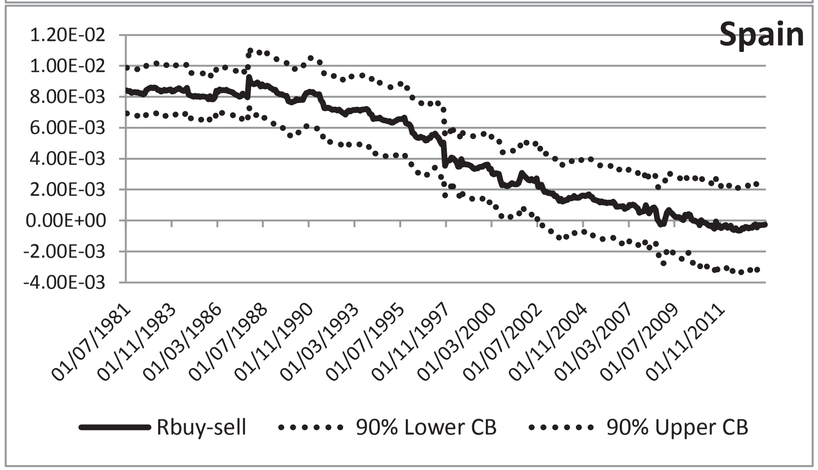


Figure 4.5 Continued







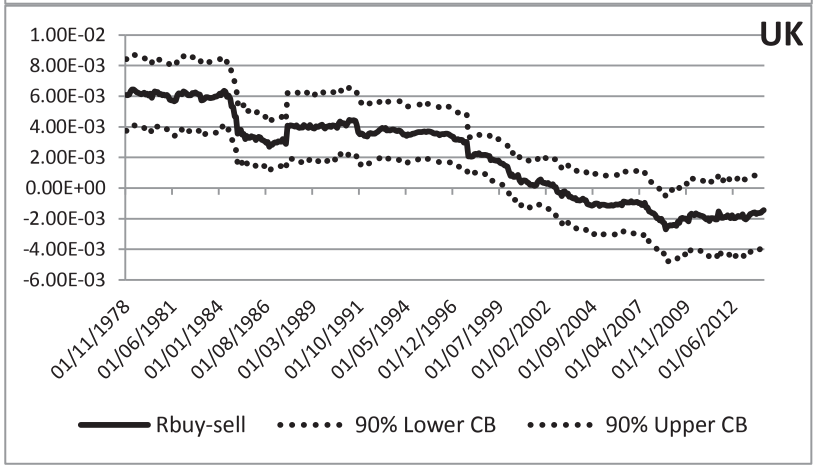
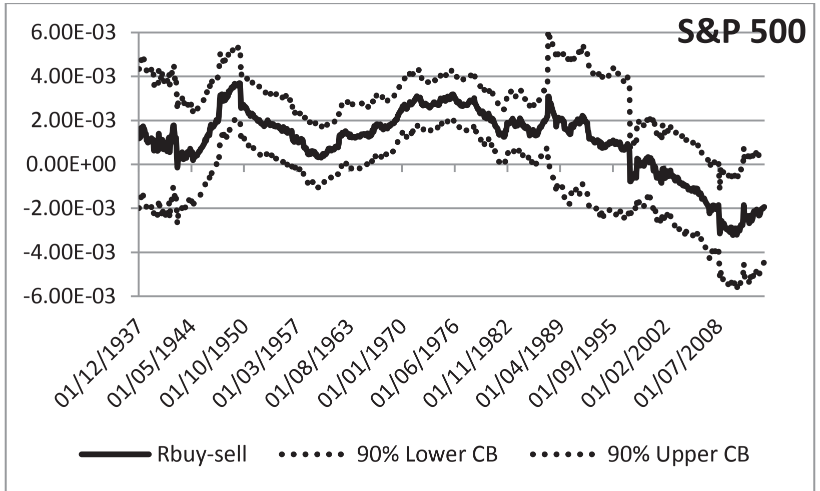
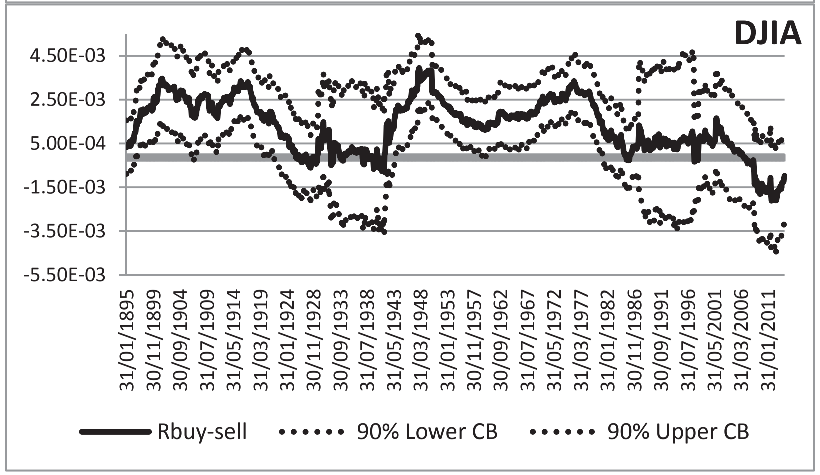


Figure 4.5 Continued





indications over time. Nevertheless, Italy seems to be the exception for which Bollinger Bands provide useful indications throughout.

Furthermore, when does predictability start turning downward? Before 1983, Bollinger Bands provided reasonably stable predictability in all 14 countries. Given that my sample of the DJIA starts earliest (in 1885), with the exception of a short period during the 1930s, Bollinger Bands consistently deliver positive returns for nearly 100 years until 1983. After the Bollinger Bands go public in 1983, however, their predictability on the DJIA drops significantly and it starts dropping on the S&P 500 after the late 1980s. After this, I gradually start to observe downward predictability in Australia, Germany, France, Hong Kong, Spain, and the United Kingdom. In contrast, predictability in Italy, Korea, Japan, New Zealand, Singapore, and Switzerland remains relatively stable until 2001. Since 2002, however, the predictability of Bollinger Bands' has decreased in nearly all markets. Moreover, during this period, Bollinger Bands' returns have changed from positive to negative, first around 1997 for the S&P 500 and the Japanese stock market and then gradually for the stock markets of Australia, Germany, France, Hong Kong, Switzerland, Spain, and the United Kingdom through March 2014. The decreasing predictability through time closely matches the rising publicity of the Bollinger Bands.

4.5.4 Economic Significance

Previous evidence suggests that the predictability of some technical indicators can disappear after accounting for transaction costs (e.g., Bessembinder & Chan 1995; Bajgrowicz & Scaillet 2012). In addition, does the changing risk affect my results? To account for these issues, I evaluate the economic significance of my results by including 1% in transaction costs when switching between risk-free assets[36] and the market. I therefore go long on Bollinger Bands' buy signals and short on their sell signals and I invest in risk-free assets when there is no signal. As examined in the introduction, I first extend my analysis on the gross annual returns of the above strategy to all my sample countries. I plot the results in Figure 4.6. The graphs show significantly decreasing returns over time in nearly all markets, with Italy being the only exception. Indeed, the strategy generated superior annual returns as high as 90.01% in the Singapore market in 1987; examples of significant returns also include 64.29% in the Korean market in 1962 and around 50% in the Italian market in 1981, in New Zealand market in 1987, in the Spanish market in 1986, and in the UK market in 1975. In all markets, the strategy generally delivered positive returns before 1983 but, even then, the returns largely turned negative after 2001 in all markets: immediately in the US market in 1983; soon after in the Japanese market, around 1990; then in a number of European stock markets, including the UK, Swiss, French, and German stock markets; and, lastly, in Asian-Pacific stock markets, including the Australian, Korean, and Hong Kong markets.

I then take into account transaction costs and risk and Table 4.4 reports my results. For each market, I first report the Sharpe ratios of the buy-and-hold strategy and of the standard Bollinger Band (20, 2) strategy. Then I report the t-statistics testing the null

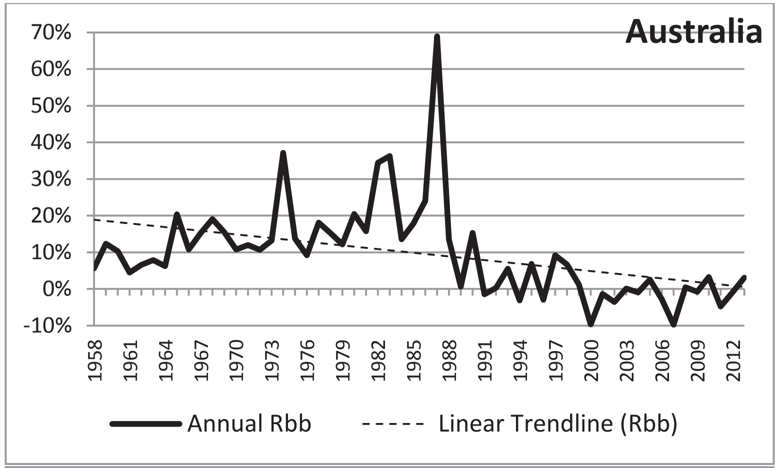
[36] I use the following risk-free rates for my analysis; three-month Treasury bill rates for Australia, France, Germany, Italy, Japan, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States. In some countries, when the three-month Treasury bill rates are not available, I use the following; Hong Kong's three-month interbank rates, Japan's seven-year government bond yield, Korea's 12-month Treasury bill rates, Korea's three-year government bond yield, New Zealand's six-month Treasury bill rates, Singapore's three-month interbank rates, the Bank of Spain's discount rate, Switzerland's three-month deposit rates, and the US central bank discount rate. I obtain all risk-free rates from the Global Financial Data database.

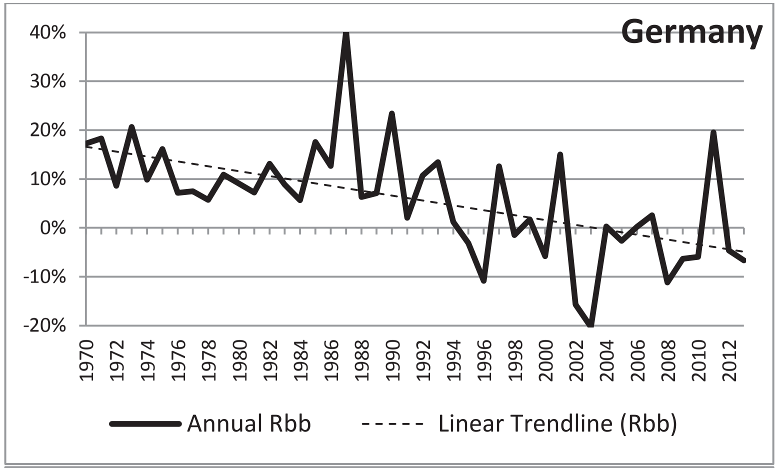
hypothesis that the two Sharpe ratios (in parentheses) equal the Sharpe ratios of the Bollinger Bands.[37] In addition I calculate Jensen's α for the Bollinger Band strategy, with the t-statistics in parentheses testing their difference from zero.[38] Panels A and B report my results for the breakout method and the Squeeze method, respectively.

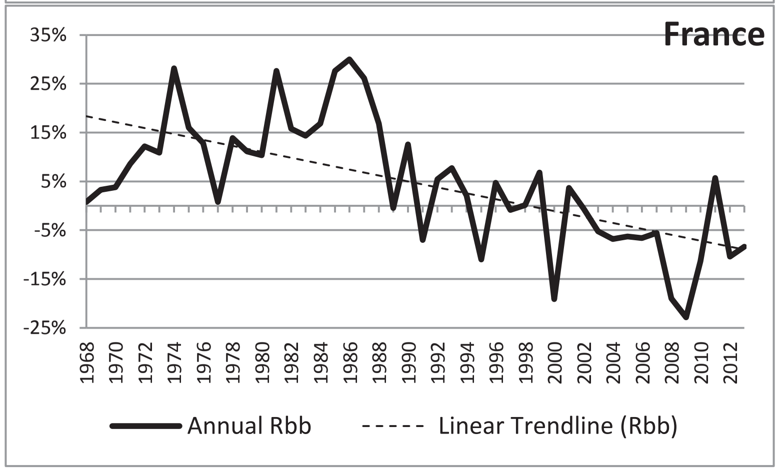
My results remain similar, considering their economic significance. For the breakout method, in the full sample, the Bollinger Bands generate significantly higher Sharpe ratios than in five markets. Before 1983, Bollinger Bands generated higher Sharpe Ratios in 10 markets; from 1983 to 2001, the number of markets drops to two, and in the last sub-sample, from 2002 on, only in one market (Italy) do Bollinger Bands still beat the market. The results from Jensen's α criteria are similar: Bollinger Bands produce significant positive α values in seven countries in the full sample. The number of markets (11) is highest in the sub-sample before 1983; then it reduces to seven after 1983 and further drops to one (Italy) after 2002. My results do not seem to change after accounting for risk and transaction costs, with Bollinger Band predictability gradually ceasing to exist with increasing public attention. Intriguingly, however, the Squeeze method seems to lose most of its predictability after accounting for risk and transaction costs, largely due to the limited signals it generates, which results in investing in risk-free assets most of the time.

[37] The significance test on the Sharpe ratios is performed according to the methodology proposed by Lo (2002) and de Roon, Eiling, Gerard, and Hillion (2012).
[38] I run the following regression to calculate Jensen's alpha: $r_{BB} - r_f = \alpha + \beta (r_m - r_f) + \varepsilon_t$, where r_{BB} represents the returns from using Bollinger Bands, r_f represents the risk-free rates, and r_m represents the market returns.

Figure 4.6: Annual Returns of Using Bollinger Bands (20, 2) in International Stock Markets







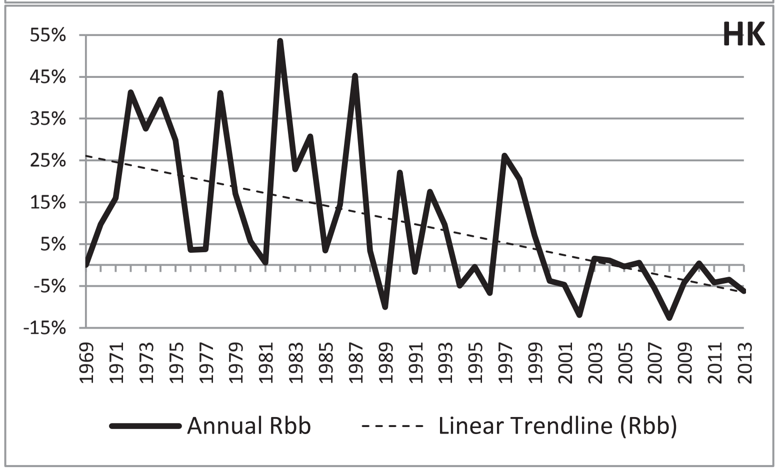


Figure 4.6 Continued

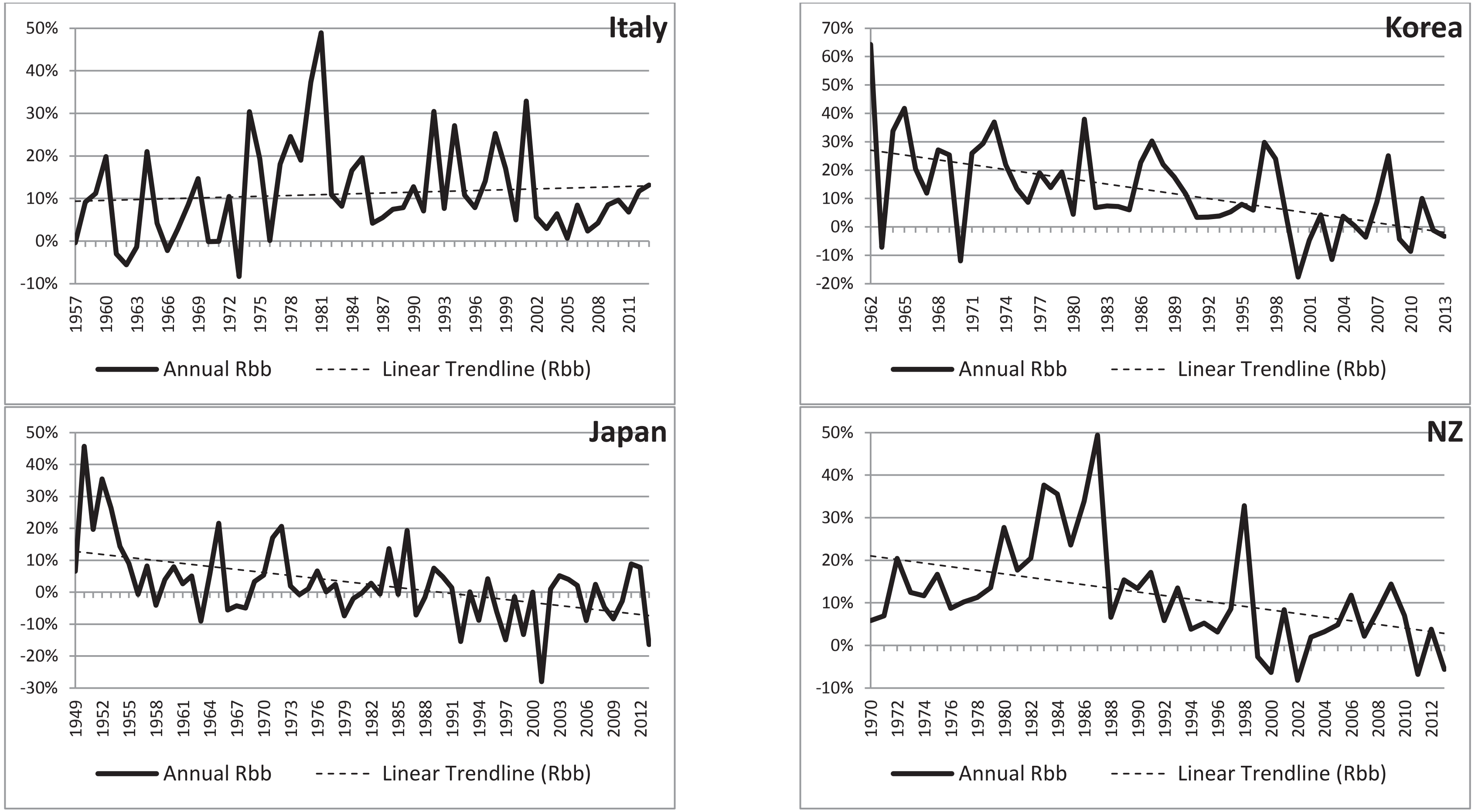


Figure 4.6 Continued

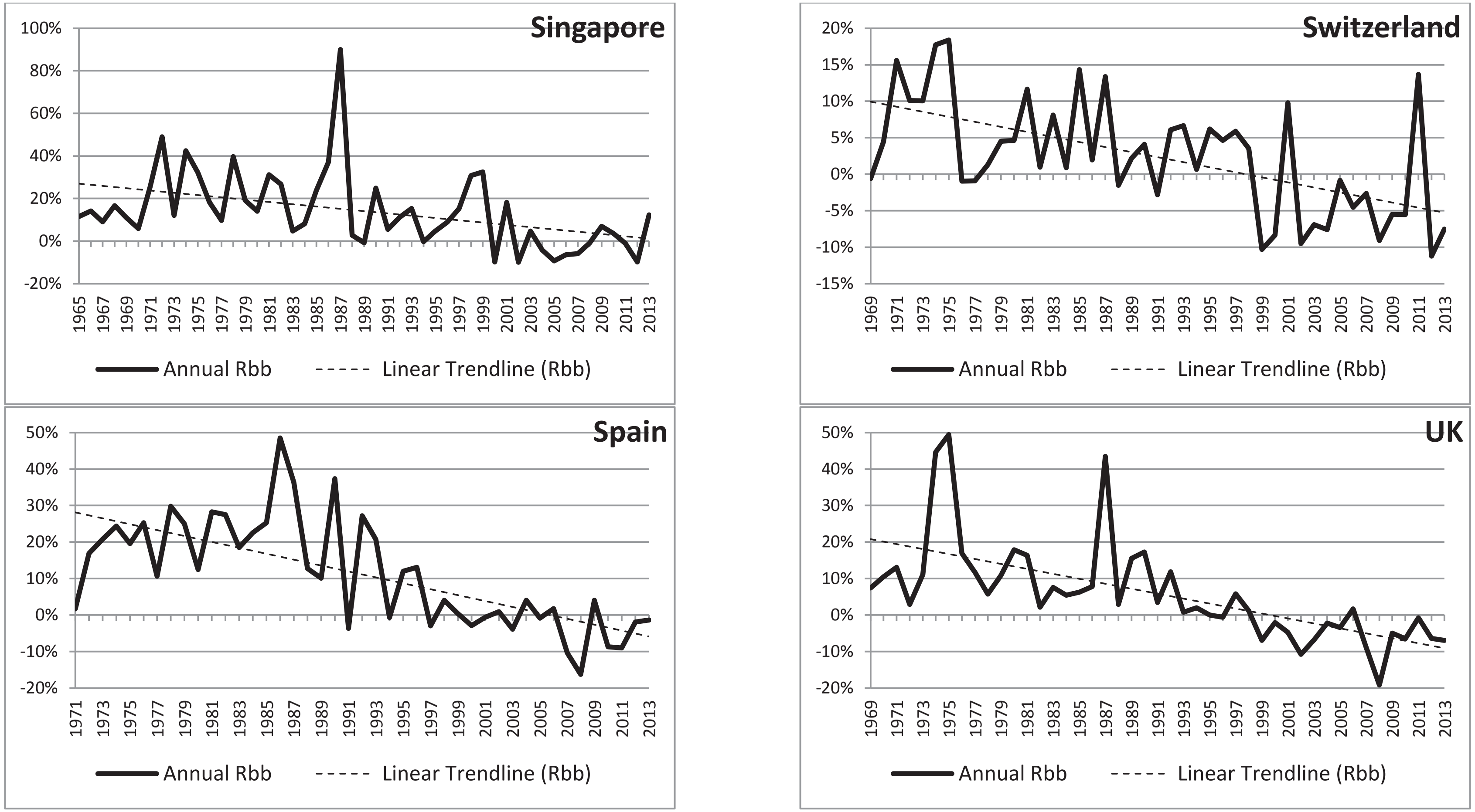


Figure 4.6 Continued

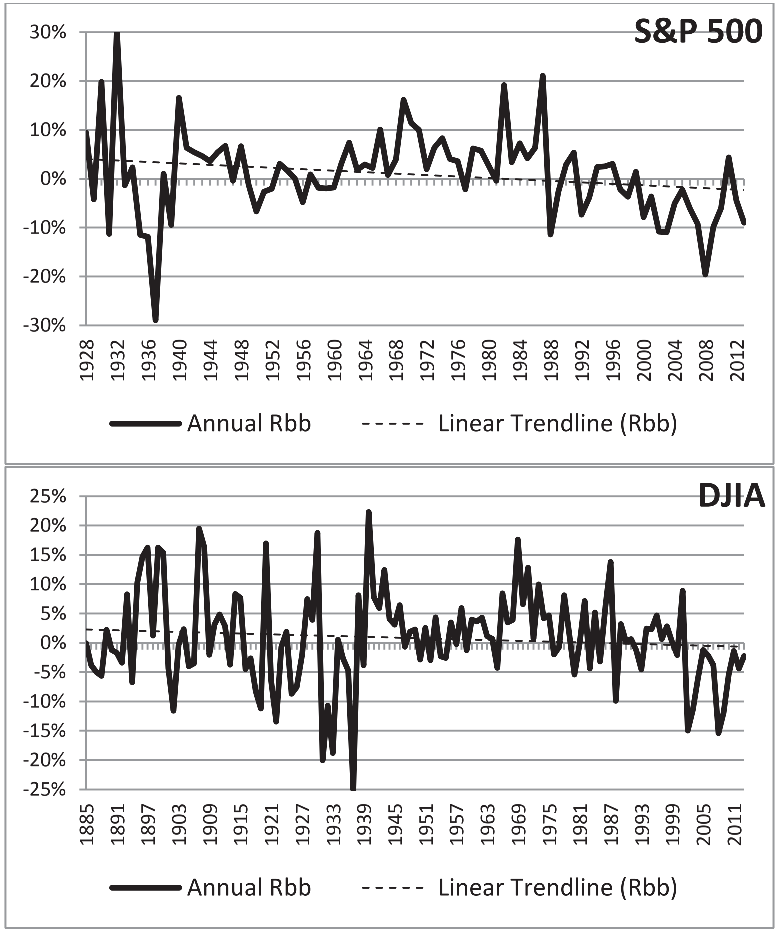


Table 4.4: Economic Significance Tests of Bollinger Bands (20, 2)

This table reports results on the economic significance tests of Bollinger bands (20, 2) for the full and the three sub-samples. For each market, I first report the Sharpe ratios of the buy-and-hold strategy and of the standard Bollinger Band (20, 2) strategy. Then I report the t-statistics testing the null hypothesis that the two Sharpe ratios (in parentheses) equal the Sharpe ratios of the Bollinger Bands. In addition I calculate Jensen's α for the Bollinger Band strategy, with the t-statistics in parentheses testing their difference from zero. Panels A and B report my results for the breakout method and the Squeeze method, respectively. I use a 10% significance level and White standard error corrected t-statistics.

	Full Sample			**Before 1983**			**1983 - 2001**			**Since 2002**		
Country	**Sharpe$_{B\&H}$ (*10^{-2})**	**Sharpe$_{BB}$ (*10^{-2})**	**α (*10^{-4})**	**Sharpe$_{B\&H}$ (*10^{-2})**	**Sharpe$_{BB}$ (*10^{-2})**	**α (*10^{-4})**	**Sharpe$_{B\&H}$ (*10^{-2})**	**Sharpe$_{BB}$ (*10^{-2})**	**α (*10^{-4})**	**Sharpe$_{B\&H}$ (*10^{-2})**	**Sharpe$_{BB}$ (*10^{-2})**	**α (*10^{-4})**
Panel A: Breakout Method (20,2)												
Australia	0.85	3.51	1.90	0.54	9.33	3.85	1.63	2.38	1.89	0.27	-3.74	-1.64
		(1.97)	**(4.37)**		**(4.63)**	**(7.30)**		(0.30)	**(1.89)**		(1.42)	**(-2.06)**
France	0.80	0.00	0.06	-1.53	5.12	2.19	3.93	1.55	0.95	-0.63	-4.94	-3.48
		(0.55)	(0.12)		**(2.78)**	**(2.94)**		(1.08)	(1.22)		(1.52)	**(-3.20)**
Germany	0.55	1.82	1.00	-2.86	9.48	2.65	2.75	3.04	1.67	-0.07	-2.32	-1.58
		(0.86)	**(2.18)**		**(4.85)**	**(5.51)**		(0.13)	**(2.37)**		(0.80)	(-1.43)
Hong Kong	1.64	2.54	2.89	1.34	5.67	6.55	2.65	2.54	3.72	0.46	-2.15	-1.49
		(0.61)	**(2.87)**		**(1.72)**	**(3.07)**		(0.05)	**(2.14)**		(0.92)	(-1.22)
Italy	-0.06	3.67	2.43	-0.77	3.26	2.30	2.03	3.55	2.36	-1.73	4.69	2.39
		(2.94)	**(4.52)**		**(2.16)**	**(2.73)**		(0.71)	**(2.45)**		**(2.24)**	**(2.54)**
Japan	1.18	0.03	0.03	2.48	1.95	1.17	0.22	-1.99	-1.33	0.03	-1.43	-1.07
		(0.95)	(0.07)		(0.32)	**(2.01)**		(0.94)	(-1.50)		(0.53)	(-0.83)
Korea	0.31	1.02	0.97	0.08	2.06	2.90	-0.51	0.30	0.31	1.92	-0.92	-0.27
		(0.65)	(1.09)		(1.32)	(1.65)		(0.39)	(0.27)		(1.02)	(-0.21)
New Zealand	-0.21	4.94	2.34	-0.44	11.63	3.49	-0.27	5.18	3.18	0.10	0.37	0.11
		(3.55)	**(5.19)**		**(4.84)**	**(6.53)**		**(2.39)**	**(3.51)**		(0.10)	(0.17)
Singapore	1.89	6.45	4.19	3.22	14.21	7.33	1.23	5.74	5.60	0.93	-0.17	0.04
		(2.94)	**(5.70)**		**(4.07)**	**(6.00)**		**(1.83)**	**(4.28)**		(0.40)	(0.04)
Spain	0.59	4.03	2.63	-6.22	16.13	7.68	3.76	5.37	3.51	-0.05	-2.37	-1.63
		(2.20)	**(4.29)**		**(7.65)**	**(7.38)**		(0.72)	**(3.67)**		(0.81)	(-1.41)
Switzerland	1.11	0.52	0.45	-1.49	4.67	1.86	4.00	0.61	0.70	-0.06	-2.42	-1.50
		(0.39)	(0.99)		**(2.33)**	**(2.77)**		(1.46)	(0.92)		(0.81)	(-1.53)
UK	0.68	0.29	0.24	-0.19	5.02	3.34	2.56	0.30	0.32	-0.25	-5.10	-3.14
		(0.27)	(0.46)		**(2.23)**	**(3.03)**		(1.00)	(0.45)		**(1.70)**	**(-3.21)**
S&P 500	0.97	-1.06	-0.44	0.49	0.30	0.24	3.26	-2.08	-0.50	0.46	-5.41	-3.22
		(1.91)	(-1.21)		(0.15)	(0.54)		**(2.19)**	(-0.53)		**(2.05)**	**(-3.24)**
DJIA	0.80	-0.98	-0.51	0.41	-0.28	-0.19	3.36	-1.98	-0.46	0.66	-4.52	-2.42
		(1.95)	**(-1.67)**		(0.66)	(-0.55)		**(2.19)**	(-0.43)		**(1.82)**	**(-2.64)**
Panel B: Squeeze Method (20,2)												
Australia	0.85	-0.39	-0.02	0.54	1.52	0.04	1.63	-0.85	-0.03	0.27	-2.67	-0.11
		(1.05)	(-0.58)		(0.55)	(1.13)		(1.19)	(-0.62)		(1.20)	(-1.53)
France	0.80	-1.03	-0.05	-1.53	-0.60	-0.03	3.93	-1.05	-0.05	-0.63	-1.32	-0.07
		(1.37)	(-1.12)		(0.39)	(-0.43)		**(2.32)**	(-0.66)		(0.28)	(-0.77)
Germany	0.55	-0.14	-0.01	-2.86	-0.94	-0.03	2.75	2.52	0.17	-0.07	-2.61	-0.23
		(0.52)	(-0.15)		(0.79)	(-0.57)		(0.11)	**(1.74)**		(1.06)	(-1.52)
Hong Kong	1.64	-0.02	0.00	1.34	1.90	0.22	2.65	-0.36	-0.03	0.46	-2.23	-0.19
		(1.23)	(-0.05)		(0.23)	(1.02)		(1.42)	(-0.25)		(1.07)	(-1.28)
Italy	-0.06	1.14	0.07	-0.77	1.24	0.08	2.03	1.72	0.10	-1.73	-0.01	0.00
		(1.01)	(1.43)		(1.13)	(1.07)		(0.15)	(1.17)		(0.70)	(-0.03)
Japan	1.18	0.33	0.00	2.48	1.20	0.05	0.22	-2.63	-0.13	0.03	2.29	0.09
		(0.77)	(0.10)		(0.82)	(0.69)		(1.36)	**(-1.78)**		(0.90)	(1.31)
Korea	0.31	0.65	0.34	0.08	0.77	0.77	-0.51	2.61	0.24	1.92	-1.03	-0.07
		(0.30)	(1.03)		(0.39)	(0.84)		(1.55)	**(1.86)**		(1.21)	(-0.62)
New Zealand	-0.21	-0.33	-0.02	-0.44	1.07	0.04	-0.27	-0.21	-0.02	0.10	-2.50	-0.09
		(0.09)	(-0.41)		(0.58)	(0.53)		(0.03)	(-0.15)		(1.04)	(-1.45)
Singapore	1.89	0.61	0.05	3.22	-1.49	-0.06	1.23	1.66	0.12	0.93	0.47	0.03
		(0.91)	(0.75)		(1.60)	(-0.49)		(0.21)	(1.12)		(0.18)	(0.30)
Spain	0.59	1.11	0.06	-6.22	2.60	0.11	3.76	2.79	0.17	-0.05	-2.49	-0.12
		(0.37)	(1.12)		**(2.95)**	(1.20)		(0.46)	**(1.88)**		(1.00)	(-1.44)
Switzerland	1.11	-0.31	-0.01	-1.49	0.25	0.01	4.00	2.36	0.06	-0.06	-2.12	-0.13
		(1.07)	(-0.33)		(0.71)	(0.14)		(0.78)	(1.63)		(0.85)	(-1.22)
UK	0.68	0.08	0.00	-0.19	0.04	0.00	2.56	0.78	0.05	-0.25	-0.96	-0.04
		(0.45)	(0.09)		(0.10)	(-0.02)		(0.84)	(0.58)		(0.29)	(-0.55)
S&P 500	0.97	-0.96	-0.04	0.49	-0.18	-0.01	3.26	-2.66	-0.09	0.46	-2.82	-0.15
		(2.04)	(-1.44)		(0.57)	(-0.21)		**(2.85)**	**(-1.85)**		(1.32)	(-1.63)
DJIA	0.80	-0.40	-0.02	0.41	0.32	0.03	3.36	-2.36	-0.11	0.66	-4.28	-0.18
		(1.44)	(-0.51)		(0.10)	(0.76)		**(2.74)**	(-1.63)		**(1.99)**	**(-2.49)**

4.6 Decline in Profitability

My sub-sample analysis above indicates apparent declines in Bollinger bands' profitability over time with their increasing popularity. In this section, I apply more formal statistical tests to directly compare the profitability across different sub-samples. Such tests tell me the sizes of declines and their statistical significance. I follow the methodology used by McLean and Pontiff (2014) and run the following regression to test the profitability of the same Bollinger Bands-based strategy above:

$$R_{BB} = \alpha + \beta_s D_s + \beta_p D_p + \varepsilon_t \qquad (2)$$

where

- R_{BB} represents the daily returns of the Bollinger Bands–based trading strategy,
- D_s is a dummy variable that equals one (zero) when the trading day is within the period 1983 - 2001, and
- D_P is a dummy variable that equals one (zero) when the trading day is within the period 2002 - 2014, and
- ε_t represents the residual term.

Bollinger Bands show strong profitability before 1983, I then refer to this period as the in-sample period, and I refer the periods 1983-2001 and 2002-2014 as the post-sample (but before publication) and post-publication periods to match the key dates of Bollinger Bands, denoted by D_s and D_p respectively. Therefore, if the introduction in 1983 and the publication in 2001 reduce the profitability, β_s and β_p should be significantly negative and their magnitudes capture the sizes of the declines. Moreover, I use *f*-test to test the difference between D_s and D_p. This further sheds lights on two issues. First, my analysis above show that the profitability decreases during 1983-2001 but disappears in most countries since 2002, therefore I expect the 2001 publication has a greater impact than the 1983 introduction, that is, D_p should be statistically smaller than D_s. Second, as discussed in Section 2, if the out-of-sample decline in profitability is due to statistical biases but not the popularity of a trading strategy, I expect D_s and D_p to be statistically equal.

I present my results in Table 4.5. I first report my sample countries, and then the coefficient estimates with corresponding t-stats for D_s and D_p respectively in the next four columns. In column 5, I report my f-test results testing the null hypothesis $D_s = D_p$. Next, I report the average daily returns of the Bollinger Bands-based trading strategy R_{BB}, followed by the percentage post-sample and post-publication declines in profitability calculated from D_s/R_{BB} and D_p/R_{BB} respectively. Lastly, I report the differences between the post-sample and post-publication declines.

Table 4.5: Decline of Profitability

This table reports results on the declines in profitability of the Bollinger Bands-based trading strategy. I first report my sample countries, and then the coefficient estimates with corresponding t-stats for D_s and D_p respectively in the next four columns. In column 5, I report my f-test results testing the null hypothesis $D_s = D_p$. Next, I report the average daily returns of the Bollinger Bands-based trading strategy R_{BB}, followed by the percentage post-sample and post-publication declines in profitability calculated from D_s/R_{BB} and D_p/R_{BB} respectively. Lastly, I report the differences between the post-sample and post-publication declines. I use a 10% significance level and White standard error corrected t-statistics.

Country	D_s ($*10^{-3}$)	t-stats	D_p ($*10^{-3}$)	t-stats	ChiSq	R_{BB} ($*10^{-3}$)	Post-sample Decline	Post-publication Decline	Difference
Australia	-0.16	-1.53	-0.56	**-5.65**	**11.11**	0.50	-31%	-112%	-81%
France	-0.19	**-1.84**	-0.77	**-5.65**	**17.55**	0.32	-60%	-238%	-178%
Germany	-0.11	-1.34	-0.56	**-4.45**	**10.72**	0.35	-32%	-158%	-126%
Hong Kong	-0.48	**-1.83**	-1.01	**-4.01**	**6.83**	0.56	-87%	-182%	-95%
Italy	0.10	0.77	-0.18	-1.39	**4.07**	0.58	17%	-32%	-48%
Japan	-0.37	**-3.48**	-0.28	**-1.92**	**0.29**	0.27	-138%	-106%	32%
Korea	-0.54	**-2.39**	-0.84	**-3.70**	**3.38**	0.65	-84%	-130%	-46%
New Zealand	0.06	0.61	-0.39	**-4.60**	**16.65**	0.58	11%	-66%	-77%
Singapore	-0.71	**-3.73**	-1.35	**-7.85**	**15.04**	0.75	-95%	-179%	-85%
Spain	-0.44	**-3.31**	-1.11	**-6.90**	**18.24**	0.58	-77%	-193%	-116%
Switzerland	-0.13	-1.29	-0.45	**-3.69**	**6.48**	0.25	-53%	-181%	-129%
UK	-0.35	**-2.75**	-0.80	**-5.31**	**13.35**	0.36	-97%	-223%	-125%
S&P 500	-0.06	-0.70	-0.39	**-3.39**	**6.28**	0.18	-35%	-218%	-184%
DJIA	-0.04	-0.47	-0.35	**-3.40**	**5.88**	0.21	-20%	-164%	-144%
Average							*-56%*	*-156%*	*-100%*

The results add further strength to my previous findings. In seven markets, D_s are statistically negative, indicating the significant drops in profitability since the 1983 introduction. The average decline is -56% across all markets and the Japanese market experiences the greatest decline of -138%. Next, D_p are significantly negative in all 14 markets expect only Italy, indicating the impact of the 2001 publication. And the declines from this period are all significantly greater than those from the 1983 introduction, even for Italy – this means that even while the strategy still shows some profitability in Italy (as shown in Table 4.1), its profitability is decreasing too. The average post-publication decline reaches -156% and the greatest decline of -238% happens in the French market. The average difference in declines from the two periods of -100% highlights the impact the publication may have- although the profitability drops since the introduction of the strategy, the publication seems to plays an important role that may have led investors to fully arbitrage any trading opportunity away. I also pool results from all countries together and run the same regression as above. The results are similar, even with different estimation methods of standard errors including country fixed-effects, country clustering and standard OLS. These results are available upon request.

4.7 Robustness Checks

4.7.1 Alternative Parameter Settings (10, 1.9) and (50, 2.1)

Bollinger (2001, p. 24) suggests that the default version of Bollinger Bands (20, 2) aims to capture intermediate-term trends, while the alternative versions (10, 1.9) and (50, 2.1) work better for relatively short- and long-terms, respectively. That is, I use 10-day (50-day) moving averages of closing prices as the middle band and the upper and lower bands are 1.9 (2.1) standard deviations from the middle band for short-term (long-term) investing. The shorter (longer) underlying period of the middle band, with tighter (wider) BandWidth, captures smaller (greater) price fluctuations. I test the predictability of these two versions of Bollinger Bands, for both the breakout and Squeeze methods. I present my results for Bollinger Bands (10, 1.9) in Tables 4.6 and 4.7, and those for Bollinger Bands (50, 2.1) in Tables 4.8 and 4.9.

The tables have same layouts as in Tables 2 and 3 and the results remain more or less the same. As expected, the short-term version (10, 1.9) produces more trading signals than the default version (20, 2), while the long-term version (50, 2.1) produces many fewer trading signals. For example, for the breakout method, the default version (20, 2) generates 51.69 signals annually, on average, the short-term version (10, 1.9) generates 64.65 signals per year, and the long-term version generates 39.20 signals per year on the full sample of the DJIA. Using the breakout method, both the alternative versions of Bollinger Bands generate (marginally) significant positive R_{buy} - R_{sell} before 1983 in all 14 markets. Then, from 1983 to 2001, R_{buy} - R_{sell} becomes insignificant in three markets for the short-term version (10, 1.9) and in seven markets for the long-term version (50, 2.1). Last, R_{buy} - R_{sell} becomes insignificant in 12 and 13 markets for the short- and long-term Bollinger Band versions, respectively, after 2002. The decreasing predictability also holds if I use the buy or sell signals alone. While the problem of the limited number of trading signals may mask the trend to some degree, especially for the long-term version (50, 2.1), I generally observe a similar decreasing trend when using the Squeeze method.

Table 4.6: Results on Bollinger Bands (10, 1.9) Breakout Method Buy/Sell Signals

This table reports the international results on Bollinger bands (10, 1.9) breakout method. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. I use a 10% significance level and White standard error corrected t-statistics.

Country	$R_m(*10^{-3})$	N(buy)	$R_{buy}(*10^{-3})$	t-stats	N(sell)	$R_{sell}(*10^{-3})$	t-stats	R_{buy}-$R_{sell}(*10^{-3})$	t-stats
Full Sample (10,1.9)									
Australia	0.26	2022	2.21	**9.12**	1557	-1.62	**-7.84**	3.82	**10.41**
France	0.27	1479	1.66	**4.39**	1235	-0.71	**-2.84**	2.37	**5.04**
Germany	0.18	1524	1.27	**3.76**	1229	-1.48	**-5.21**	2.75	**6.35**
Hong Kong	0.45	1564	3.17	**5.40**	1100	-0.49	-1.59	3.67	**3.93**
Italy	0.19	1822	2.99	**9.07**	1624	-1.48	**-5.16**	4.47	**9.59**
Japan	0.25	2336	1.75	**5.81**	1827	-0.11	-1.24	1.86	**4.32**
Korea	0.44	1941	3.42	**6.25**	1572	-0.43	**-1.67**	3.85	**5.84**
New Zealand	0.20	1536	2.82	**11.57**	1231	-1.34	**-6.16**	4.16	**11.01**
Singapore	0.33	1796	3.24	**9.24**	1393	-2.71	**-8.62**	5.95	**10.49**
Spain	0.26	1327	2.90	**7.40**	1119	-1.72	**-5.13**	4.62	**8.81**
Switzerland	0.19	1471	1.17	**3.65**	1231	-1.31	**-5.12**	2.49	**5.83**
UK	0.27	1474	1.27	**3.40**	1216	-1.16	**-4.43**	2.44	**5.15**
S&P 500	0.20	2859	0.91	**3.09**	2342	0.02	-0.73	0.89	**2.48**
DJIA	0.18	4455	1.05	**5.13**	3755	0.02	-0.86	1.02	**3.91**
Before 1983 (10,1.9)									
Australia	0.21	959	3.07	**10.98**	775	-2.64	**-9.94**	5.72	**14.14**
France	0.11	445	3.16	**6.48**	426	-2.19	**-4.80**	5.36	**8.69**
Germany	0.00	450	2.01	**6.98**	418	-2.34	**-7.89**	4.35	**11.38**
Hong Kong	0.50	516	4.36	**3.75**	339	-1.79	**-1.84**	6.14	**3.36**
Italy	0.12	792	2.99	**6.22**	740	-0.90	**-2.15**	3.89	**5.51**
Japan	0.39	1411	2.25	**7.03**	998	-0.33	**-2.37**	2.58	**5.30**
Korea	0.62	902	4.47	**4.46**	607	-0.49	-1.07	4.96	**4.22**
New Zealand	0.18	457	2.83	**9.34**	410	-2.66	**-9.50**	5.49	**13.44**
Singapore	0.53	787	4.01	**8.71**	535	-3.60	**-8.74**	7.60	**10.68**
Spain	-0.26	296	4.73	**9.53**	317	-4.19	**-7.71**	8.92	**12.88**
Switzerland	-0.02	445	1.73	**4.35**	435	-2.03	**-4.95**	3.76	**6.71**
UK	0.24	440	2.45	**3.77**	421	-2.94	**-5.31**	5.39	**6.07**
S&P 500	0.14	1913	1.36	**4.34**	1610	-0.49	**-2.06**	1.85	**4.43**
DJIA	0.13	3501	1.30	**6.24**	3024	-0.26	**-1.98**	1.57	**5.61**
1983 - 2001 (10,1.9)									
Australia	0.40	667	2.08	**4.11**	478	-1.21	**-3.41**	3.28	**3.91**
France	0.53	675	2.21	**3.77**	478	-0.66	**-2.29**	2.86	**3.95**
Germany	0.34	707	1.64	**3.18**	504	-1.54	**-3.96**	3.18	**4.70**
Hong Kong	0.57	679	3.62	**4.03**	451	-0.65	-1.34	4.27	**2.79**
Italy	0.45	622	3.99	**6.42**	514	-1.69	**-3.56**	5.68	**6.64**
Japan	0.06	583	1.01	1.64	520	0.71	1.07	0.30	0.33
Korea	0.31	685	3.47	**4.88**	662	-0.45	-1.16	3.92	**4.42**
New Zealand	0.26	676	3.98	**8.63**	516	-0.79	**-2.16**	4.77	**6.32**
Singapore	0.22	609	3.75	**5.58**	541	-3.18	**-5.08**	6.93	**5.99**
Spain	0.63	678	3.51	**5.91**	472	-1.66	**-4.01**	5.18	**6.61**
Switzerland	0.40	681	1.54	**2.92**	467	-1.41	**-3.90**	2.95	**4.06**
UK	0.39	689	1.45	**2.90**	474	-1.08	**-3.42**	2.52	**3.97**
S&P 500	0.44	606	0.52	0.19	434	0.06	-0.71	0.46	0.53
DJIA	0.47	628	0.39	-0.18	429	0.25	-0.41	0.14	0.15
Since 2002 (10,1.9)									
Australia	0.15	396	0.32	0.32	304	0.35	0.32	-0.02	-0.03
France	0.04	359	-1.24	-1.61	331	1.11	1.31	-2.36	**-2.06**
Germany	0.12	367	-0.36	-0.59	307	-0.22	-0.38	-0.14	-0.11
Hong Kong	0.21	369	0.69	0.58	310	1.15	1.04	-0.46	-0.34
Italy	-0.07	408	1.46	**2.45**	370	-2.37	**-3.53**	3.83	**4.35**
Japan	0.10	342	0.95	0.96	309	-0.75	-0.91	1.71	1.28
Korea	0.34	354	0.62	0.33	303	-0.28	-0.68	0.90	0.73
New Zealand	0.12	403	0.85	**2.07**	305	-0.51	-1.58	1.36	**2.35**
Singapore	0.21	400	0.96	1.22	317	-0.43	-0.93	1.39	1.40
Spain	0.07	353	0.19	0.15	330	0.57	0.59	-0.38	-0.32
Switzerland	0.10	345	-0.27	-0.56	329	-0.23	-0.48	-0.04	-0.04
UK	0.11	345	-0.57	-0.99	321	1.05	1.32	-1.61	-1.57
S&P 500	0.16	340	-0.92	-1.45	298	2.71	**3.25**	-3.63	**-3.24**
DJIA	0.16	326	-0.44	-0.85	302	2.59	**3.35**	-3.03	**-3.00**

Table 4.7: Results on Bollinger Bands (10, 1.9) Squeeze Method Buy/Sell Signals

This table reports the international results on Bollinger bands (10, 1.9) Squeeze method. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. I use a 10% significance level and White standard error corrected t-statistics.

Country	$R_m(*10^{-3})$	N(buy)	$R_{buy}(*10^{-3})$	t-stats	N(sell)	$R_{sell}(*10^{-3})$	t-stats	R_{buy}-$R_{sell}(*10^{-3})$	t-stats
					Full Sample (10,1.9)				
Australia	0.26	40	4.39	**2.91**	37	-3.02	**-2.22**	7.41	**5.19**
France	0.27	30	2.91	1.26	35	-2.66	-1.51	5.57	**2.94**
Germany	0.18	36	3.05	1.62	36	-1.84	-1.14	4.89	**2.62**
Hong Kong	0.45	30	5.17	1.39	34	-3.75	-1.31	8.92	**3.38**
Italy	0.19	46	4.92	**2.58**	24	-1.49	-0.66	6.41	**2.53**
Japan	0.25	51	2.72	1.50	42	-0.53	-0.43	3.25	**1.74**
Korea	0.44	39	0.61	0.05	37	-1.86	-0.71	2.47	0.73
New Zealand	0.20	37	1.68	1.08	33	-2.24	**-1.68**	3.92	**2.50**
Singapore	0.33	31	3.28	1.31	46	-1.33	-0.90	4.61	**2.40**
Spain	0.26	25	2.52	0.92	23	-1.17	-0.56	3.69	1.32
Switzerland	0.19	28	1.24	0.57	45	-1.36	-1.06	2.60	1.58
UK	0.27	39	1.04	0.45	30	-1.93	-1.13	2.97	**1.68**
S&P 500	0.20	79	4.34	**3.18**	61	-1.42	-1.10	5.76	**3.81**
DJIA	0.18	114	2.47	**2.30**	73	-1.61	-1.43	4.08	**3.78**
					Before 1983 (10,1.9)				
Australia	0.21	19	3.77	**2.06**	16	-4.04	**-2.25**	7.81	**4.76**
France	0.11	5	7.87	**1.85**	14	-2.38	-1.00	10.26	**2.00**
Germany	0.00	8	3.01	1.49	9	-2.40	-1.26	5.41	1.31
Hong Kong	0.50	7	9.78	1.13	6	-3.26	-0.42	13.04	**2.08**
Italy	0.12	18	4.44	1.49	8	1.51	0.32	2.93	0.70
Japan	0.39	34	4.09	**2.32**	23	0.44	0.03	3.64	**2.04**
Korea	0.62	18	-2.98	-0.63	17	-1.38	-0.34	-1.60	-0.34
New Zealand	0.18	8	2.62	1.22	13	-1.80	-1.25	4.43	**2.27**
Singapore	0.53	11	1.02	0.16	16	-2.74	-1.26	3.76	**1.90**
Spain	-0.26	7	4.33	1.43	2	-7.72	-1.24	12.04	**4.60**
Switzerland	-0.02	7	-0.23	-0.07	18	-2.27	-1.19	2.04	0.95
UK	0.24	10	1.34	0.30	7	-0.37	-0.14	1.71	0.49
S&P 500	0.14	49	4.47	**2.61**	43	-0.94	-0.61	5.41	**3.08**
DJIA	0.13	89	3.07	**2.64**	62	-1.43	-1.18	4.50	**3.72**
					1983 - 2001 (10,1.9)				
Australia	0.40	10	6.57	**1.98**	12	-3.22	-1.27	9.79	**3.24**
France	0.53	12	0.97	0.14	12	-2.30	-0.91	3.27	0.98
Germany	0.34	17	3.19	1.15	18	-4.49	**-2.02**	7.68	**3.53**
Hong Kong	0.57	13	5.73	1.01	18	-4.12	-1.08	9.85	**2.61**
Italy	0.45	15	7.33	**2.05**	9	-5.12	-1.29	12.45	**2.88**
Japan	0.06	11	0.45	0.10	6	-1.78	-0.34	2.23	0.48
Korea	0.31	11	8.31	**1.66**	13	-2.95	-0.74	11.26	**1.70**
New Zealand	0.26	16	1.26	0.38	12	-2.83	-1.02	4.08	1.19
Singapore	0.22	14	7.64	**1.88**	20	-0.29	-0.15	7.93	**2.35**
Spain	0.63	11	3.55	0.81	13	-0.83	-0.44	4.37	1.12
Switzerland	0.40	11	3.17	0.96	17	-0.55	-0.41	3.72	1.51
UK	0.39	17	3.18	1.29	16	-2.91	-1.48	6.09	**2.82**
S&P 500	0.44	13	3.07	0.91	12	-3.08	-1.17	6.15	1.64
DJIA	0.47	11	-1.73	-0.68	9	-2.00	-0.69	0.27	0.10
					Since 2002 (10,1.9)				
Australia	0.15	11	3.48	1.08	9	-0.96	-0.33	4.44	1.40
France	0.04	13	2.80	0.70	9	-3.58	-0.76	6.37	**2.30**
Germany	0.12	11	2.86	0.62	9	4.02	0.80	-1.15	-0.28
Hong Kong	0.21	10	1.22	0.21	10	-3.37	-0.74	4.59	1.00
Italy	-0.07	13	2.82	0.88	7	-0.25	-0.04	3.07	0.75
Japan	0.10	6	-0.85	-0.15	13	-1.69	-0.41	0.84	0.19
Korea	0.34	10	-1.41	-0.37	7	-1.02	-0.24	-0.39	-0.07
New Zealand	0.12	13	1.62	0.81	8	-2.07	-0.93	3.70	**1.89**
Singapore	0.21	6	-2.76	-0.62	10	-1.17	-0.37	-1.59	-0.55
Spain	0.07	7	-0.92	-0.18	8	-0.10	-0.03	-0.82	-0.15
Switzerland	0.10	10	0.16	0.02	10	-1.11	-0.33	1.26	0.35
UK	0.11	12	-2.25	-0.68	7	-1.28	-0.30	-0.97	-0.25
S&P 500	0.16	17	4.93	1.51	6	-1.55	-0.32	6.47	1.23
DJIA	0.16	14	2.00	0.57	2	-5.14	-0.62	7.14	**3.01**

Table 4.8: Results on Bollinger Bands (50, 2.1) Breakout Method Buy/Sell Signals

This table reports the international results on Bollinger bands (50, 2.1) breakout method. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. I use a 10% significance level and White standard error corrected t-statistics.

Country	$R_m(*10^{-3})$	N(buy)	$R_{buy}(*10^{-3})$	t-stats	N(sell)	$R_{sell}(*10^{-3})$	t-stats	R_{buy}-$R_{sell}(*10^{-3})$	t-stats
Full Sample (50,2.1)									
Australia	0.26	1288	1.49	**4.71**	820	-1.05	**-4.07**	2.54	**4.44**
France	0.27	951	1.48	**3.13**	733	-1.05	**-3.00**	2.52	**3.42**
Germany	0.18	875	0.74	1.51	683	-0.62	**-1.91**	1.36	**1.81**
Hong Kong	0.45	1136	2.63	**3.75**	577	0.00	-0.56	2.63	**1.70**
Italy	0.19	1186	2.51	**6.18**	907	-0.68	**-2.04**	3.18	**4.54**
Japan	0.25	1535	1.01	**2.44**	1003	0.46	0.56	0.55	0.79
Korea	0.44	1368	3.16	**4.88**	763	1.88	**1.96**	1.28	1.24
New Zealand	0.20	1067	2.03	**6.88**	706	-1.63	**-5.66**	3.66	**6.18**
Singapore	0.33	1256	2.73	**6.48**	758	-2.07	**-5.13**	4.79	**5.13**
Spain	0.26	850	2.63	**5.43**	658	-0.53	-1.60	3.16	**3.65**
Switzerland	0.19	996	1.17	**3.03**	725	-0.50	**-1.84**	1.67	**2.35**
UK	0.27	936	1.32	**2.89**	682	-1.00	**-3.00**	2.32	**2.96**
S&P 500	0.20	1795	0.91	**2.49**	1331	-0.39	**-1.83**	1.30	**2.07**
DJIA	0.18	2802	0.87	**3.31**	2176	-0.34	**-2.20**	1.21	**2.72**
Before 1983 (50, 2.1)									
Australia	0.21	608	2.29	**6.52**	408	-2.00	**-5.72**	4.28	**6.49**
France	0.11	318	2.15	**3.71**	237	-2.56	**-4.25**	4.71	**5.05**
Germany	0.00	243	1.13	**2.97**	224	-1.67	**-4.24**	2.80	**4.08**
Hong Kong	0.50	365	4.38	**3.24**	175	-0.50	-0.59	4.88	**1.65**
Italy	0.12	554	2.64	**4.64**	378	0.44	0.48	2.21	**2.06**
Japan	0.39	900	1.46	**3.31**	515	-0.34	**-1.76**	1.80	**2.37**
Korea	0.62	637	4.40	**3.75**	303	1.10	0.34	3.30	**1.94**
New Zealand	0.18	297	2.31	**6.19**	268	-2.17	**-6.49**	4.48	**7.48**
Singapore	0.53	582	3.60	**6.74**	226	-1.94	**-3.51**	5.54	**5.29**
Spain	-0.26	168	3.13	**5.00**	149	-3.16	**-4.03**	6.29	**5.62**
Switzerland	-0.02	252	1.25	**2.43**	304	-1.11	**-2.29**	2.36	**2.96**
UK	0.24	322	2.81	**3.82**	239	-2.82	**-3.95**	5.64	**4.21**
S&P 500	0.14	1188	1.14	**2.86**	938	-0.90	**-2.66**	2.03	**2.78**
DJIA	0.13	2198	0.99	**3.70**	1778	-0.48	**-2.41**	1.47	**3.18**
1983 - 2001 (50, 2.1)									
Australia	0.40	469	1.21	**1.69**	240	0.16	-0.37	1.04	0.91
France	0.53	502	1.77	**2.44**	292	-1.48	**-3.09**	3.25	**2.89**
Germany	0.34	477	1.04	1.43	262	-1.14	**-2.31**	2.18	**1.85**
Hong Kong	0.57	494	2.62	**2.34**	247	-0.99	-1.30	3.61	1.49
Italy	0.45	471	3.18	**4.37**	298	-1.56	**-2.60**	4.74	**4.15**
Japan	0.06	403	0.69	0.93	303	2.35	**2.94**	-1.66	-1.20
Korea	0.31	506	2.79	**3.34**	308	2.58	**2.43**	0.21	0.15
New Zealand	0.26	464	2.68	**4.75**	288	-1.10	**-2.14**	3.78	**3.14**
Singapore	0.22	453	2.67	**3.39**	313	-3.21	**-4.00**	5.88	**3.15**
Spain	0.63	461	3.14	**4.32**	289	-0.60	**-1.72**	3.74	**3.00**
Switzerland	0.40	537	1.40	**2.30**	217	-0.18	-0.87	1.58	1.06
UK	0.39	442	0.99	1.35	254	-1.73	**-3.69**	2.72	**2.44**
S&P 500	0.44	469	0.63	0.39	180	-0.37	-1.01	1.00	0.51
DJIA	0.47	441	0.66	0.36	201	-0.84	**-1.71**	1.51	0.79
Since 2002 (50, 2.1)									
Australia	0.15	211	-0.18	-0.45	172	-0.51	-0.83	0.33	0.22
France	0.04	131	-1.27	-1.03	204	1.34	1.26	-2.61	-1.42
Germany	0.12	155	-0.77	-0.74	197	1.27	1.07	-2.04	-1.06
Hong Kong	0.21	277	0.34	0.14	155	2.16	1.56	-1.82	-0.71
Italy	-0.07	161	0.07	0.15	231	-1.36	-1.59	1.43	1.02
Japan	0.10	232	-0.17	-0.26	185	-0.40	-0.42	0.23	0.10
Korea	0.34	225	0.50	0.16	152	2.02	1.35	-1.51	-0.67
New Zealand	0.12	306	0.78	1.65	150	-1.69	**-3.24**	2.46	**2.19**
Singapore	0.21	221	0.55	0.42	219	-0.56	-0.95	1.11	0.75
Spain	0.07	221	1.19	1.09	220	1.34	1.23	-0.14	-0.08
Switzerland	0.10	207	0.46	0.43	204	0.07	-0.03	0.39	0.24
UK	0.11	172	-0.63	-0.78	189	2.29	**2.41**	-2.92	**-1.74**
S&P 500	0.16	138	-0.10	-0.23	213	1.81	**1.80**	-1.91	-1.20
DJIA	0.16	163	-0.17	-0.34	197	1.52	1.54	-1.70	-1.02

Table 4.9: Results on Bollinger Bands (50, 2.1) Squeeze Method Buy/Sell Signals

This table reports the international results on Bollinger bands (50, 2.1) Squeeze method. I consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, I first report my sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, I report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. I perform the same test for the sell signals and report my results. In the last two columns, I repeat my results from Table 4.1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. I use a 10% significance level and White standard error corrected t-statistics.

Country	$R_m(*10^{-3})$	N(buy)	$R_{buy}(*10^{-3})$	t-stats	N(sell)	$R_{sell}(*10^{-3})$	t-stats	R_{buy}-$R_{sell}(*10^{-3})$	t-stats
				Full Sample (50,2.1)					
Australia	0.26	29	3.45	**1.91**	13	-2.49	-1.10	5.94	**1.84**
France	0.27	19	4.06	1.44	12	0.29	0.01	3.77	1.12
Germany	0.18	24	1.16	0.45	16	0.57	0.15	0.59	0.22
Hong Kong	0.45	22	10.15	**2.44**	10	-16.58	**-2.88**	26.73	**3.18**
Italy	0.19	21	5.58	**1.99**	28	-0.41	-0.26	5.99	**2.06**
Japan	0.25	28	1.40	0.52	23	-2.65	-1.19	4.05	1.23
Korea	0.44	37	3.39	0.91	17	6.23	1.21	-2.84	-0.62
New Zealand	0.20	32	1.25	0.72	8	-5.06	**-1.79**	6.31	**2.04**
Singapore	0.33	31	2.78	1.09	20	-0.34	-0.24	3.11	1.63
Spain	0.26	16	3.81	1.16	15	-4.54	-1.52	8.35	**3.39**
Switzerland	0.19	17	-0.60	-0.33	15	5.11	**1.95**	-5.72	-1.51
UK	0.27	25	1.34	0.50	18	-0.97	-0.49	2.31	0.70
S&P 500	0.20	37	0.95	0.39	36	4.04	**1.99**	-3.09	**-1.77**
DJIA	0.18	76	1.47	1.06	40	-0.97	-0.68	2.44	1.54
				Before 1983 (50, 2.1)					
Australia	0.21	17	3.70	**1.91**	9	-4.32	**-1.80**	8.03	**2.24**
France	0.11	3	1.91	0.33	3	5.05	0.91	-3.14	-1.09
Germany	0.00	6	3.45	1.48	5	-2.48	-0.97	5.93	**1.67**
Hong Kong	0.50	5	41.46	**4.21**	5	-20.47	**-2.16**	61.93	**3.09**
Italy	0.12	11	4.06	1.07	9	1.80	0.41	2.27	0.59
Japan	0.39	13	2.08	0.66	17	0.43	0.02	1.65	0.52
Korea	0.62	14	5.05	0.69	7	11.26	1.16	-6.21	-0.77
New Zealand	0.18	12	0.89	0.44	3	-7.74	**-2.41**	8.63	1.48
Singapore	0.53	17	4.87	**1.73**	7	-1.95	-0.64	6.82	**3.07**
Spain	-0.26	4	-1.80	-0.36	7	-6.74	**-2.02**	4.94	1.15
Switzerland	-0.02	7	-2.11	-0.69	2	-3.93	-0.69	1.82	0.32
UK	0.24	11	2.99	0.79	5	-2.15	-0.46	5.14	0.71
S&P 500	0.14	19	0.68	0.20	25	2.85	1.17	-2.17	-0.99
DJIA	0.13	60	0.83	0.51	32	-1.19	-0.72	2.02	1.11
				1983 - 2001 (50, 2.1)					
Australia	0.40	5	9.73	**2.12**	0	.	.	.	.
France	0.53	11	3.64	0.95	7	-1.48	-0.49	5.12	1.37
Germany	0.34	8	-1.14	-0.41	4	-2.84	-0.63	1.70	0.44
Hong Kong	0.57	11	2.00	0.26	4	-11.13	-1.27	13.13	1.29
Italy	0.45	7	9.43	**1.83**	12	-0.84	-0.35	10.28	**1.88**
Japan	0.06	6	0.64	0.11	2	-11.93	-1.28	12.57	0.80
Korea	0.31	15	3.72	0.83	7	0.22	-0.01	3.50	0.57
New Zealand	0.26	15	2.73	0.91	2	-0.48	-0.10	3.20	0.61
Singapore	0.22	8	1.75	0.29	5	1.84	0.25	-0.09	-0.02
Spain	0.63	5	7.07	1.21	4	-4.19	-0.81	11.26	**2.43**
Switzerland	0.40	8	0.06	-0.10	8	3.53	0.92	-3.47	-0.59
UK	0.39	8	2.18	0.57	9	-4.17	-1.53	6.36	1.42
S&P 500	0.44	14	0.54	0.04	6	7.83	**1.73**	-7.29	**-1.98**
DJIA	0.47	14	4.26	1.32	5	1.89	0.30	2.37	1.02
				Since 2002 (50, 2.1)					
Australia	0.15	7	-1.64	-0.46	4	1.63	0.29	-3.27	-0.50
France	0.04	5	6.27	0.98	2	-0.64	-0.07	6.91	0.73
Germany	0.12	10	1.62	0.32	7	4.69	0.82	-3.08	-0.69
Hong Kong	0.21	6	-1.00	-0.19	1	-18.92	-1.26	17.92	**19.92**
Italy	-0.07	3	2.17	0.33	7	-2.50	-0.54	4.67	1.17
Japan	0.10	9	0.91	0.16	4	-11.12	-1.43	12.03	1.44
Korea	0.34	8	-0.14	-0.09	3	8.53	0.95	-8.67	-0.93
New Zealand	0.12	5	-2.31	-0.81	3	-5.43	-1.44	3.12	0.75
Singapore	0.21	6	-1.80	-0.42	8	-0.29	-0.12	-1.51	-0.56
Spain	0.07	7	4.69	0.83	4	-1.03	-0.15	5.72	1.37
Switzerland	0.10	2	2.00	0.23	5	11.27	**2.14**	-9.26	**-2.33**
UK	0.11	6	-2.82	-0.59	4	7.71	1.26	-10.53	**-6.51**
S&P 500	0.16	4	3.66	0.54	5	5.47	0.92	-1.81	-0.44
DJIA	0.16	2	1.22	0.13	3	-3.30	-0.50	4.52	0.79

4.7.2 Alternative BandWidth Settings

For the Squeeze method, I set the precondition on BandWidth to a six-month minimum by default, which may be too strict. I then repeat my analysis using three alternative BandWidth settings. The first alternative BandWidth setting triggers a trading signal when BandWidth reaches its six-month low, instead of a six-month minimum, where BandWidth is defined as a six-month low when it falls in the bottom 10% of its distribution. The second and third alternative settings set the BandWidth to three-month and 12-month minima to capture relatively short- and long-term low values of BandWidth. I present my results in Table 4.10.

Table 4.10 has the same layout as Table 4.1. Generally, my results remain similar: The Squeeze method shows decreasing predictability across time in its alternative versions, although the trend is weaker when BandWidth is defined as its 12-month minimum. In this case, more price fluctuations are smoothed out, which leads to an even lower number of trading signals than for the default version, which can mask the underlying trend.

Table 4.10: International Results on Bollinger Bands Squeeze Method with Alternative BandWidth Settings

This table reports the international results on Bollinger bands (20, 2) Squeeze method with Alternative BandWidth settings. I consequently report the results for the full sample and the three sub-samples in. For each sample period, I report the market returns R_m, the average spread between conditional buy and sell returns $R_{buy} - R_{sell}$, and the t-statistics testing H1, that $R_{buy} - R_{sell}$ is not different from zero. I use a 10% significance level and White standard error corrected t-statistics.

	Full Sample			**Before 1983**			**1983-2001**			**Since 2002**		
Country	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**
Squeeze Method (20,2): Bandwidth=6-month low												
Australia	0.26	3.77	**5.88**	0.21	5.54	**6.65**	0.40	3.81	**3.12**	0.15	-0.76	-0.57
France	0.27	1.16	1.05	0.11	5.28	**3.29**	0.53	0.82	0.42	0.04	-2.79	-1.32
Germany	0.18	3.93	**3.97**	0.00	5.20	**4.92**	0.34	6.18	**4.00**	0.12	-2.11	-0.74
Hong Kong	0.45	5.99	**3.34**	0.50	11.70	**2.87**	0.57	3.79	1.52	0.21	2.37	0.80
Italy	0.19	4.70	**4.91**	0.12	4.69	**3.20**	0.45	4.38	**2.77**	-0.07	5.03	**2.61**
Japan	0.25	4.23	**5.33**	0.39	4.98	**5.38**	0.06	1.62	1.02	0.10	6.11	**2.36**
Korea	0.44	6.05	**2.40**	0.62	8.03	1.58	0.31	7.45	**2.98**	0.34	0.53	0.26
New Zealand	0.20	5.26	**6.57**	0.18	5.19	**4.59**	0.26	5.88	**3.95**	0.12	4.34	**2.39**
Singapore	0.33	5.50	**5.75**	0.53	6.06	**5.02**	0.22	7.24	**3.91**	0.21	2.34	1.30
Spain	0.26	4.43	**4.02**	-0.26	5.45	**3.55**	0.63	5.12	**3.29**	0.07	1.59	0.61
Switzerland	0.19	3.36	**3.48**	-0.02	4.67	**2.89**	0.40	5.03	**3.11**	0.10	-0.26	-0.15
UK	0.27	2.17	**1.78**	0.24	3.09	**1.79**	0.39	3.43	1.55	0.11	-1.29	-0.80
S&P 500	0.20	2.70	**4.09**	0.14	4.01	**4.86**	0.44	0.89	0.55	0.16	-1.30	-0.94
DJIA	0.18	3.13	**5.71**	0.13	3.81	**6.32**	0.47	1.19	0.56	0.16	0.21	0.13
Squeeze Method (20,2): Bandwidth=3-month minimum												
Australia	0.26	3.87	**2.97**	0.21	6.14	**2.52**	0.40	3.26	**1.81**	0.15	1.98	0.97
France	0.27	3.37	**1.65**	0.11	8.29	**3.20**	0.53	0.86	0.22	0.04	0.49	0.15
Germany	0.18	4.72	**2.50**	0.00	5.70	**3.64**	0.34	8.81	**2.80**	0.12	-3.92	-0.97
Hong Kong	0.45	4.51	1.14	0.50	7.58	1.14	0.57	-0.90	-0.16	0.21	4.59	0.53
Italy	0.19	6.27	**3.42**	0.12	7.32	**2.80**	0.45	5.79	**1.71**	-0.07	5.41	1.33
Japan	0.25	4.75	**3.27**	0.39	7.51	**4.25**	0.06	-3.89	-1.42	0.10	5.74	1.54
Korea	0.44	7.76	1.26	0.62	7.15	0.63	0.31	12.67	**3.84**	0.34	-2.47	-0.78
New Zealand	0.20	4.79	**2.78**	0.18	5.16	**2.27**	0.26	9.51	**2.46**	0.12	-5.57	**-2.96**
Singapore	0.33	4.59	**2.44**	0.53	3.49	1.38	0.22	6.80	**1.88**	0.21	0.76	0.27
Spain	0.26	6.72	**3.18**	-0.26	11.14	**3.45**	0.63	6.09	**2.04**	0.07	1.35	0.30
Switzerland	0.19	4.05	**2.30**	-0.02	3.88	**1.71**	0.40	7.51	**2.28**	0.10	-1.18	-0.34
UK	0.27	4.63	**2.70**	0.24	9.14	1.52	0.39	4.89	**2.16**	0.11	0.93	0.46
S&P 500	0.20	3.02	**2.83**	0.14	4.78	**3.60**	0.44	-0.41	-0.24	0.16	-0.72	-0.27
DJIA	0.18	3.09	**3.36**	0.13	4.48	**4.13**	0.47	0.02	0.01	0.16	-3.11	-1.21
Squeeze Method (20,2): Bandwidth=12-month minimum												
Australia	0.26	1.08	0.84	0.21	3.10	**2.88**	0.40	1.26	0.59	0.15	-1.26	-0.44
France	0.27	-2.94	-1.04	0.11	-1.85	-0.74	0.53	-0.22	-0.05	0.04	-10.38	**-2.62**
Germany	0.18	2.40	0.64	0.00	3.31	1.19	0.34	10.40	1.43	0.12	-4.37	-0.76
Hong Kong	0.45	-3.02	-0.67	0.50	-0.30	-0.08	0.57	-4.40	-1.39	0.21	-13.32	-1.43
Italy	0.19	5.06	**1.94**	0.12	-1.02	-0.30	0.45	8.40	**2.95**	-0.07	9.02	1.21
Japan	0.25	4.55	1.63	0.39	8.26	**2.37**	0.06	-8.72	-1.35	0.10	7.46	**3.49**
Korea	0.44	4.94	0.90	0.62	-0.58	-0.07	0.31	19.80	**2.16**	0.34	0.33	0.07
New Zealand	0.20	4.61	1.54	0.18	-1.21	-0.43	0.26	3.42	0.73	0.12	.	**.**
Singapore	0.33	5.47	1.57	0.53	-4.40	-0.84	0.22	17.00	**2.77**	0.21	-1.45	-0.36
Spain	0.26	3.29	1.48	-0.26	3.56	1.51	0.63	3.44	1.11	0.07	2.18	0.32
Switzerland	0.19	0.96	0.36	-0.02	5.90	**2.74**	0.40	3.05	**2.87**	0.10	-3.00	-0.67
UK	0.27	2.10	1.23	0.24	0.16	0.04	0.39	3.60	1.48	0.11	0.30	0.14
S&P 500	0.20	-0.30	-0.17	0.14	0.79	0.38	0.44	-1.26	-0.54	0.16	-1.13	-0.22
DJIA	0.18	2.65	**1.67**	0.13	3.73	**2.05**	0.47	-1.10	-0.23	0.16	-3.80	**-2.22**

4.7.3 Other Robustness Checks

Alternatively, I use the GARCH (1, 1) model to further check my results for potential heteroskedasticity problems, as well as the robust regression for possible outliers, and I again find similar results. My results are also robust to the 2008 global financial crisis if I exclude sample periods since 2008. I present these robustness check results in Tables 4.11 to 4.13, respectively. My results also remain the same if I consider economic significance without transaction costs, if I consider a 10-day holding period after a trading signal is generated, or if I use the Wald test instead of the t-test. Also, I construct a time variable that equals 1/100 in the first trading day and increases by 1/100 in each consecutive day in my sample, and I regress the time variable against returns of the Bollinger Bands-based strategy for each country, the estimates are all significantly negative confirming the significant downward profitability over time. To save space, these results are available upon request.

Table 4.11: International Results on Bollinger Bands (20, 2) – GARCH (1, 1)

This table reports the international results on Bollinger bands (20, 2) using GARCH (1, 1) estimates. I consequently report the results for the full sample and the three sub-samples in. For each sample period, I report the market returns R_m, the average spread between conditional buy and sell returns R_{buy} - R_{sell}, and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, I report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. I use a 10% significance level and White standard error corrected t-statistics.

	Full Sample			**Before 1983**			**1983-2001**			**Since 2002**		
Country	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**
Panel A: Breakout Method (20,2)												
Australia	0.26	2.53	**12.11**	0.21	3.92	**13.68**	0.40	0.91	1.76	0.15	0.19	0.39
France	0.27	1.61	**4.36**	0.11	3.86	**5.86**	0.53	1.72	**2.85**	0.04	-3.33	-4.09
Germany	0.18	2.82	**9.54**	0.00	3.54	**9.16**	0.34	2.95	**5.75**	0.12	-1.86	-2.52
Hong Kong	0.45	2.45	**3.43**	0.50	5.05	**4.04**	0.57	2.22	1.99	0.21	-0.40	-0.56
Italy	0.19	2.64	**7.35**	0.12	2.39	**4.37**	0.45	3.52	**4.44**	-0.07	1.87	**3.55**
Japan	0.25	0.52	1.76	0.39	0.52	1.43	0.06	-0.34	-0.52	0.10	1.51	1.33
Korea	0.44	1.53	**5.57**	0.62	1.84	**4.80**	0.31	0.97	1.40	0.34	1.42	1.24
New Zealand	0.20	3.63	**9.63**	0.18	4.20	**9.14**	0.26	4.87	**7.00**	0.12	1.55	**3.12**
Singapore	0.33	4.30	**12.08**	0.53	5.78	**11.39**	0.22	3.78	**3.60**	0.21	1.60	1.90
Spain	0.26	4.13	**11.75**	-0.26	5.93	**10.75**	0.63	4.76	**7.38**	0.07	-2.36	-3.28
Switzerland	0.19	2.17	**6.56**	-0.02	3.83	**5.65**	0.40	2.20	**5.39**	0.10	-0.70	-0.81
UK	0.27	1.75	**4.41**	0.24	3.79	**4.52**	0.39	1.99	**3.45**	0.11	-1.87	-2.91
S&P 500	0.20	1.07	**4.70**	0.14	1.72	**6.21**	0.44	-0.16	-0.27	0.16	-1.97	-2.76
DJIA	0.18	1.09	**6.07**	0.13	1.41	**6.72**	0.47	0.45	0.82	0.16	-0.56	-0.95
Panel B: Squeeze Method (20,2)												
Australia	0.26	3.01	1.59	0.21	4.55	1.64	0.40	2.27	0.56	0.15	-0.15	-0.03
France	0.27	0.65	0.26	0.11	2.90	0.62	0.53	0.79	0.12	0.04	-2.95	-0.75
Germany	0.18	5.53	1.75	0.00	4.32	1.83	0.34	13.00	2.10	0.12	-3.84	-0.55
Hong Kong	0.45	2.50	0.49	0.50	0.50	0.10	0.57	-6.17	-0.84	0.21	-5.67	-0.68
Italy	0.19	6.55	2.58	0.12	6.10	1.45	0.45	6.62	1.19	-0.07	4.98	0.75
Japan	0.25	4.91	2.46	0.39	6.68	2.59	0.06	-6.03	-0.99	0.10	11.50	1.50
Korea	0.44	13.70	0.40	0.62	14.70	0.21	0.31	16.60	1.45	0.34	-0.08	-0.01
New Zealand	0.20	3.56	1.73	0.18	6.56	1.41	0.26	0.16	0.04	0.12	-8.10	-0.96
Singapore	0.33	5.44	2.06	0.53	1.48	0.41	0.22	9.42	1.67	0.21	3.21	0.42
Spain	0.26	6.92	2.20	-0.26	7.20	1.90	0.63	9.85	1.58	0.07	-0.72	-0.11
Switzerland	0.19	4.12	2.14	-0.02	5.86	1.07	0.40	8.39	2.59	0.10	-2.40	-0.38
UK	0.27	4.09	2.10	0.24	-0.89	-0.12	0.39	6.50	1.72	0.11	1.40	0.47
S&P 500	0.20	1.43	1.26	0.14	2.55	1.41	0.44	-0.26	-0.07	0.16	-5.84	-3.90
DJIA	0.18	2.60	2.15	0.13	4.55	**3.17**	0.47	-1.17	-0.39	0.16	-5.59	-3.67

Table 4.12: International Results on Bollinger Bands (20, 2) – Robust Regression

This table reports the international results on Bollinger bands (20, 2) using robust regression estimates. I consequently report the results for the full sample and the three sub-samples in. For each sample period, I report the market returns R_m, the average spread between conditional buy and sell returns R_{buy} - R_{sell}, and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, I report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. I use a 10% significance level and White standard error corrected t-statistics.

	Full Sample			**Before 1983**			**1983-2001**			**Since 2002**		
Country	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**chi-stats**
Panel A: Breakout Method (20,2)												
Australia	0.26	2.82	**103.86**	0.21	4.56	**163.85**	0.40	1.71	**10.46**	0.15	-0.30	0.21
France	0.27	1.35	**11.32**	0.11	3.58	**30.02**	0.53	0.93	2.28	0.04	-2.81	**10.33**
Germany	0.18	2.58	**61.27**	0.00	3.91	**84.75**	0.34	2.03	**14.00**	0.12	-0.16	0.03
Hong Kong	0.45	1.63	**6.77**	0.50	6.58	**16.94**	0.57	1.20	1.67	0.21	-0.41	0.27
Italy	0.19	3.61	**79.82**	0.12	3.58	**31.52**	0.45	3.58	**24.90**	-0.07	3.62	**27.91**
Japan	0.25	0.80	**6.06**	0.39	2.21	**31.98**	0.06	-1.19	**3.29**	0.10	-1.10	1.09
Korea	0.44	2.45	**33.89**	0.62	3.05	**27.97**	0.31	3.34	**17.89**	0.34	-1.34	2.33
New Zealand	0.20	3.02	**89.03**	0.18	4.32	**125.69**	0.26	3.15	**22.39**	0.12	1.49	**7.37**
Singapore	0.33	3.39	**76.40**	0.53	4.66	**89.31**	0.22	3.83	**23.46**	0.21	0.31	0.14
Spain	0.26	4.36	**94.33**	-0.26	7.50	**109.61**	0.63	3.95	**32.44**	0.07	0.18	0.04
Switzerland	0.19	1.10	**9.93**	-0.02	2.60	**19.51**	0.40	0.35	0.49	0.10	-0.64	0.60
UK	0.27	1.65	**16.58**	0.24	4.67	**27.72**	0.39	1.05	**3.79**	0.11	-0.69	0.93
S&P 500	0.20	0.57	**5.47**	0.14	1.38	**20.94**	0.44	-1.34	**6.32**	0.16	-1.28	**3.57**
DJIA	0.18	0.72	**12.14**	0.13	1.21	**25.94**	0.47	-1.48	**7.37**	0.16	-0.99	**2.79**
Panel B: Squeeze Method (20,2)												
Australia	0.26	3.10	**5.74**	0.21	4.93	**4.01**	0.40	1.56	0.45	0.15	1.34	0.30
France	0.27	0.81	0.09	0.11	-1.81	0.65	0.53	-3.88	0.59	0.04	-1.15	0.05
Germany	0.18	5.57	**8.83**	0.00	4.70	**3.76**	0.34	9.88	**6.64**	0.12	-0.60	0.03
Hong Kong	0.45	0.72	0.04	0.50	3.93	0.74	0.57	-4.73	0.66	0.21	-4.89	0.39
Italy	0.19	5.30	**11.78**	0.12	6.61	**9.47**	0.45	5.06	**3.87**	-0.07	3.85	0.50
Japan	0.25	4.61	**5.94**	0.39	5.81	**6.31**	0.06	-5.23	1.10	0.10	10.55	**6.63**
Korea	0.44	4.43	**4.01**	0.62	3.47	2.17	0.31	9.48	**3.14**	0.34	-0.47	0.01
New Zealand	0.20	1.02	0.27	0.18	4.45	1.25	0.26	0.80	0.02	0.12	-8.34	**14.04**
Singapore	0.33	4.41	**4.54**	0.53	1.63	0.67	0.22	8.04	**3.79**	0.21	3.81	0.55
Spain	0.26	5.18	**5.33**	-0.26	5.58	**3.85**	0.63	7.57	**3.48**	0.07	-1.34	0.06
Switzerland	0.19	3.38	**2.86**	-0.02	6.24	**8.04**	0.40	8.20	**9.54**	0.10	-4.63	1.10
UK	0.27	3.27	**3.27**	0.24	2.14	0.21	0.39	6.07	**4.24**	0.11	0.55	0.06
S&P 500	0.20	1.03	0.93	0.14	2.50	**3.95**	0.44	-0.77	0.09	0.16	-5.82	**4.11**
DJIA	0.18	1.43	1.99	0.13	3.50	**7.31**	0.47	-2.11	0.70	0.16	-5.84	**18.61**

Table 4.13: International Results on Bollinger Bands (20, 2) Adjusted for the 2008 Crisis

This table reports the international results on Bollinger bands (20, 2) excluding the 2008 crisis period. I consequently report the results for the full sample and the three sub-samples in. For each sample period, I report the market returns R_m, the average spread between conditional buy and sell returns R_{buy} - R_{sell}, and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, I report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. I use a 10% significance level and White standard error corrected t-statistics.

	Full Sample			Before 1983			1983-2001			Since 2002		
Country	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**	**R_m (*10^{-3})**	**R_{buy}-R_{sell} (*10^{-3})**	**t-stats**
Panel A: Breakout Method (20,2)												
Australia	0.26	3.77	**7.74**	0.21	5.04	**9.95**	0.40	3.25	**3.03**	0.15	-0.84	-0.78
France	0.27	2.68	**4.77**	0.11	4.11	**5.67**	0.53	2.39	**2.54**	0.04	-1.01	-0.58
Germany	0.18	3.06	**5.95**	0.00	4.25	**9.16**	0.34	3.43	**3.91**	0.12	-1.59	-0.84
Hong Kong	0.45	5.05	**3.81**	0.50	8.17	**3.69**	0.57	4.18	**2.04**	0.21	-0.58	-0.38
Italy	0.19	3.77	**6.50**	0.12	3.70	**4.51**	0.45	4.19	**4.17**	-0.07	2.81	**2.32**
Japan	0.25	1.60	**3.09**	0.39	2.50	**4.05**	0.06	-0.31	-0.30	0.10	2.05	1.11
Korea	0.44	2.56	**2.77**	0.62	3.41	**2.24**	0.31	2.02	**1.78**	0.34	0.28	0.11
New Zealand	0.20	4.13	**7.88**	0.18	4.65	**9.75**	0.26	4.72	**4.74**	0.12	1.12	1.42
Singapore	0.33	6.21	**7.91**	0.53	7.03	**7.94**	0.22	7.19	**5.09**	0.21	-1.12	-0.73
Spain	0.26	5.17	**8.20**	-0.26	8.25	**9.96**	0.63	4.78	**4.64**	0.07	0.15	0.10
Switzerland	0.19	2.30	**4.15**	-0.02	3.60	**5.17**	0.40	2.04	**2.12**	0.10	-0.85	-0.56
UK	0.27	2.77	**4.63**	0.24	5.31	**4.81**	0.39	2.09	**2.63**	0.11	-1.73	-1.10
S&P 500	0.20	1.34	**2.97**	0.14	1.95	**3.74**	0.44	0.46	0.40	0.16	-2.82	**-2.08**
DJIA	0.18	1.32	**4.04**	0.13	1.57	**4.56**	0.47	0.99	0.76	0.16	-2.02	-1.53
Panel B: Squeeze Method (20,2)												
Australia	0.26	3.38	**2.52**	0.21	4.95	**2.57**	0.40	3.02	1.07	0.15	-2.57	-1.61
France	0.27	1.82	0.61	0.11	2.90	0.84	0.53	0.06	0.01	0.04	8.38	**2.58**
Germany	0.18	8.76	**3.91**	0.00	4.32	**2.43**	0.34	13.01	**3.00**	0.12	5.12	**2.11**
Hong Kong	0.45	4.24	0.90	0.50	12.71	**1.71**	0.57	-6.17	-1.09	0.21	-5.43	-0.75
Italy	0.19	6.34	**3.42**	0.12	6.10	**2.37**	0.45	7.45	**2.29**	-0.07	4.06	**1.77**
Japan	0.25	4.74	**2.39**	0.39	6.75	**2.95**	0.06	-6.02	-1.40	0.10	10.76	**2.98**
Korea	0.44	16.18	1.18	0.62	14.41	0.70	0.31	16.56	**2.49**	0.34	4.62	0.73
New Zealand	0.20	3.91	1.43	0.18	5.31	1.55	0.26	5.17	1.04	0.12	-8.48	**-8.28**
Singapore	0.33	5.34	**2.11**	0.53	1.47	0.48	0.22	9.80	**2.40**	0.21	0.97	0.13
Spain	0.26	7.17	**2.81**	-0.26	7.75	**2.57**	0.63	9.84	**2.51**	0.07	-3.19	-0.51
Switzerland	0.19	5.18	**2.90**	-0.02	5.86	**4.03**	0.40	8.39	**3.74**	0.10	-0.15	-0.04
UK	0.27	4.37	**2.12**	0.24	3.90	0.87	0.39	5.84	**2.07**	0.11	0.60	0.21
S&P 500	0.20	2.14	1.52	0.14	3.50	**2.21**	0.44	-0.35	-0.20	0.16	-5.40	-0.81
DJIA	0.18	3.30	**2.91**	0.13	4.54	**3.45**	0.47	-1.17	-0.50	0.16	-7.09	**-9.48**

4.8 Conclusion

Bollinger Bands have received growing attention since the introduction in 1983 in the United States and, in particular, since publication of the book *Bollinger on Bollinger Bands* in 2001. Associated with this growing popularity, I discover the gradual downward profitability of using Bollinger Bands in international stock markets. Using Bollinger Bands indeed generates superior returns before 1983, whereas the returns turn negative in the United States immediately after 1983 and in the Japanese market around 1990; then in European stock markets, including the UK, Swiss, French, and German stock markets; and, lastly, in Asian-Pacific stock markets, including the Australian, Korean, and Hong Kong markets. Since 2002, Bollinger Bands have largely lost their predictive ability in major stock markets. My results indicate the impact of investor overuse on the profitability of a useful trading strategy and warn of the danger of investing in many so-called return predictability anomalies.

Chapter 5 Technical Analysis: A Cross-country Analysis

5.1 Introduction

Whether technical analysis predicts future stock returns is a long-debated question. Current answers vary greatly, depending on where these strategies are used; even the exact same technical trading strategies can show substantially different profitability in different countries. For example, Brock, Lakonishok, and LeBaron (1992) find 26 simple technical trading strategies generate significant returns in the US market from 1896 to 1986. But since their seminal work, researchers have carried out the same analysis in other markets and found mixed results. Hudson, Dempsey, and Keasey (1996) find the same technical trading rules do not outperform the buy-and-hold strategy in the UK stock market from 1980 to 1991 after accounting for transaction costs. Bessembinder and Chan (1995) document the outperformance of these rules against the buy-and-hold strategy in the Malaysian, Thai, and Taiwanese stock markets but not in the Hong Kong, Japanese, or Korean stock markets during 1975–1991. Ito (1999) also finds these rules generate higher returns in the Indonesian, Mexican, and Taiwanese stock markets than in the Japanese, US, and Canadian stock markets during 1980–1996. By using the same 26 strategies on a sample of 50 countries from 1994 to 2014, my preliminary analysis confirms the mixed predictability above and this conclusion continues to hold when I use risk-adjusted returns. To illustrate, trading on a basic technical indicator (the variable length moving average, or VMA (1, 50)) generates an average monthly risk-adjusted return as high as 2.9% in the Venezuelan market, but also as low as -16.8% in the

Brazilian market, that is, a difference of nearly 20% per month. Overall, this indicator shows statistically significant predictive ability in 36 markets of my sample. The results are more or less similar for the other 25 strategies. Therefore a natural question is why does the profitability of technical trading strategies differ across countries?

I propose three possible explanations for the cross-country differences: investor individualism, market development and integrity, and information uncertainty. The first explanation, investor individualism, measures investors' likelihood to herd in each country. Investors from more culturally individualistic (collectivistic) countries are less (more) likely to herd and thus make different (the same) investment decisions. As suggested by Irwin and Park (2007), such behavior could relate closely to the root cause of what makes technical analysis work: trends. Technical analysis handbooks[39] suggest that when enough traders make the same decision, prices are shifted away from their fundamental values due to the changed aggregate supply of and demand for the security. Since technical analysis theory also assumes that investors tend to repeat themselves, prices tend to follow trends due to the repeated herding behavior. So, if the theory holds, I expect higher technical trading profits in less individualistic countries. Previous theoretical studies support the role of such behavior. Schmidt (2002) shows that technical traders' concerted actions can move the market price in a direction favoring their strategy because such actions affect market liquidity and the move is linearly related to excess demand. Froot, Scharfstein, and Stein (1992, p. 1480) also argue that

[39] Examples of such textbooks include those of Kahn (2010) and Kirkpatrick and Dahlquist (2011).

> The very fact that a large number of traders use chartist models may be enough to generate positive profits for those traders who already know how to chart. Even stronger, when such methods are popular, it is optimal for speculators to choose to chart.

Although I have no direct empirical evidence from the technical analysis literature before this study, Chui, Titman, and Wei (2010) find the momentum strategy—another trend-following strategy—generates significantly higher profits in more individualistic countries in their sample of 41 stock markets from 1984 to 2003. They argue that people in individualistic countries are more likely to be overconfident about the precision of their information and more prone to self-attribution bias than people in collectivistic countries are. Because such overconfidence is positively related to momentum profits, the profits are higher in more individualistic countries. On the other hand, Schmeling (2008) also finds the sentiment-based strategy—a closely-related strategy that analyzes investor behavior—generates higher profits in more collectivistic countries in a sample of 18 industrialized countries from 1985 to 2005. Motivated by these studies that indicate the importance of herd-like behavior, I investigate the possible role of such behavior in explaining the country-varying profitability of technical strategies.

My second explanation relates to the different market development and integrity levels across countries. On a broader level, as pointed out by Korajczyk (1996) and Levine and Zeros (1996), generally, more arbitrage opportunities exist in less developed and/or integrated markets due to factors such as higher costs of information, less investor sophistication, and higher risks. The cross-country studies mentioned above (Schmeling (2008); Chui, Titman, and Wei (2010)) also find that returns are more predictable in less developed and/or integrated markets by using the momentum and sentiment strategies. More specifically, since technical analysis primarily relies on non-fundamental information such as past prices to predict future returns, I then expect higher technical trading profits when non-fundamental information plays a more important role and this is more likely the case in less developed and/or integrated markets. Theoretical studies such as those by Treynor and Ferguson (1985) and Brown and Jennings (1987) support the view that technical analysis is more useful when prices are not revealing (of fundamental information). Consistent with their argument, Neely et al. (2014) document empirical evidence of stronger predictive abilities of many widely used technical indicators during recession periods—when non-fundamental information plays a more important role—in predicting US equity risk premiums from 1950 to 2011. I then examine the role of market development and integrity in explaining the cross-country profitability of technical trading strategies.

Third, the degree of information uncertainty could also be relevant for several reasons. First, many studies, including those of Hirshleifer (2001), Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), and Jiang, Yi and Zhang (2005), document that investors' psychological biases are increased when there is more uncertainty. Therefore, as argued earlier, if investors' behavioral bias (particularly the herd-like bias) explains technical trading profits, its explanatory power should be stronger with greater information uncertainty. In addition, Zhang (2006) argues that short-term price continuation (i.e., trends) is due to investor behavioral bias and trends are more detectable with greater information uncertainty. This explains the author's finding that momentum strategy as a trend following a strategy generates higher profits in the case of greater information uncertainty, because in this case investors overreact more. Since technical analysis also relies on trends, I test whether information uncertainty relates to technical trading profits. Moreover, as argued earlier, technical analysis primarily uses non-fundamental information. Since investors tend to rely more on such non-fundamental information when facing greater information uncertainty, I also expect higher technical profits with greater information uncertainty under this conjecture. Previous theoretical evidence of Brown and Jennings (1989) and Zhu and Zhou (2009) confirm that technical analysis is more effective when investors face greater information uncertainty[40] and empirical evidence on US stock cross sections, such as that of Han, Yang, and Zhou (2013), also shows that technical strategies generate higher returns on portfolios that exhibit greater information uncertainty. Therefore, this study uses information uncertainty as the third explanation for the different profitability for technical strategies across countries.

My results show that all three explanations hold. As expected, technical trading profits are higher in countries where investors are less culturally individualistic, in less developed and/or integrated markets, and in markets that exhibit greater information uncertainty. Among the three explanations, that of investor individualism shows the

[40] Zhu and Zhou (2009) derive a theoretical model that shows technical moving average rules add value to common asset allocation rules that invest fixed proportions of wealth in stocks and the usefulness is more apparent when there is uncertainty about which model truly governs the stock prices, due to factors such as the cost of collecting and processing information when reliable predictive variables are hard to find. Brown and Jennings (1989) document that rational investors can gain from forming expectations based on historical prices and this gain is an increasing function of the volatility (uncertainty) of the asset. They further point out that a decrease in the variance of the historical and/or current fundamental information leads to the increased value of technical analysis. This relation is reversed for relatively small values of either variance.

strongest explanatory power, explaining 21 out of the 26 technical trading strategies' different profitability across countries. Market development and integrity and information uncertainty explain the profitability of 16 and 14 trading strategies, respectively.

The conclusions are robust to several additional checks. First, the results do not change if I control for a number of macroeconomic risk factors. While the three explanations hold in both economic expansion and recession periods, technical trading profits are significantly higher during economic contractions in international stock markets. This is consistent with previous findings in the US market (e.g., Neely et al. (2014)). Second, I primarily use Hofstede's (2001) cultural individualism index, a composite index for market development and integrity, and a composite index for information uncertainty to proxy for the three explanations, respectively. The composite indices are formed from a number of different proxies for each explanation to best eliminate noise in the individual proxies. Nevertheless, the conclusions are the same if I use an alternative individualism index from House et al. (2004) or if I use the individual proxies for the other two explanations. Moreover, I confirm my results on an alternative sample of the first 20 years of each market. This has two implications: First, I show that technical trading profits are higher during the first 20 years (than those in the main sample from 1994 to 2014), which confirms the role of market development and integrity because the markets are less developed in the earlier sample. Second, the robust explanatory power of investor individualism could lend further confidence to my results. Furthermore, my results remain robust if I employ an orthogonalization approach to ensure each explanation provides additional explanatory power; the results are also robust to different standard error correction methods.

While most papers in the technical analysis field present time-series analyses, this paper contributes to the literature with the first piece of cross-country evidence. I find simple technical trading rules generate positive profits in many countries and the profitability is related to investors' cultural individualism, stock market development and integrity, and information uncertainty. This study could well reconcile some previous mixed results on the efficiency of technical analysis. Furthermore, as well as confirming many previous theoretical and empirical explanations for technical trading profits at the cross-country level, I present for the first time results on the relevancy of herd-like behavior. This may be of particular interest, since such behavior is a fundamental belief of technical analysis theories. A number of theoretical studies have emphasized its importance, but there has been no empirical evidence until this study. Rather than show the importance of the herd-like behavior specifically, the findings also add new evidence to the strand of literature that uses behavioral reasons to explain technical profits.[41] Since cultural values are likely to be quite persistent over time, technical profits are likely to persist over time as well, which may be why practitioners never give up on technical analysis even though its value has been questioned by academics.[42] In addition, given that momentum profits are higher

[41] For example, Friesen, Weller, and Dunham (2009) show that technical trading profits are relevant to the degree of investor behavior bias, particularly the confirmation bias. They suggest that traders who acquire information and trade on the basis of that information tend to bias their interpretation of subsequent information in the direction of their original view. This produces autocorrelations and price movement patterns that can predict future prices. Neely et al. (2014) also point out that the ability to capture changes in investor sentiment becomes crucial in deciding the efficiency of a technical indicator. Menkhoff (2010) suggests that the usefulness of technical analysis is more likely to be evident if financial market prices are influenced by non-fundamental factors, such as investors' behavioral biases.

[42] For example, Menkhoff (2010) finds that 87% of the 692 fund managers surveyed in five countries (the United States, Germany, Switzerland, Italy, and Thailand) use technical analysis. Taylor and Allen (1992) report that at least 90% of the chief forex dealers based in London surveyed in November 1988 place some weight on technical analysis, especially in shorter horizons. Lui and Mole (1998) find that over 85% of forex dealers surveyed in Hong Kong use some degree of technical analysis. Billingsley and Chance (1996) find that about 60% of commodity trading advisors rely heavily or exclusively on computer-guided technical trading systems. Fung and Hsieh (1997) estimate style factors for commodity trading advisors and conclude that trend following is the single dominant strategy.

in more individualistic countries (Chui, Titman, and Wei (2010)) while technical profits are higher in more collectivistic countries, using the individualism index could bridge the two trend-following strategies and help investors choose the appropriate strategy, depending on the country in which they invest. Last but not least, using an up-to-date sample of 50 countries—the most comprehensive sample yet—I naturally perform an out-of-sample test of the profitability of the widely used 26 technical strategies. Different from many studies that suggest the profitability diminishes over time, I find the strategies generate positive profits in most of my sample countries. All in all, despite the academic scrutiny they have received, my results suggest technical analysis still has considerable practical value in international stock markets.

5.2 Three Explanations and Data

5.2.1 Individualism Indices

The primary measure I use for investors' herd-like behavior is the Hofstede (2001) cultural individualism index. Specifically, this index measures the degree to which individuals are culturally integrated into groups, where people in more individualistic (collectivistic) cultures are less (more) likely to herd. Such cultural individualism–collectivism is a part of Hofstede's cultural dimensions theory, which was one of the first that could be quantified and used to explain observed differences between cultures.[43] The index is constructed from the results of a world-wide survey of employee values of the multinational company IBM in the 1960s and 1970s. Since then, this index has been

[43] Hofstede's cultural dimensions theory consists of six dimensions: individualism–collectivism, uncertainty avoidance, power distance, masculinity–femininity, long-term orientation, and indulgence–self-restraint. See http://en.wikipedia.org/wiki/Hofstede's_cultural_dimensions_theory.

reexamined by a number of scholars (e.g., Fernandez et al. (1997); Merritt (2000)); generally the values are quite persistent over time, even with different samples.

In the finance field, Schmeling (2008) and Chui, Titman, and Wei (2010) use this index to measure investor individualism in different countries. In individualistic cultures, individuals tend to view themselves as "an autonomous, independent person", while in collectivistic cultures, individuals view themselves "not as separate from the social context but as more connected and less differentiated from others" (Markus and Kitayama (1991, p. 226)). The authors also suggest that investors from more individualistic cultures are more likely to be overconfident since they rely heavily on their own investment decisions. This explains why momentum profits are higher in more individualistic countries, where investors are more overconfident. Therefore, by using the same index as a measure for individualism, the testable hypothesis of my study is that if technical profits are due to investors' herded trading, it should be higher in less individualistic countries, where investors are more likely to make the same investment decisions as others.

The Hofstede (2001) individualism index is available from Hofstede's website for 78 cultures.[44] Due to stock market data availability, I use 50 countries in my sample. I plot the individualism index scores for these 50 countries in descending order in Figure 5.1. Across all sample countries, Ecuador has the lowest index value, eight, indicating low individualism and the United States has the highest value, 91, indicating high individualism. In general, Western countries such as the United States, Australia, the United Kingdom, Canada, and the Netherlands are more individualistic. In contrast, less

[44] See http://www.geerthofstede.nl/dimension-data-matrix.

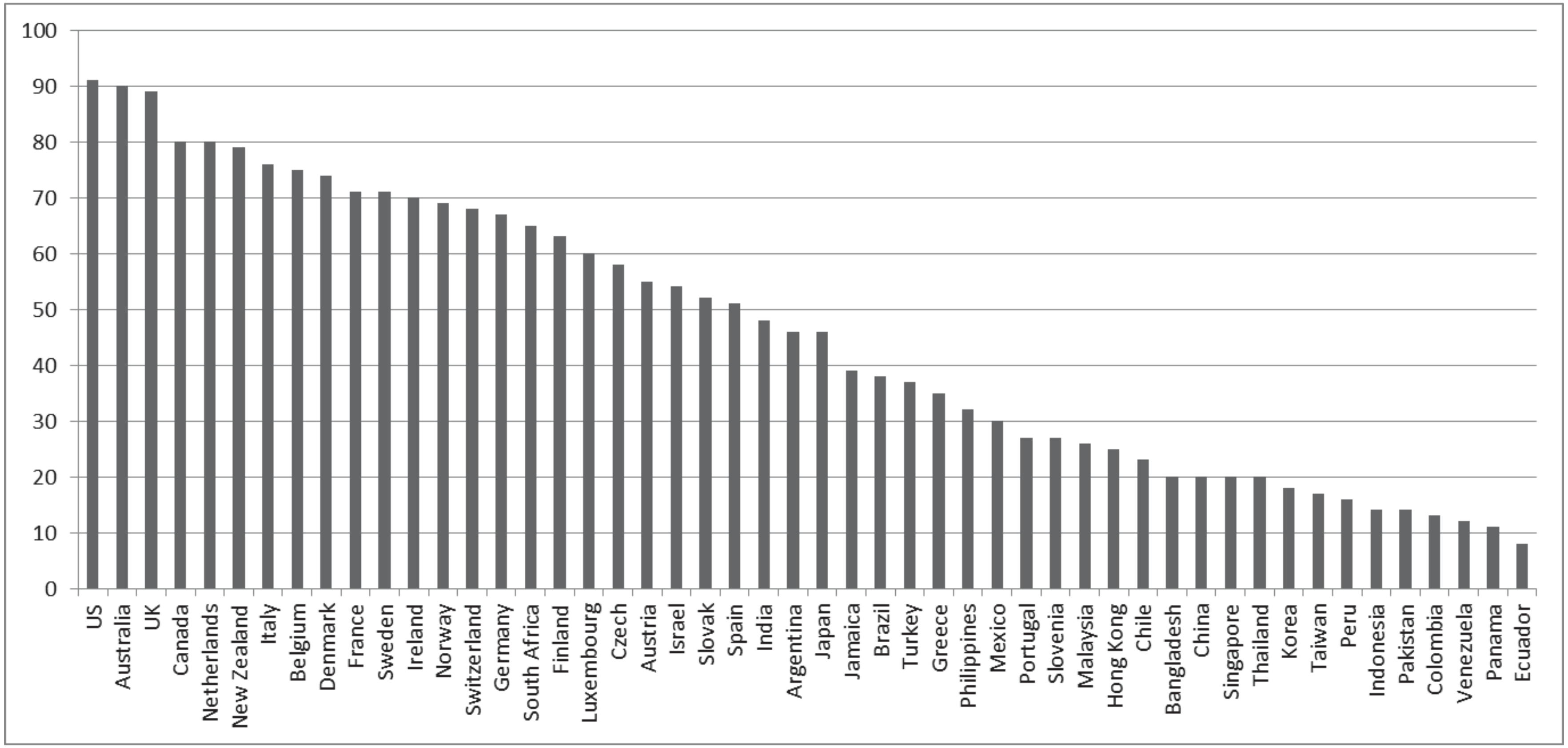
developed and eastern countries such as Ecuador, Panama, Venezuela, Colombia, and Pakistan are more collectivistic. Japan, Argentina, and India are in the middle.

Similar to Chui, Titman, and Wei (2010), I employ an alternative measure for individualism: the Global Leadership and Organizational Behavior Effectiveness (GLOBE) institutional collectivism index constructed by House et al. (2004).[45] This index is available for 39 countries in my sample and was constructed by surveying thousands of middle managers in various organizations in three industries, including financial services, food processing and telecommunication services. Therefore, it represents institutional collectivism. For consistency, I multiply the original collectivism index by -1 to obtain the alternative individualism (as opposed to collectivism) index.

I also check the results by the individualism index constructed by Tang and Koveos (2008) alternatively. Their study offers an update of the Hofstede cultural value dimensions by using economic variables, the authors argue that changes in economic conditions are the source of cultural dynamics. This index is available for 46 countries in my sample.

[45] The GLOBE research project includes nine dimensions: uncertainty avoidance, power distance, collectivism I—societal collectivism, collectivism II—in-group collectivism, gender egalitarianism, assertiveness, future orientation, performance orientation, and humane orientation. Some of these dimensions are correlated with those of Hofstede's study; however, they differ since the GLOBE study distinguishes between cultural values and cultural practices. I use the cultural practice values of the institutional collectivism dimension as my alternative measure since it is designed to reflect the same construct as Hofstede's individualism dimension (see http://en.wikipedia.org/wiki/Cross-cultural_leadership).

Figure 5.1: Hofstede's Individualism Index



5.2.2 Market Development and Market Integrity

I employ a number of proxies to measure overall stock market development and integrity. The first proxy for stock market development is stock market size, since it is positively correlated with the ability to mobilize capital and diversify risk. This proxy has been used in many previous studies, including those of Levine and Zeros (1996), Beck, Demirgüç-Kunt, and Levine (2000), and Stulz and Williamson (2003), and I follow these studies to measure stock market size by using the ratio of market capitalisation (i.e., the total value of all listed shares) divided by the gross domestic product (GDP). Stock market sizes are updated annually; by the end of 2012, Hong Kong was the biggest market and Slovak the smallest. My second measure for stock market development is the age of the stock market. As suggested by Shynkevich (2012, p. 195), "a series of studies argue technical analysis power varies, market maturity matters since more arbitrage opportunities presumably exist in younger markets than in mature ones." Other studies, including those of Ready (2002), Hsu and Kuan (2005), Qi and Wu (2006), and Hsu, Hsu, and Kuan (2010), also view stock market age as a proxy for stock market development. For simplicity and consistency, I assume the stock markets start trading when their data first become available in the Global Financial Data database, which provides extensive time-series stock market data. In my sample, the United Kingdom is the oldest stock market, with data starting in 1693, followed by the United States, with a starting year of 1791. Slovak and Slovenia are the youngest markets, starting in 1993. In addition, I include transaction costs as my third proxy for stock market development. The idea is that more developed stock markets generally have lower transaction costs. I use an index constructed by Chan, Covrig, and Ng (2005) that reflects average transaction costs in different international stock markets. In my sample, trading in Japan, the Netherlands, and the United States incur relatively low transaction costs, while the costs are highest in the Philippines, Colombia, and Venezuela.

My measures for stock market integrity are taken from the seminal study of La Porta et al. (1998). I include four indices from this study that measure investor protection, anti-director rights, ownership concentration, and insider trading, respectively. The idea is that in more integrated markets, laws generally enforce better investor and creditor protection, less ownership concentration, and less insider trading. These measures are widely used in previous studies, including those of Morck, Yeung, and Yu (2000), Schmeling (2008), and Chui, Titman, and Wei (2010).

As well as using the individual proxies above, I also construct a single composite index of the individual proxies to measure stock market development and integrity. This is motivated by Baker and Wurgler (2006), who construct a composite sentiment measure from the first principle component of individual sentiment proxies. This leaves out noise in the individual proxies and avoids a possible multicollinearity problem from including all these proxies together. My first principle component explains 40.74% of the variation in the individual proxies. This indicates that most variations of the proxies are noise and using the individual proxies directly could reduce the accuracy of my results. By the first principle component measure, the stock markets of the United Kingdom, the United States, Hong Kong, and Japan are the best developed in my sample, while the stock markets of Colombia, Greece, Mexico, and Philippine are the least developed.

5.2.3 Information Uncertainty

This study includes three proxies for information uncertainty. First, I use aggregate stock market turnover. When information is uncertain, stock market turnover increases because investors trade more due to their heterogeneous beliefs. Blume, Easley, and O'Hara (1994) provide theoretical evidence that volume information provides insights into aggregate supply uncertainty and such insights add value to technical analysis. Previous empirical studies also widely use turnover as a proxy for information uncertainty. For example, Jiang, Lee, and Zhang (2005) suggest more information-uncertain firms generally have higher turnovers, and these firms generally earn lower future returns. In addition, Lee and Swaminathan (2000) and Verardo (2009) also use turnover to proxy information uncertainty and find momentum profits are higher for more information-uncertain stocks that exhibit higher turnovers. Therefore, I use turnover as the first measure for information uncertainty and expect higher technical trading profits in countries with greater turnover.

My second measure for information uncertainty is the volatility of cash flow growth rates. Based on the findings of the previous literature (e.g., (Minton and Schrand (1999)), greater historical cash flow volatility is associated with greater uncertainty about future cash flows, that is, greater uncertainty about future earnings. Similarly, Jiang, Lee, and Zhang (2005) define highly information-uncertain firms as companies whose expected cash flows are less "knowable" and find that estimating these firms' fundamental value is inherently less reliable and more volatile. Along this line, Zhang (2006) uses cash flow volatility as a proxy for information uncertainty and finds that momentum returns are higher on more information-uncertain stocks as measured by higher cash flow volatility.

Hence, if technical analysis is more useful when fundamental information is less precise, I expect this is more likely the case when cash flow volatility is greater.

Last, I use the book-to-market ratio as another alternative proxy for information uncertainty. This is because firms with high book-to-market ratios generally face a greater risk of distress (Griffin and Lemmon (2002)); are likely to have persistently low earnings, higher financial leverage, more earnings uncertainty; and are also more likely to cut dividends compared to their low BE/ME counterparts (Fama and French (1995); Chen and Zhang (1998)). Zhang (2006) confirms his results (as above) that momentum profits are higher on more information-uncertain stocks by using the book-to-market ratio as an alternative proxy and Han, Yang, and Zhou (2013) find technical trading profits are also higher for these stocks. Therefore, at a cross-country level, I examine whether technical trading profits are higher in countries with higher book-to-market ratios.

I follow Chui, Titman, and Wei (2010) to measure these three proxies at the cross-country level for information uncertainty. I measure a country's stock market turnover by dividing the country's monthly dollar trading volume of the Datastream Global Index by this index's market capitalisation. The volatility of the cash flow growth rates of country *j* in year *y* is the standard deviation of this country's monthly cash flow growth rates in the 60-month period prior to year *y* and the cash flow of country *j* in month *t* is the ratio between the price index of this country's Global Index and the price-to-cash flow index of the same Global Index. I also use the book-to-market ratio of the country's Datastream Global Index. Similar to the above, I also estimate the first principle component of the three proxies for information uncertainty. The first principle component explains 31.03% of the variations of the proxies and, generally, information uncertainty is greater in

Argentine, Venezuelan, and Colombian markets and smaller in the United States, Pakistan, and the United Kingdom.

5.2.4 Other Data

I obtain my stock market data from the Global Financial Data database. I include all countries that have daily aggregate stock market index data available for the 20-year period from March 1994 to March 2014, for a total of 50 countries. Market returns are calculated as the log differences of the index prices between days t and $t - 1$. I report the stock market indices used for each country in Appendix 3.1, as well as the average market returns for the 20-year period. Moreover, my analysis requires the use of risk-free rates to calculate risk-adjusted returns. I also collect these data from the Global Financial Data and a detailed description of the data is also available in Appendix 3.1.

My study also uses a number of macroeconomic variables, including NBER business cycles, a January dummy, world stock market returns calculated by using the MSCI World Index, the GDP per capita growth rate, changes in exchange rates, dividend yields, and a dummy for developed (vs. developing) economies. I include the business cycle dummy because Neely et al. (2014) suggest that technical trading profits are higher during recessions. I also include a January dummy to take into account the possible January effect. In addition, I distinguish between developed and developing countries, since Park and Irwin (2007) suggest that technical trading rules are profitable in emerging markets but not in developed markets for stock indices. The rest of the variables are common macroeconomic risk factors. These data are from various sources, as stated in Appendix 3.2.

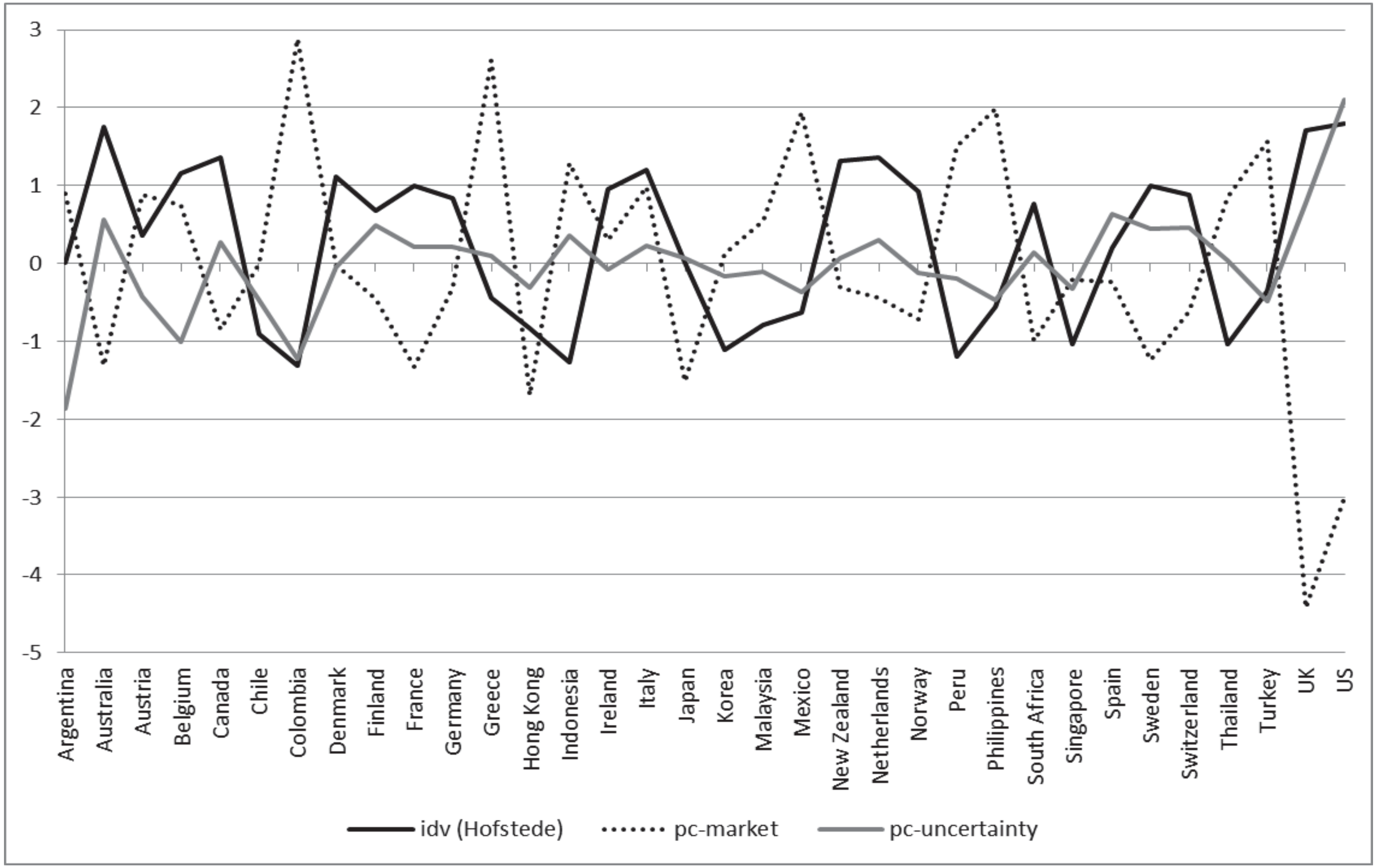
5.2.5 Preliminary Checks

Since I examine three explanations simultaneously, it is important to consider the correlations between the explanations to avoid problems such as multicollinearity. The correlations between Hofstede's individualism index and the composite index of market development and integrity (*pc-market*) and the composite index of information uncertainty (*pc-uncertainty*) are -0.61 and 0.49, respectively. The correlation between *pc-market* and *pc-uncertainty* is -0.62.[46] This seems to indicate that these explanations are correlated to some degree.

I then plot the three explanations in Figure 5.2. Since the first principle components (*pc-market* and *pc-uncertainty*) are calculated from standardized raw proxies, I also standardize the individualism index for easy comparison. Moreover, *pc-market* and *pc-uncertainty* are time-series and cross-sectional variables, while individualism is only cross sectional. For a clearer illustration, I plot the average values of *pc-market* and *pc-uncertainty* for each country to reflect cross-country relations. The black solid and dotted lines plot individualism and *pc-market* and the black dotted line plots *pc-uncertainty*. Overall, although the three proxies are correlated to some degree, each of them seems to provide information different from the other two explanations. I examine this in more detail in the following.

[46] Because the data availability for each explanation is different, the analysis in this section is based on the 34 countries for which I have data for all three explanations.

Figure 5.2: Cross-Country Correlations of the Three Explanations



5.3 Methodology

5.3.1 Technical Indicators

I use the 26 technical trading rules studied in Chapter 2. These trading rules have been widely studied in the literature; therefore, I use them to avoid any danger of data snooping from searching for other ex-ante profitable technical trading rules. Moreover, these rules are formed from using only past prices, to which I have relative easy data access; this allows me to include as many countries as possible in my analysis. The 26 trading rules can be classified into three categories: 10 VMA rules, 10 fixed-length moving average (FMA) rules, and six trading range break (TRB) rules. Since I have discussed these rules in detail in Chapter 2, I directly proceed to examine their predictive ability in international stock markets.

5.3.2 Predictive Ability of Technical Indicators

I first replicate my analysis in Chapter 2 to check preliminarily the predictive ability of the 26 technical trading rules in my 50-country sample. The methodology is similar to that of Chapter 2. To quickly recall, I run the following regression for each country:

$$r_t = \alpha + \beta D_{t-1} + \varepsilon_t$$

where

- r_t represents the daily market returns,
- D_{t-1} is a dummy variable that equals one (zero) when a buy (sell) signal is generated, and

- ε_t represents the residual term.

According to the regression model, the average buy and sell returns are captured by $\alpha + \beta$ and α, respectively. Therefore, the difference between the average buy and sell returns is captured by β. Under the null hypothesis that technical trading strategies do not produce useful trading signals, returns conditional on technical buy signals should not differ statistically from those conditional on sell signals and therefore β should not be statistically different from zero.[47] Moreover, if the technical rules anticipate correct market trends, the buy and sell returns should be positive and negative, respectively. This means β should be positive. I use White standard errors corrected t-statistics to account for possible heteroskedasticity. I use a 10% significance level throughout the study.

5.3.3 Risk-Adjusted Returns of Technical Trading Strategies

I now calculate the returns of actual trading strategies that use the technical trading rules. Specifically, I long (short sell) the market index when technical buy (sell) trading signals are generated and I invest in risk-free assets when there is no signal. It is important to evaluate the returns of the actual technical trading strategies since some technical rules only generate a few signals each year. In this case, trading solely on the technical rule may still be economically inefficient, even if the average returns per signal are high.

[47] Brock, Lakonishok, and LeBaron (1992) also study the buy and sell returns by themselves, separately. They perform t-tests to study the differences between the mean buy/sell returns and the same period's unconditional market returns. The technical trading rules have no predictive power if the null hypothesis that returns conditional on technical trading signals are not statistically different from unconditional returns cannot be rejected. I perform these tests and find similar results. These results are available upon request.

Moreover, to account for the possibility that higher technical returns may simply be compensation for higher risk, I calculate risk-adjusted returns by estimating Jensen's α. I run the following regression for each country:

$$r_t^p - r_t^f = \alpha + \beta(r_t^m - r_t^f) + \varepsilon_t$$

where

- r_t^p represents the returns of technical trading strategies,
- r_t^f represents the risk-free rates,
- r_t^m represents the daily returns of the MSCI World Index, and
- ε_t represents the residual term.

I use Jensen's α estimates as my risk-adjusted returns; they represent the excess returns generated by technical trading strategies after accounting for cross-country differences on risks. The benchmark is the MSCI World Index.

5.3.4 Cross-Country Analysis on Technical Trading Profits

I run the regression below to carry out the cross-country analysis of technical trading profits for each of the 26 trading strategies:

$$Rjt = \alpha + \beta_1 Idv_j + \beta_2 Market_{jt} + \beta_3 Uncertainty_{jt} + \beta_4 Macro_{jt} + \varepsilon_{jt}$$

where

- R_{jt} represents the risk-adjusted returns of the technical trading strategies,

- Idv_j represents the individualism index for country j,
- $Market_{jt}$ represents the measure for stock market development and integrity for country j at time t,
- $Uncertainty_{jt}$ represents the measure for information uncertainty for country j at time t,
- $Macro_{jt}$ represents the macroeconomic risk factors for country j at time t, and
- ε_{jt} represents the residual term.

Petersen (2009) points out that for empirical studies that use panel data, residuals may be correlated across time or across firms (in my case, across countries), which leads to biased estimates of ordinary least squares standard errors. Regarding this issue, my main results use standard errors clustered by country for several reasons: (1) Most of my proxies do not exhibit a time effect (e.g., the individualism index and the measures for market integrity from La Porta et al. (1998)); (2) this study includes 240 months and 50 countries and Petersen (2009) and Thompson (2011) both suggest clustering on the smaller dimension is more efficient and clustering on both time and countries works best when the two dimensions have similar clusters; and (3) the results from using standard errors clustered by both time and countries are close to those from using standard errors clustered by country only, which indicates a weak time effect on standard errors. Moreover, I also use a number of other standard error-correcting methods and my main conclusion remains similar. I discuss these in more detail in the robustness check section (Section 6).

5.4 Technical Trading Profits

In this section, I analyze the predictive abilities of the 26 technical trading strategies. First, I replicate the study of Brock, Lakonishok, and LeBaron (1992), as described in Section 3.2, with my 50-country sample and I present my results in Table 5.1. Because my results are similar across the 26 strategies, for brevity I discuss only the detailed results for the VMA (1, 50), the FMA (1, 50), and the TRB (1, 50) rules in Table 5.1. These rules are the most basic versions of the rules in the VMA, FMA, and TRB families, respectively. I report the results for the rest of the rules in Appendix 3.3. In Table 5.1, for each rule I report the average spreads between the returns conditional on the buy and sell signals, as well as the *t*-statistics testing the null hypothesis that the spreads are not statistically different from zero.

In general, the technical rules show mixed predictive abilities across countries. The VMA (1, 50), FMA (1, 50), and TRB (1, 50) rules produce significantly positive spreads in 36, 13, and 27 countries, respectively. This indicates that the null hypothesis of no predictability can be rejected in most cases. However, the average spreads are significantly negative in a few cases: the VMA (1, 50) and FMA (1, 50) rules produce significantly negative spreads in Brazil and the FMA (1, 50) rule also produces a significantly negative spread in Ecuador. These results indicate the technical rules reversely predict the market in these cases. While the results from the rest of the rules are similar, the VMA rules generally work more efficiently than the FMA and TRB rules. On average, the VMA rules reject the null hypothesis in 27 countries, that is, just over half of the sample countries. The FMA and TRB rules reject the null hypothesis in 15 countries and 21 countries, on average, respectively. Moreover, the short-term rules constructed

Table 5.1: Predictive Abilities of Simple Technical Indictors in International Stock Markets

This table reports the predictive abilities of three simple technical indicators—VMA (1, 50), FMA (1, 50), and TRB (1, 50)—in 50 international stock markets during the period 1994:03 to 2014:03. The term R_{buy} - R_{sell} measures the average spreads between returns conditional on the buy and sell signals generated by the same indicator. The *t*-statistics are from testing the null hypothesis that R_{buy} - R_{sell} equals zero. If the technical indicators do not produce useful trading signals, R_{buy} - R_{sell} should not be statistically different from zero. The *t*-statistics are White standard errors corrected and I highlight significance at the 10% level in boldface.

Country	VMA(1,50)		FMA(1,50)		TRB(1,50)	
	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats
Argentina	1.64	**2.93**	10.34	1.08	25.74	**2.56**
Australia	0.34	1.11	7.31	1.44	1.50	0.36
Austria	1.41	**3.83**	3.49	0.55	11.62	**2.09**
Bangladesh	2.69	**5.50**	19.30	**1.97**	45.44	**5.16**
Belgium	0.78	**2.17**	1.71	0.35	9.31	1.39
Brazil	-12.34	**-3.48**	-88.08	**-1.87**	-37.65	-0.93
Canada	0.63	**1.74**	0.64	0.12	1.06	0.19
Chile	1.47	**6.01**	16.51	**3.04**	19.84	**4.39**
China	1.90	**3.31**	30.98	**2.91**	16.08	1.60
Colombia	2.15	**5.31**	27.05	**2.60**	24.22	**3.13**
Czech	1.55	**3.69**	10.16	1.49	29.58	**3.35**
Denmark	1.14	**3.19**	2.41	0.35	12.77	**2.10**
Ecuador	0.56	1.31	-25.66	**-2.48**	16.66	**2.33**
Finland	1.11	**1.96**	0.67	0.07	8.04	0.92
France	0.37	0.87	-3.19	-0.51	-5.98	-1.01
Germany	0.90	**2.01**	7.38	1.10	0.46	0.07
Greece	2.29	**4.53**	23.04	**2.07**	23.13	**2.89**
Hong Kong	1.07	**2.08**	-3.70	-0.41	2.75	0.37
India	1.24	**2.59**	6.85	0.70	11.93	**1.78**
Indonesia	2.33	**4.56**	37.61	**3.68**	33.52	**4.34**
Ireland	1.37	**3.20**	-4.13	-0.51	11.69	**1.83**
Israel	0.98	**2.06**	10.23	0.97	17.98	**1.97**
Italy	1.13	**3.06**	0.75	0.10	7.48	1.12
Jamaica	1.78	**5.86**	12.15	1.21	35.78	**5.67**
Japan	0.48	1.10	10.23	1.54	-3.19	-0.52
Korea	1.38	**2.75**	17.60	**1.91**	-0.59	-0.08
Luxembourg	1.62	**4.35**	7.15	1.08	29.08	**4.29**
Malaysia	1.58	**3.75**	9.67	1.22	22.50	**3.41**
Mexico	1.11	**2.20**	9.34	1.11	11.86	1.36
New Zealand	0.31	1.36	4.98	1.08	5.26	1.37
Netherlands	0.50	1.11	8.06	1.22	3.55	0.52
Norway	1.53	**3.32**	1.05	0.12	18.10	**2.44**
Pakistan	2.02	**4.08**	29.49	**3.05**	35.52	**3.26**
Panama	1.51	**8.21**	-1.43	-0.33	-20.44	-0.54
Peru	2.67	**6.18**	23.54	**2.34**	37.78	**5.01**
Philippines	1.61	**3.70**	11.43	1.24	21.47	**2.83**
Portugal	1.70	**4.95**	15.41	**2.18**	22.77	**4.05**
South Africa	0.57	1.35	-1.33	-0.21	4.31	0.68
Singapore	0.92	**2.32**	7.03	1.06	20.24	**3.50**
Slovak	0.55	1.45	0.94	0.14	14.25	**2.19**
Slovenia	2.36	**6.16**	21.47	**1.94**	27.87	**3.84**
Spain	0.65	1.49	4.23	0.59	-3.25	-0.46
Sweden	0.96	**2.04**	-5.63	-0.78	-6.46	-0.95
Switzerland	0.54	1.42	-5.61	-1.02	4.40	0.74
Taiwan	1.40	**3.34**	11.34	1.45	-0.99	-0.15
Thailand	1.85	**3.93**	10.00	0.93	26.53	**3.44**
Turkey	0.92	1.19	26.24	**1.74**	21.31	**1.94**
UK	-0.11	-0.29	1.07	0.24	-6.01	-1.09
US	-0.13	-0.32	-4.85	-0.96	-5.54	-0.93
Venezuela	3.01	**5.84**	24.16	**2.27**	54.89	**4.92**

from using more near-term price information works better than the long-term rules. For example, the rules using a time frame of 50 days show predictive abilities in 24 countries, on average, while the rules using a time frame of 200 days show predictive abilities in only 14 countries, on average. This finding is consistent with the arguments of Allen and Taylor (1989) and Frankel and Froot (1990), which investors normally use technical analysis for short-term forecasting and use fundamental analysis for long-term forecasting. Overall, my preliminary analysis confirms that the technical trading rules no longer produce useful trading signals in some countries, such as the United States, this is consistent with my findings in Chapter 2, and in some countries (e.g., Brazil and Ecuador) the technical rules even show reverse predictive ability. However, the same technical rules still show strong predictive ability in many countries. Such cross-country differences are the primary motivation for my analysis.

I then calculate the monthly risk-adjusted returns from using the 26 technical rules, as discussed in Section 3.3, and I present the results in Table 5.2. Similarly, I focus on the results of the three most basic rules, since the results of the rest of the rules are similar and are reported in Appendix 3.3. To illustrate the profitability of the technical trading strategies, I also report the monthly average market returns for each country for comparison. The results show that using the VMA (1, 50) rule produces positive risk-adjusted returns in 45 countries, except in Brazil, Ecuador, Turkey, the United Kingdom, and the United States. Moreover, the technical returns in the 45 countries are all higher than the market returns. These results also suggest that technical trading profits do not exist just in developing markets or just in developed markets. For example, the technical trading profits in developed markets such as Greece, Luxembourg, and Portugal are among the highest in my sample, although the profits are negative in other developed markets, such as the United States and the United Kingdom. Moreover, while I discover positive technical trading profits in most developing countries, I find these rules show no profitability in developing markets such as Ecuador and Brazil. Nevertheless, I test this issue more formally later by using a dummy variable for developed versus developing economies.

Overall, the average monthly return of the VMA (1, 50) rule is 0.70% across all countries, in contrast to the average monthly market return of 0.03%. However, the returns show great variations across countries. The corresponding standard deviation of the returns is 2.62%, more than three times the average return. The strategy produces the highest average return in the Venezuelan market, 2.9%, which is 17 times higher than that market's average return of 0.16%. In contrast, the same strategy generates the most significant loss in the Brazil market, -16.80% per month. Therefore, using the exactly same trading strategy can incur a difference in returns of nearly 20% per month in different markets.

Consistent with my previous findings, the VMA rules work most efficiently across all rules. But even with the least efficient FMA rules, the FMA (1, 50) rule generates higher returns than the market in 29 countries and the average return is 0.05% over all countries, still higher than the average market return of 0.03%. The standard deviation of the returns is 0.58% and the difference between the highest average return of 0.67% (in China) and the lowest average return of -3.62% (in Brazil) per month is 4.3%. The results from the TRB (1, 50) rule are similar, generating an average return of 0.59% across all markets,

Table 5.2: Risk-Adjusted Profits of Technical Trading Strategies

This table reports the average monthly market returns and the average monthly risk-adjusted returns of using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50) in 50 international stock markets during the period 1994:03 to 2014:03. For each technical indicator, I long (short sell) the market index when a buy (sell) signal is generated and I invest in risk-free assets when there is no signal. I then estimate the risk-adjusted returns by estimating the monthly Jensen's alpha. I also report the means and standard deviations of the returns.

Country	R_m (%)	VMA(1,50) (%)	FMA(1,50) (%)	TRB(1,50) (%)
Argentina	0.058	1.198	0.054	0.916
Australia	0.018	0.144	0.115	-0.038
Austria	0.015	1.459	0.080	0.634
Bangladesh	0.085	2.294	0.338	1.926
Belgium	0.020	0.787	-0.005	0.496
Brazil	0.072	-16.804	-3.615	-1.858
Canada	0.023	0.581	-0.036	0.125
Chile	0.030	1.289	0.309	0.890
China	0.023	1.684	0.670	0.699
Colombia	0.051	1.548	0.465	0.945
Czech	-0.008	1.391	0.158	1.013
Denmark	0.033	1.114	-0.028	0.630
Ecuador	0.010	-0.023	-0.576	0.424
Finland	0.028	1.031	-0.060	0.488
France	0.015	0.356	-0.138	-0.256
Germany	0.016	0.929	0.168	0.119
Greece	0.001	1.848	0.473	0.894
Hong Kong	0.014	1.047	-0.146	0.206
India	0.033	0.920	0.057	0.518
Indonesia	0.049	1.709	0.647	1.218
Ireland	0.016	1.300	-0.167	0.541
Israel	0.042	0.653	0.148	0.685
Italy	0.028	1.028	-0.015	0.333
Jamaica	0.033	0.871	0.047	1.185
Japan	-0.017	0.645	0.326	-0.038
Korea	0.015	1.112	0.396	-0.106
Luxembourg	0.016	1.650	0.123	1.397
Malaysia	0.005	1.393	0.214	0.972
Mexico	0.052	0.642	0.042	0.430
New Zealand	0.006	0.120	0.074	0.150
Netherlands	0.015	0.484	0.185	0.227
Norway	0.040	1.414	-0.044	0.760
Pakistan	0.041	1.620	0.585	1.515
Panama	0.065	1.305	-0.034	0.911
Peru	0.051	2.470	0.418	1.760
Philippines	0.019	1.290	0.137	0.829
Portugal	0.007	1.646	0.333	1.023
South Africa	0.045	0.788	-0.070	0.329
Singapore	0.001	0.739	0.143	0.754
Slovak	-0.007	0.148	-0.073	0.495
Slovenia	0.023	1.842	0.311	1.187
Spain	0.024	0.619	0.089	-0.100
Sweden	0.031	0.957	-0.194	-0.062
Switzerland	0.018	0.619	-0.203	0.302
Taiwan	0.005	1.407	0.217	-0.036
Thailand	-0.005	1.773	0.314	1.104
Turkey	0.134	-0.545	0.109	0.520
UK	0.015	-0.236	-0.056	-0.279
US	0.026	-0.094	-0.234	-0.160
Venezuela	0.157	2.901	0.299	2.768
Average	0.030	0.701	0.047	0.588
Std	0.032	2.618	0.581	0.696

with a standard deviation of 0.70%, and the gap between the highest average return of 2.77% (in Venezuela) and its lowest counterpart of -1.86% (in Brazil) is 4.63% per month. To summarise, technical analysis still shows considerable profitability in stock markets, although such profitability depends on the market of the investment. Therefore, why does the profitability differ across countries? In other words, in which market(s) should I use technical trading strategies?

5.5 Cross-Country Analysis

In this section, I carry out cross-country analysis on whether the proposed three explanations relate to the varying profitability. The explanations are investor individualism, stock market development and integrity, and information uncertainty. I use the methodology in Section 3.4 and the results are reported in Table 5.3.

The first column of Table 5.3 reports the explanatory variable(s) included in the regression(s).[48] In the second to fourth columns, I report the coefficient estimates for the explanatory variables and the associated *t*-statistics for the VMA (1, 50), FMA (1, 50), and TRB (1,50) rules, respectively. The *t*-statistics are estimated by using standard errors clustered by country and I highlight those significant *t*-statistics in boldface at the 10% significance level. In the last column, I summarise my results from all 26 trading rules. For example, the 21 (-) in the last column of Panel A means that the investors' individualism explains the varying profitability of 21 out of the 26 technical strategies. Moreover, the negative sign in parentheses indicates that individualism explains all 21

[48] I start by using the first principle components of the market development and integrity factor and the information uncertainty factor. The results from using individual proxies are also discussed later, as robustness checks.

Table 5.3: Cross-Country Analysis of Technical Trading Profits – Cluster by Country

This table reports the results of the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50). Panel A reports the parameter estimates and the associated *t*-statistics when using Hofstede's individualism index as the explanation. Panel B reports those when using Hofstede's individualism index and the first principle component of the market development and integrity proxies as explanations. Panel C reports those when using Hofstede's individualism index and the first principle components of the market development and integrity proxies and information uncertainty proxies as explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use the 10% significance level and standard errors clustered by country.

Factors	VMA(1,50) *(10^{-3})	FMA(1,50) *(10^{-3})	TRB(1,50) *(10^{-3})	no. of significant results across all 26 Strategies
Panel A: Investor Individualism				
(1) idv (Hofstede)	-0.104	-0.039	-0.128	21 (-)
	(-1.77)	**(-2.22)**	**(-4.11)**	
Panel B: Investor Individualism + Market Development				
(1) idv (Hofstede)	-0.093	-0.048	-0.060	21 (-)
	(-3.05)	**(-2.9)**	**(-2)**	
(2) pc-market	1.191	0.240	1.572	16 (+)
	(1.87)	(0.94)	**(4.45)**	
Panel C: Investor Individualism + Market Development + Information Uncertainty				
(1) idv (Hofstede)	-0.105	-0.049	-0.063	21 (-)
	(-3.67)	**(-3.04)**	**(-2.09)**	
(2) pc-market	2.132	0.388	2.184	16 (+)
	(4.15)	(1.4)	**(4.89)**	
(3) pc-uncertainty	2.253	0.087	1.558	14 (+)
	(2.43)	(0.2)	**(2.02)**	
Max no. of countries			50	
Min no. of countries			34	

strategies' profitability negatively. In addition, since I discover possible correlations among the explanatory variables (in Section 2.5), I use the procedure that includes, first, only one explanatory variable in the regression, then I add the second variable to the regression, and, last, I run the regression with all three variables. This approach allows me to examine the additional explanatory power of the added variable(s) and to check the stability of the indication of the base variable(s). If the correlations among the variables affect my conclusions, I should find the added variable(s) show no significance in predicting the cross-country differences and/or the base variable(s) show unstable predictive ability after the additional variable(s) are included.[49] I start by using investor individualism as the base variable, then I add the market development and integrity variable, and I further add the information uncertainty variable in the last step. The results are reported in Panels A to C of Table 5.3, respectively. Since the data availability for each variable differs, the last two rows report the maximum and minimum numbers of countries included in the regressions.

The results from Panel A of Table 5.3 indicate that investor individualism shows strong explanatory power for the cross-country profitability of technical strategies. It explains the trading profits of 21 rules negatively (the rest of the results are marginally significant). This means that technical trading profits are higher in countries where investors are less individualistic, that is, more likely to herd. I then add market development and integrity to my regression. The results in Panel B show that this variable[50] positively explains the technical trading profits for strategies, so technical trading profits are higher in countries where the markets are less developed and/or integrated. Moreover, the parameter estimates and significance levels of individualism are reasonably stable after the additional variable is included. Therefore, market integrity and development provide additional explanatory power to my model. I then further include the information uncertainty variable. The results in Panel C show that information uncertainty positively

[49] A better approach to analyze the additional explanatory power of the variables could be to use an orthogonalization approach that only includes residuals from the regression of additional explanatory factors against the explanatory factor(s) already included. I start with the simplest technique by including the factors directly and then check the robustness of the results from using the orthogonalization approach in a later section.
[50] I construct *pc-market* so that higher values represent better stock market development and integrity; I describe the detailed approach in Appendix 3.1.

explains the technical trading profits of 14 rules,[51] so technical trading profits are higher in countries with greater information uncertainty. Apart from showing the additional explanatory power of information uncertainty, the results also confirm the predictive abilities of the other two explanations.

To summarise, I find that technical trading profits are higher in countries where the investors are less individualistic, the markets are less developed and/or integrated, and information uncertainty is greater. These findings are consistent with my expectations. Among the three explanations, investor individualism shows the strongest predictive ability that explains most of the rules' profitability, while information uncertainty shows the weakest predictive ability but, even then, it explains over half of the 26 trading rules' profitability. Moreover, each of the three explanations adds extra explanatory power to the model.

5.6 Robustness Checks

5.6.1 Macroeconomic Variables

I include a number of macroeconomic risk factors in the regression to check if my conclusions are robust. The results are available in Table 5.4.

Table 5.4 has the same column layout as Table 5.3 and the results for the three main explanations and the macroeconomic variables are in Panels A and B, respectively. The results in Panel A show that investor individualism negatively predicts the cross-country profitability for 21 technical trading strategies; moreover, market development and

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[51] Higher values of *pc-uncertainty* reflect greater information uncertainty. The detailed description of *pc-uncertainty* is given in Appendix 3.1.

Table 5.4: Regression with Macroeconomic Variables

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50) with the macroeconomic control variables. Panel A reports the parameter estimates and the associated *t*-statistics for my three main explanations and Panel B reports those for the macroeconomic variables. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use the 10% significance level and the standard errors clustered by country.

	VMA(1,50) *(10^{-3})	**FMA(1,50) *(10^{-3})**	**TRB(1,50) *(10^{-3})**	**no. of significant results across all 26 Strategies**
Panel A: Main Variables				
(1) idv (Hofstede)	-0.154	-0.033	-0.068	21 (-)
	(-4.16)	**(-2.15)**	**(-2.01)**	
(2) pc-market	2.457	0.448	2.033	21 (+)
	(5.87)	**(1.72)**	**(6.05)**	
(3) pc-uncertainty	2.184	-0.117	2.079	16 (+)
	(2.66)	(-0.32)	**(2.74)**	
Panel B: Macroeconomic Variables				
(1) cycle	10.782	1.586	5.155	21 (+)
	(8.54)	(1.5)	**(4.54)**	
(2) jan	3.915	-5.109	5.584	11 (+), 5 (-)
	(1.45)	**(-3.35)**	**(2.29)**	
(3) world	6.960	0.613	4.610	12 (+), 3 (-)
	(0.94)	(0.19)	(1.2)	
(4) gdp_gw	-43.302	31.118	-29.811	0
	(-0.87)	(1.04)	(-0.63)	
(5) cfx	-20.789	3.631	6.798	5 (+), 8 (-)
	(-1.93)	(0.71)	(1.47)	
(6) dividend	2.113	-0.427	0.892	16 (+)
	(3.02)	(-0.93)	**(1.74)**	
(7) hdi	2.559	0.070	-0.029	0
	(1.26)	(0.07)	(-0.02)	
no. of countries			30	

integrity and information uncertainty explain 21 and 16 of the trading strategies' profitability, respectively. While these results confirm the importance of the three explanations, interestingly, the predictive abilities of market development and integrity and of information uncertainty are both strengthened after the macroeconomic variables are included. These two explanations explain 16 and 14 of the strategies' profitability, respectively, before the macroeconomic factors are included, as shown in Table 5.3.

In addition, the results in Panel B of Table 5.4 indicate that technical trading profits are higher during recession periods for 21 of the trading strategies I examine, in line with previous literature (e.g., Neely et al. (2014)). Moreover, technical trading profits are also higher in countries with higher dividend yields for 16 of the technical trading rules I examine. This is also consistent with theory, since higher dividend yields generally proxy for greater overall macroeconomic risk. The rest of the proxies generally show mixed predictive abilities across different technical trading strategies, indicating that my results are not likely to be explained by the January effect, overall world stock market returns, different GDP per capita growth rates across countries, or changes in exchange rates. Moreover, the results also indicate that the three explanations hold in both developed and developing countries. In addition, technical trading profits are not higher in either developed or developing countries after controlling for the three explanations.

5.6.2 Alternative Individualism Index

The GLOBE individualism index provides an alternative measure of investor individualism. Compared to Hofstede's individualism index, the GLOBE index measures the individualism of institutional managers only and is available for a smaller sample of countries (Hofstede's index is available for 50 countries in my sample, while the GLOBE index is available for only 38 countries). Nevertheless, I want to avoid the risk of relying solely on a single proxy (for the individualism explanation). Therefore, I replicate my analysis using the GLOBE individualism index and present my results in Table 5.5.

My main conclusion remains robust, although the explanatory power is somewhat weaker for investor individualism and information uncertainty. The GLOBE individualism index negatively explains the profitability of 10 strategies at the 10% significance level; however, considering that the explanatory power is quite marginal for five other strategies (with *t*-statistics around -1.60), I conclude this explanation still holds for the alternative proxy. Similarly, information uncertainty significantly predicts the profitability of eight trading strategies; however, the predictive ability is marginally significant for another 10 strategies. Lastly, market development and integrity still shows strong predictive ability for all 26 technical trading strategies. Therefore, I can confirm my results by using an alternative measure for individualism.

I also check the results by using the individualism index constructed by Tang and Koveos (2008) alternatively. The results are available in Panel B of Table 5.5. I find that investor individualism explains the profitability of 21 strategies negatively; market development and integrity and information uncertainty explain the profitability of 16 and 14 strategies respectively. These results are very similar to those by using the Hofstede's individualism index. Therefore, I can confirm my results by using alternative measures for individualism.

Table 5.5: Alternative Individualism Index

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50). I use the GLOBE individualism index and the individualism index constructed by Tang and Koveos (2008) alternatively and the other two variables are the first principle components of the market development and integrity proxies and information uncertainty proxies. For each technical indicator, I report the parameter estimates and the associated *t*-statistics of the three explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use the 10% significance level and the standard errors clustered by country.

Factors	**VMA(1,50) *(10^{-3})**	**FMA(1,50) *(10^{-3})**	**TRB(1,50) *(10^{-3})**	**no. of significant results across all 26 Strategies**
Panel A: GLOBE Individualism Index				
(1) idv (GLOBE)	-2.172	-0.399	-0.929	10 (-)
	(-1.66)	(-0.49)	(-0.57)	
(2) pc-market	3.053	0.963	2.608	26 (+)
	(5.68)	**(3.28)**	**(5.98)**	
(3) pc-uncertainty	1.943	0.058	1.449	8 (+)
	(1.79)	(0.12)	**(1.61)**	
no. of countries			27	
Panel B: Tang and Koveos (2008) Individualism Index				
(1) idv (Tang&Koveos (2008))	-0.077	-0.046	-0.082	21 (-)
	(-1.84)	**(-3.17)**	**(-2.73)**	
(2) pc-market	2.157	0.271	1.761	16 (+)
	(3.86)	(1.15)	**(4.66)**	
(3) pc-uncertainty	2.133	0.049	1.545	13 (+)
	(2.39)	(0.11)	**(2.08)**	
no. of countries			33	

5.6.3 Individual Proxies

My analysis above is based on using the first principle components of a number of proxies for the explanation of stock market development and integrity and the explanation of information uncertainty. One could wonder what would happen if I used the individual proxies. I discuss my findings from using the individual proxies for these two explanations in this section and the results are reported in Table 5.6. Panel A presents the parameter estimates and the associated *t*-statistics for each proxy used to regress against the technical trading profits. Panel B presents the results from including all the proxies jointly for the same explanation. In addition, to test the joint significance of these proxies, I use the Wald test to test the hypothesis that all the coefficients of the proxies for the same explanation jointly equal zero. The Wald test results are also reported in Panel B, with *chi*-statistics and the corresponding *p*-values in parentheses.

The results in Panel A of Table 5.6 show that the individual proxies' predictive power varies largely. For market development and integrity, the stock market size, stock market age, and transaction costs show significant predictive power for the varying profitability of technical strategies. The profits are higher in smaller markets, younger markets, and in markets with higher transaction costs. These results are consistent with my hypothesis that technical trading profits are likely to be higher in less developed markets. However, some proxies for market integrity shows limited predictive power: Different degrees of investor protection (creditor, anti-director) and the likelihood of insider trading (sh_vo) show no predictive power, while ownership concentration shows limited predictive power for six trading strategies' profitability; technical trading profits are higher in countries with higher concentrations of share ownership, as expected. Moreover, the

Table 5.6: Individual Proxy Analysis

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50). I use individual proxies for the market development and integrity and information uncertainty explanations. I report the parameter estimates and the associated *t*-statistics for each proxy. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. Panel A presents the parameter estimates and the associated *t*-statistics for each proxy used to regress against the technical trading profits. Panel B presents the results from including all the proxies jointly for the same explanation. In addition, to test the joint significance of these proxies, I use Wald tests to test the hypothesis that all the coefficients of the proxies for the same explanation jointly equal zero. The Wald test results are also reported in Panel B and the *chi*-statistics and corresponding *p*-values are in parentheses. I use the 10% significance level and the standard errors clustered by country.

Factors	Panel A: Individual Regression				Panel B: Joint Regression by Factor			
	VMA(1,50) $*(10^{-3})$	**FMA(1,50) $*(10^{-3})$**	**TRB(1,50) $*(10^{-3})$**	**no. of significant results across all 26 Strategies**	**VMA(1,50) $*(10^{-3})$**	**FMA(1,50) $*(10^{-3})$**	**TRB(1,50) $*(10^{-3})$**	**no. of significant results across all 26 Strategies**
Market Development and Market Integrity								
(1) size	-0.015	-0.009	-0.019	16 (-)	-0.003	-0.006	-0.008	8 (-)
	(-1.2)	**(-2.13)**	**(-2.37)**		(-0.21)	(-1.43)	(-1.22)	
(2) age	0.047	0.012	0.050	21 (+)	0.027	0.006	0.015	0
	(3.54)	**(2.08)**	**(5.71)**		(1.3)	(1.24)	(1.5)	
(3) tran	0.125	0.030	0.097	26 (+)	0.092	0.039	0.043	25 (+)
	(3.58)	**(3)**	**(4.63)**		**(2.67)**	**(3.5)**	**(2.25)**	
(4) creditor	2.152	0.578	0.384	0	0.705	0.590	0.321	5 (+)
	(0.76)	(0.86)	(0.49)		(0.92)	**(2.19)**	(0.64)	
(5) anti-director	-0.745	-0.103	-0.830	0	-1.082	-0.546	-0.005	10 (-)
	(-0.81)	(-0.38)	(-1.07)		**(-1.84)**	**(-2.37)**	(-0.01)	
(6) ownership	-11.777	-1.962	18.692	6 (+)	-4.248	-3.804	13.661	6 (+)
	(-0.39)	(-0.29)	**(3.22)**		(-0.39)	(-0.95)	**(1.83)**	
(7) sh_vo	-14.523	-1.124	0.689	0	0.656	0.663	1.352	0
	(-0.77)	(-0.27)	(0.2)		(0.17)	(0.52)	(0.66)	
Wald test					**8.99**	**14.07**	**19.22**	26
					(<0.0001)	**(<0.0001)**	**(<0.0001)**	
Information Uncertainty								
(1) turnover	0.007	0.001	0.004	0	0.044	0.009	0.026	14 (+)
	(1.21)	(0.65)	(1.14)		**(2.4)**	(1.29)	(1.36)	
(2) cf_vol	12.299	2.533	9.198	6 (+)	1.302	0.081	8.147	6 (+)
	(0.95)	(0.73)	**(2.73)**		(0.17)	(0.03)	**(2.5)**	
(3) b/m	-1.381	-0.879	-0.636	5 (-)	-1.989	-0.947	-0.650	12 (-)
	(-1.24)	**(-2.05)**	(-0.73)		**(-1.65)**	**(-2.02)**	(-0.72)	
Wald test					**2.85**	1.79	**3.68**	16
					(0.0492)	(0.1639)	**(0.0196)**	
Max no. of countries	50				41			
Min no. of countries	36				36			

predictive power of the proxies for information uncertainty is also limited. Stock market turnover shows no significant predictive power. Cash flow volatility (cf_vol) positively predicts six strategies' profitability, while the book-to-market ratio negatively predicts five strategies' profitability. Nevertheless, the results from the latter two proxies indicate technical trading profits are higher in countries with greater information uncertainty, which normally exhibit higher cash flow volatilities and have lower book-to-market ratios. These findings are also in line with my hypothesis.

I then perform a joint test for each explanation that includes all the proposed proxies for this explanation. For the market development and integrity explanation, I find the predictive abilities of stock market size and stock market age are both significantly reduced in the joint test. Stock market size only predicts eight trading strategies' profitability (compare to that of 16 strategies when use individually) and stock market age shows no predictive ability while it predicts 25 strategies' profitability in Panel A of Table 5.6. On the other hand, the market integrity proxies' predictive abilities increase in the joint test. Specifically, the degree of creditor protection positively predicts five trading strategies' profitability, while the degree of anti-director rights negatively predicts 10 trading strategies' profitability; neither of these two proxies shows any predictive ability individually. However, the results for creditor protection are somewhat intriguing, since they indicate that technical trading profits are higher in more integrated stock markets, contrary to my hypothesis. Lastly, the predictive abilities of transaction costs and ownership concentration are relatively stable, while insider trading shows no predictability, either individually or jointly. Moreover, for all 26 trading strategies, the Wald test results strongly reject the null hypothesis that all the proxies for market development and integrity jointly show no predictive power. This again supports the importance of the explanation. Apart from confirming my previous findings, another important implication of the individual regression results is that my conclusion could vary, depending on the proxy used. Since it may be arbitrageurs and difficult to pick the best proxies and also since the instable predictive ability discovered in the joint test could be a sign of multicollinearity, using the first principle component instead of the individual proxies best avoids these problems.

For the information uncertainty explanation, the predictive abilities of both turnover and the book-to-market ratio increase greatly in the joint test and the predictive ability of cash flow volatility is relatively stable. Turnover significantly predicts 14 strategies' profitability and the book-to-market ratio shows predictive ability for 12 trading strategies' profitability; both these two proxies show very limited predictive ability, however, when used individually. Since the null hypothesis of the Wald test is rejected in 16 cases, indicating the predictive ability of the explanation overall, the increased predictive ability could be a sign of an omitted variable bias. This further raises the concern of using the individual proxies and calls for the use of first principle components.

5.6.4 Alternative Sample Period

In this section, I study the robustness of my results by using an alternative sample period: the first 20 years of each stock market. This provides two benefits. First, as discussed above, stock market age is a common proxy for market development and integrity and my results from Section 6.3 also confirm that technical trading profits are higher in younger markets that are less developed and/or integrated. Therefore, if my findings above are robust, I should find profitability in the first 20 years to be greater than in my main sample period from 1994 to 2014. This is because the markets should be less developed and/or integrated in their first 20 years compared the most recent 20 years. Second, if investor individualism explains cross-country profitability, I should be able to confirm this finding for the alternative sample as well. This is because, by using the first 20 years of each market, I actually hold market development and integrity equal for each market, since the markets should have similar development statuses in their first 20 years. Therefore, I can double-check if the individualism explanation holds by itself. I replicate my analysis in Section 3.2 on this sample and present my results in Table 5.7.

The first column in Table 5.7 reports my sample countries and the second column gives the first 20-year sample periods for each country. Then I report my results for the VMA (1, 50), FMA (1, 50), and TRB (1, 50) rules. I use the earliest 20 years' daily data for each market available from the Global Financial Data database. The United States is the oldest market, which starts in 1928, and the Czech, Panamanian, and Ecuadorian markets are the youngest in this sample, starting in 1994. The results indicate that the VMA (1, 50), FMA (1, 50), and TRB (1, 50) rules generate a significantly positive R_{buy} - R_{sell} in 47, 37, and 35 countries, respectively. Recall that the same rules produce a significantly positive R_{buy} - R_{sell} in 36, 13, and 27 countries in Section 4 for the period 1994–2014. Comparing the results from the two sample periods indicates that technical trading rules show stronger predictive abilities during the first 20 years. With similar results for the rest of the 23 technical trading strategies, I can confirm that the technical trading profits are higher when the markets are less developed and/or integrated.

Table 5.7: Predictive Abilities of Simple Technical Indictors in International Stock Markets – First 20 Years

This table reports the predictive abilities of three simple technical indicators—VMA (1, 50), FMA (1, 50), and TRB (1, 50)—in 50 international stock markets during the first 20 years of each market. The term R_{buy} - R_{sell} measures the average spreads between returns conditional on the buy and sell signals generated by the same indicator. The *t*-statistics are from testing the null hypothesis that R_{buy} - R_{sell} equals zero. If the technical indicators do not produce useful trading signals, R_{buy} - R_{sell} should not be statistically different from zero. The *t*-statistics are White standard errors corrected and I highlight significance at the 10% level in boldface.

Country	Sample Begins	Sample Ends	VMA(1,50)		FMA(1,50)		TRB(1,50)	
			R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats
Argentina	Jan-67	Jan-87	4.86	**5.71**	47.11	**3.15**	80.62	**5.23**
Australia	Feb-58	Feb-78	1.63	**7.54**	21.72	**3.90**	23.47	**5.26**
Austria	Sep-85	Sep-05	1.80	**6.58**	24.95	**3.31**	3.84	0.18
Bangladesh	Feb-90	Feb-10	2.53	**5.90**	15.83	**1.95**	49.29	**4.69**
Belgium	Feb-85	Feb-05	1.29	**4.40**	12.00	**2.31**	19.77	**3.22**
Brazil	Feb-92	Feb-12	2.92	**4.40**	-6.08	-0.66	37.75	**3.26**
Canada	Jan-90	Jan-10	0.98	**4.18**	7.92	**1.96**	9.69	**2.15**
Chile	Feb-75	Feb-95	3.61	**10.52**	46.26	**4.36**	-6.35	-0.10
China	Jan-91	Jan-11	2.91	**3.97**	31.50	**2.58**	34.19	**2.44**
Colombia	Feb-92	Feb-12	2.30	**5.47**	26.08	**2.51**	26.20	**3.04**
Czech	Apr-94	Apr-14	1.55	**3.69**	10.16	1.49	29.58	**3.35**
Denmark	Feb-79	Feb-99	1.44	**6.28**	13.42	**2.11**	65.30	1.42
Ecuador	Feb-94	Feb-14	0.55	1.29	-25.66	**-2.46**	17.02	**2.39**
Finland	Feb-91	Feb-11	1.73	**3.71**	-1.47	-0.15	21.43	**2.97**
France	Oct-68	Oct-88	1.64	**5.41**	8.96	1.45	28.32	**4.63**
Germany	Feb-70	Feb-90	1.35	**6.59**	18.71	**3.80**	-13.15	-0.47
Greece	Nov-88	Nov-08	2.53	**5.23**	25.82	**2.21**	41.19	**4.42**
Hong Kong	Dec-69	Dec-89	3.21	**4.58**	64.73	**3.97**	33.96	**1.65**
India	May-79	May-99	1.17	**2.17**	1.91	0.19	68.71	1.27
Indonesia	May-83	May-03	3.19	**6.70**	31.77	**2.09**	5.54	0.13
Ireland	Feb-88	Feb-08	1.68	**4.98**	16.27	**1.88**	67.54	1.35
Israel	Jul-81	Jul-01	1.91	**4.08**	12.94	1.02	27.97	**3.02**
Italy	Jan-57	Jan-77	1.22	**3.68**	15.74	**2.36**	17.67	**3.16**
Jamaica	Nov-91	Nov-11	2.68	**7.50**	19.12	**1.65**	61.20	**3.72**
Japan	Jun-49	Jun-69	1.45	**5.11**	8.81	1.45	8.50	**1.76**
Korea	Feb-62	Feb-82	0.68	1.09	-3.75	-0.32	24.59	**3.02**
Luxembourg	Feb-85	Feb-05	1.67	**6.19**	6.51	0.97	34.53	**6.34**
Malaysia	Feb-80	Feb-00	2.56	**4.96**	-0.64	-0.05	33.16	**3.86**
Mexico	Feb-85	Feb-05	3.41	**4.92**	40.29	**3.18**	33.12	**2.65**
New Zealand	Feb-70	Feb-90	2.26	**9.22**	18.18	**3.00**	3.52	0.11
Netherlands	Feb-80	Feb-00	0.13	0.38	9.25	**1.97**	3.82	0.60
Norway	Feb-83	Feb-03	1.79	**4.55**	17.57	**2.20**	22.78	**3.70**
Pakistan	Feb-89	Feb-09	2.59	**5.22**	26.90	**2.82**	49.71	**4.55**
Panama	Apr-94	Apr-14	1.51	**8.21**	-1.43	-0.33	-20.44	-0.54
Peru	Feb-82	Feb-02	6.78	**13.15**	41.62	**2.89**	397.58	1.34
Philippines	Feb-86	Feb-06	2.97	**5.81**	23.85	**2.04**	91.24	**1.69**
Portugal	Feb-86	Feb-06	2.81	**8.62**	21.14	**2.92**	34.82	**5.33**
South Afica	Jun-86	Jun-06	1.23	**3.22**	15.56	**2.12**	12.39	**1.70**
Singapore	Aug-65	Aug-85	2.40	**8.03**	38.20	**5.27**	-3.27	-0.08
Slovak	Nov-93	Nov-13	1.19	**2.79**	3.23	0.46	15.16	**2.29**
Slovenia	Feb-93	Feb-13	2.70	**7.02**	25.55	**2.37**	28.34	**4.01**
Spain	Sep-71	Sep-91	2.24	**7.11**	29.67	**2.87**	27.32	**4.09**
Sweden	Feb-80	Feb-00	1.93	**4.91**	15.20	**1.96**	17.70	**2.98**
Switzerland	Feb-69	Feb-89	1.03	**4.16**	13.82	**2.49**	10.60	**2.15**
Taiwan	Feb-67	Feb-87	1.69	**5.58**	11.62	**1.85**	46.20	**1.91**
Thailand	May-75	May-95	2.53	**6.88**	9.47	1.01	35.18	**5.33**
Turkey	Nov-87	Nov-07	1.97	**2.24**	38.94	**2.08**	12.72	0.35
UK	Jan-69	Jan-89	1.67	**5.04**	22.84	**2.49**	22.46	**3.62**
US	Feb-28	Feb-48	0.88	**2.08**	4.36	0.64	9.28	1.14
Venezuela	Feb-94	Feb-14	3.02	**5.83**	23.52	**2.20**	20.06	0.55

I then calculate the risk-adjusted returns during the first 20 years. I use the same methodology discussed in Section 3.3 whereas, due to data availability, I use the US three-month T-bill rate as a proxy for the risk-free rates in all countries and the benchmark is Global Financial Data's world price index, available from the Global Financial Data database. I present my results in Panel A of Table 5.8. On average, the VMA (1,50), FMA (1,50), and TRB (1,50) rules generate monthly risk-adjusted returns of 2.13%, 0.32%, and 1.50% respectively; as expected, these are all significantly higher than the 0.70%, 0.05%, and 0.59% during the period from 1994 to 2014. Moreover, the corresponding standard deviations of the returns of 1.43%, 0.33%, and 2.32%, respectively, indicate that profitability still varies largely across countries, even after controlling for differences in market development and integrity across countries.

Therefore, I re-examine if the variations in profitability can be explained by investor individualism. I regress Hofstede's individualism index against the first 20 years' risk-adjusted returns and the results are reported in Panel B of Table 5.8. During the first 20 years, I find individualism negatively predicts the profitability of 13 trading strategies at the 10% significance level and many results from the rest of the 13 rules are marginally significant. These findings confirm the predictive ability of individualism after fully eliminating the impact of stock market development and integrity.

Table 5.8: Risk-Adjusted Profits of Technical Trading Strategies – First 20 Years

Panel A of this table reports the average monthly market returns and the average monthly risk-adjusted returns using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50) in 50 international stock markets during the first 20 years of each market. For each technical indicator, I long (short sell) the market index when a buy (sell) signal is generated and I invest in risk-free assets when there is no signal. I then estimate the risk-adjusted returns by estimating the monthly Jensen's alpha. I also report the means and standard deviations of the returns. Panel B reports the results that use Hofstede's individualism index to explain the cross-country differences in profitability during the first 20 years. I report the parameter estimates and associated *t*-statistics and I also summarise the number of significant estimates and their signs for all 26 technical indicators. I use the 10% significance level and the standard errors clustered by country.

Country	R_m (%)	VMA(1,50) (%)	FMA(1,50) (%)	TRB(1,50) (%)
Panel A: Risk-adjusted Returns				
Argentina	0.311	5.628	0.908	4.316
Australia	0.015	1.450	0.411	1.000
Austria	0.039	1.676	0.482	-0.149
Bangladesh	0.067	2.391	0.309	1.855
Belgium	0.037	1.224	0.195	0.948
Brazil	0.219	4.239	-0.244	3.037
Canada	0.029	0.815	0.132	0.460
Chile	0.205	4.359	0.733	0.551
China	0.080	2.860	0.635	1.796
Colombia	0.072	2.264	0.592	1.316
Czech	-0.013	1.530	0.183	1.262
Denmark	0.047	1.187	0.153	2.475
Ecuador	0.008	0.406	-0.517	0.617
Finland	0.038	1.612	-0.098	1.055
France	0.027	1.363	0.080	1.066
Germany	0.026	1.066	0.361	0.574
Greece	0.038	2.414	0.571	1.852
Hong Kong	0.056	2.981	1.312	1.081
India	0.070	0.999	-0.055	2.406
Indonesia	0.032	3.037	0.516	0.397
Ireland	0.044	1.606	0.317	2.102
Israel	0.160	2.531	0.242	1.976
Italy	0.008	0.963	0.332	0.636
Jamaica	0.060	2.426	0.321	2.734
Japan	0.043	1.656	0.195	0.685
Korea	0.055	0.681	-0.183	1.388
Luxembourg	0.047	1.608	0.083	1.577
Malaysia	0.029	2.489	-0.208	1.485
Mexico	0.165	4.010	0.900	2.423
New Zealand	0.040	1.943	0.318	-0.469
Netherlands	0.061	0.140	0.179	0.332
Norway	0.043	1.646	0.311	0.982
Pakistan	0.038	2.368	0.588	2.122
Panama	0.065	1.383	-0.021	-1.996
Peru	0.388	8.622	0.661	15.758
Philippines	0.058	2.914	0.497	3.528
Portugal	0.054	2.511	0.323	1.685
South Afica	0.049	1.254	0.336	0.603
Singapore	0.043	2.225	0.680	-0.898
Slovak	0.016	1.055	0.048	0.585
Slovenia	0.037	2.652	0.443	1.423
Spain	0.023	1.672	0.449	0.922
Sweden	0.095	1.936	0.175	1.022
Switzerland	0.008	0.674	0.245	0.373
Taiwan	0.046	1.561	0.235	2.087
Thailand	0.052	2.319	0.118	1.636
Turkey	0.160	2.518	0.836	0.220
UK	0.036	1.387	0.411	0.856
US	-0.005	0.923	0.123	0.460
Venezuela	0.165	3.539	0.460	1.016
Average	0.070	2.134	0.321	1.503
Std	0.077	1.426	0.327	2.321
Panel B: Regression Results				
idv (Hofstede)		-0.257	-0.023	-0.190
		(-3.34)	(-1.26)	(-1.27)
no. of significant results across all 26 Strategies		13 (-)		

5.6.5 Orthogonalization Approach

As Jacobsen and Marquering (2008) show, to distinguish among different explanatory variables that are possibly correlated, an orthogonalization approach may be more precise. Therefore I follow their procedure and run the regressions below:

$$pc\text{-}market = \mu + \delta idv + \varepsilon_{\{idv\}}^{market}$$

$$pc\text{-}uncertainty = \eta + \gamma_1 idv + \gamma_2 pc\_market + \varepsilon_{\{idv,market\}}^{uncertainty}$$

where

- *pc-market* is the first principle component of the market development and integrity proxies,
- *pc-uncertainty* is the first principle component of the information uncertainty proxies,
- *idv* is Hofstede's individualism index,
- $\varepsilon_{\{idv\}}^{market}$ is the residual term of the regression that regresses *idv* against *pc-market*, and
- $\varepsilon_{\{idv,market\}}^{uncertainty}$ is the residual term of the regression that regresses *idv* and *pc-market* against *pc-uncertainty*.

In the above regressions, I use investor individualism as my base variable; therefore, $\varepsilon_{\{idv\}}^{market}$ captures the additional information that the market development and integrity explanation adds on top of individualism and $\varepsilon_{\{idv,market\}}^{uncertainty}$ captures the additional information that the information uncertainty explanation contributes in addition to the individualism and market development and integrity explanations. Then, I run the following regression to examine the explanatory power of the additional information:

$$r = \alpha + \beta_1 idv + \beta_2 \varepsilon_{\{idv\}}^{market} + \beta_3 \varepsilon_{\{idv,market\}}^{uncertainty} + \varepsilon$$

where

- *r* represents the risk-adjusted returns of the technical trading strategies,
- *idv* represents Hofstede's individualism index,
- $\varepsilon_{\{idv\}}^{market}$ is the residual term of the regression that regresses *idv* against *pc-market*,
- $\varepsilon_{\{idv,market\}}^{uncertainty}$ is the residual term of the regression that regresses *idv* and *pc-market* against *pc-uncertainty*, and
- ε is the error term.

I present my results in Table 5.9. These results are highly consistent with my main analysis: All three explanations show significant predictive ability for the cross-country profitability of technical strategies and technical trading profits are higher in less culturally individualistic, less developed and/or integrated, and more information-uncertain markets. In addition, individualism, market development and integrity, and information uncertainty explain 21, 16, and 14 strategies' profitability, respectively, exactly the same as my main findings in Table 5.3. Moreover, using the additional information that each explanation provides instead of the original explanation further reduces possible multicollinearity among explanations and my results confirm that the three explanations each add explanatory power to the model.

Table 5.9: Orthogonalization Approach

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50) via an orthogonalization approach. The term *idv* is Hofstede's individualism index and $\varepsilon_{\{idv\}}^{market}$ is the residual term of the regression that regress the *idv* against the *pc-market* and $\varepsilon_{\{idv,market\}}^{uncertainty}$ is the residual term of the regression that regress the *idv* and *pc-market* against the *pc-uncertainty*. Therefore, $\varepsilon_{\{idv\}}^{market}$ captures the additional information that the market development and integrity explanation adds on top of the individualism explanation and $\varepsilon_{\{idv,market\}}^{uncertainty}$ captures the additional information that the information uncertainty explanation contributes in addition to the individualism and market development and integrity explanations. For each technical indicator, I report the parameter estimates and the associated *t*-statistics of the three explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use the 10% significance level and the standard errors clustered by country.

Factors	**VMA(1,50) *(10^{-3})**	**FMA(1,50) *(10^{-3})**	**TRB(1,50) *(10^{-3})**	**no. of significant results across all 26 Strategies**
(1) idv (Hofstede)	-0.152	-0.062	-0.121	21 (-)
	(-4.72)	**(-5.21)**	**(-4.82)**	
(2) $\varepsilon_{\{idv\}}^{market}$	1.570	0.367	1.795	16 (+)
	(2.54)	(1.45)	**(4.36)**	
(3) $\varepsilon_{\{idv,market\}}^{uncertainty}$	2.253	0.087	1.558	14 (+)
	(2.43)	(0.2)	**(2.02)**	
no. of countries		34		

5.6.6 Alternative Standard Error Correction Methods

As Petersen (2009) and Thompson (2011) show, the results from using panel data can be misleading if the proper standard error correction method is not used. While standard errors clustered by country suits my needs best, I also replicate my analysis by using several alternative standard error correction methods. The methods include the standard ordinary least squares method, which corrects for the heteroskedasticity problem but does not account for correlations among residuals; the Fama–MacBeth method, which corrects for the time effect among residuals, that is, the residuals are correlated over time but not across different countries; and clustering on time and countries, which accounts for both time and country effects among residuals, that is, the residuals are correlated over time as well as across countries. I present the results of using the three methods in Panels A to C, respectively, of Table 5.10.

Generally, my main conclusions remain robust to using different standard error correction methods. Individualism and market development and integrity generally show similar predictive abilities across these different methods. However, the results for information uncertainty are somewhat less significant, especially when using the Fama–MacBeth method. Although information uncertainty shows no predictive ability at the 10% significance level in this case, for about half of my rules, the predictive ability is marginal (*t*-statistics >1). Nevertheless, while the main conclusions of this study do not change, the results in this section also shed some light on the importance of using an appropriate standard error correction method.

Table 5.10: Alternative Standard Error Correction Methods

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50). The variables include Hofstede's individualism index, the first principle component of the market development and integrity proxies, and the first principle component of the information uncertainty proxies. For each technical indicator, I report the parameter estimates and the associated *t*-statistics of the three explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use alternative standard error correction methods, including standard ordinary least squares, Fama–Macbeth, and clustering by time and country, and the results are reported in Panels A to C, respectively. I use the 10% significance level.

Factors	**VMA(1,50) *(10^{-3})**	**FMA(1,50) *(10^{-3})**	**TRB(1,50) *(10^{-3})**	**no. of significant results across all 26 Strategies**
Panel A: Standard OLS				
(1) idv (Hofstede)	-0.105	-0.049	-0.063	21 (-)
	(-2.89)	**(-2.59)**	**(-2.48)**	
(2) pc-market	**2.130**	**0.388**	**2.180**	16 (+)
	(3.2)	(1.12)	**(4.67)**	
(3) pc-uncertainty	2.250	0.087	1.560	11 (+)
	(2.15)	(0.17)	**(2.17)**	
Panel B: Fama-Macbeth				
(1) idv (Hofstede)	-0.100	-0.040	-0.050	18 (-)
	(-1.89)	**(-2.09)**	(-1.61)	
(2) pc-market	1.541	0.459	1.813	16 (+)
	(2.58)	(1.35)	**(3.95)**	
(3) pc-uncertainty	0.981	0.075	0.840	0
	(0.97)	(0.12)	(1.15)	
Panel C: Cluster on Time and Countries				
(1) idv (Hofstede)	-0.105	-0.049	-0.063	20 (-)
	(-2.17)	**(-2.46)**	**(-1.69)**	
(2) pc-market	**2.132**	0.388	2.184	16 (+)
	(4.1)	(1.37)	**(4.58)**	
(3) pc-uncertainty	2.253	0.087	1.558	6 (+)
	(1.77)	(0.16)	(1.51)	
no. of countries		34		

5.6.7 Risk-Adjusted Returns by Using Local Benchmarks

In the main analysis, I use the MSCI world index as the benchmark to calculate risk-adjusted returns. This may raise the concern on the possible impact of exchange rate fluctuations on the risk-adjusted returns. Therefore, I also calculate Jensen's α by using local benchmarks, that is, the major stock market indices in the sample countries. I report the results in Table 5.11.

Table 5.11 has the same layout to Table 5.2. In general the results are nearly the same compared with the results from using the MSCI world index (in Table 5.2). The VMA (1,50) and TRB (1,50) rules generate slightly lower average profit across all countries while the FMA(1,50) rule generates slightly higher average profit, and the standard deviations are also similar indicating that the returns vary largely across countries. I then replicate the cross-country analysis by using the risk-adjusted returns from using local benchmarks; the results are in Table 5.12. 21 strategies generate higher returns in less individualistic countries, 16 strategies generate higher returns in less developed and/or integrated markets, and 17 strategies generate higher returns in more information uncertain markets. The results are highly consistent with my main results, note that the information uncertainty explanation shows even stronger predictive ability in this case – it predicts 14 strategies profitability in the main analysis.

Table 5.11: Risk-adjusted Profits of Technical Trading Strategies by Using Local Benchmarks

This table reports the average monthly market returns and the average monthly risk-adjusted returns of using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50) in 50 international stock markets during the period 1994:03 to 2014:03. For each technical indicator, I long (short sell) the market index when a buy (sell) signal is generated and I invest in risk-free assets when there is no signal. I then estimate the risk-adjusted returns by estimating the monthly Jensen's alpha. The benchmarks are local stock market indices. I also report the means and standard deviations of the returns.

Country	R_m (%)	VMA(1,50) (%)	FMA(1,50) (%)	TRB(1,50) (%)
Argentina	0.058	1.179	0.047	0.895
Australia	0.018	0.141	0.118	-0.041
Austria	0.015	1.409	0.071	0.601
Bangladesh	0.085	2.281	0.343	1.869
Belgium	0.020	0.763	-0.001	0.479
Brazil	0.072	-15.763	-3.495	-1.488
Canada	0.023	0.591	-0.029	0.120
Chile	0.030	1.251	0.307	0.848
China	0.023	1.672	0.636	0.729
Colombia	0.051	1.455	0.470	0.884
Czech	-0.008	1.267	0.162	0.985
Denmark	0.033	1.109	-0.027	0.620
Ecuador	0.010	0.067	-0.566	0.425
Finland	0.028	1.009	-0.078	0.453
France	0.015	0.324	-0.131	-0.266
Germany	0.016	0.903	0.172	0.113
Greece	0.001	1.850	0.472	0.911
Hong Kong	0.014	0.993	-0.152	0.190
India	0.033	0.907	0.049	0.495
Indonesia	0.049	1.759	0.673	1.211
Ireland	0.016	1.291	-0.158	0.531
Israel	0.042	0.647	0.201	0.674
Italy	0.028	0.973	-0.013	0.316
Jamaica	0.033	0.975	0.070	1.266
Japan	-0.017	0.450	0.289	-0.116
Korea	0.015	1.107	0.400	-0.109
Luxembourg	0.016	1.604	0.120	1.365
Malaysia	0.005	1.370	0.211	0.957
Mexico	0.052	0.711	0.103	0.422
New Zealand	0.006	0.101	0.085	0.132
Netherlands	0.015	0.457	0.191	0.221
Norway	0.040	1.459	-0.075	0.794
Pakistan	0.041	1.657	0.569	1.541
Panama	0.065	0.938	-0.029	0.657
Peru	0.051	2.407	0.391	1.701
Philippines	0.019	1.283	0.146	0.824
Portugal	0.007	1.583	0.312	1.027
South Africa	0.045	0.883	-0.042	0.328
Singapore	0.001	0.692	0.135	0.754
Slovak	-0.007	0.109	-0.108	0.559
Slovenia	0.023	1.884	0.317	1.224
Spain	0.024	0.598	0.094	-0.096
Sweden	0.031	0.941	-0.166	-0.074
Switzerland	0.018	0.607	-0.194	0.289
Taiwan	0.005	1.344	0.211	-0.067
Thailand	-0.005	1.753	0.317	1.100
Turkey	0.134	-0.691	0.122	0.604
UK	0.015	-0.245	-0.059	-0.286
US	0.026	-0.068	-0.237	-0.160
Venezuela	0.157	1.967	0.229	2.001
Average	0.030	0.679	0.049	0.568
Std	0.032	2.460	0.563	0.626

Table 5.12: Cross-Country Analysis by using Local Benchmarks

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50), and TRB (1, 50). I use the Hofstede's individualism index and the first principle components of the market development and integrity proxies and information uncertainty proxies as explanations. The returns are Jensen's α calculated from using local benchmarks. For each technical indicator, I report the parameter estimates and the associated *t*-statistics of the three explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use the 10% significance level and the standard errors clustered by country.

Factors	**VMA(1,50) *(10^{-3})**	**FMA(1,50) *(10^{-3})**	**TRB(1,50) *(10^{-3})**	**no. of significant results across all 26 Strategies**
(1) idv (Hofstede)	-0.102	-0.047	-0.060	21 (-)
	(-3.57)	**(-2.92)**	**(-2.02)**	
(2) pc-market	2.151	0.421	2.204	16 (+)
	(3.87)	(1.57)	**(4.85)**	
(3) pc-uncertainty	2.408	0.031	1.567	17 (+)
	(2.8)	(0.07)	**(2.17)**	
no. of countries			33	

5.6.8 Other Checks

I perform a number of additional robustness checks and find my conclusions hold continuously. First, as pointed out by previous studies (e.g., Lo and MacKinlay (1990)), using long sample periods best safeguards the results from possible data snooping bias. This issue is particularly important in the technical analysis field, since previous studies such as my results in Chapter 2 find the same set of technical trading strategies' profitability can completely disappear in an out-of-sample test using fresh data (these strategies show significant in-sample profitability). To check whether my results on the predictive ability of technical analysis are data driven, I use the longest samples available for each country to replicate my analysis in Section 4. My findings of the mixed predictive abilities of the 26 trading rules remain similar. This lends further confidence to my results, since such mixed predictive abilities are the precondition of the cross-country analysis.

Second, to examine whether technical trading strategies have any profitability after including transaction costs, I calculate one-way break-even transaction costs for all the 26 trading strategies in the 50 sample countries. The break-even transaction costs equal the average monthly risk-adjusted returns divided by the total number of trading signals per month. Overall, the TRB rules perform best. In most sample countries (at least 35 of the total 50 countries), the break-even transaction costs are higher than 25 bps. The TRB rules generate the highest break-even transaction cost of 482 bps in the Venezuela markets. In over half of the markets (26 out of 50), the break-even costs are higher than 100 bps. The FMA rules generate break-even transaction costs higher than 10 bps in 60% of the sample countries and higher than 25 bps in 40% of the sample countries approximately. The break-even cost is highest in the India market of 230 bps. And the break-even costs are higher than 100 bps in 15 markets. However, the VMA rules do not seem to show much profitability after including the transaction costs. This is probably due to that the VMA rules basically generate trading signals every day. In summary, consistent with previous findings, we find in some countries (like the US); technical trading strategies do not seem to outperform the market after considering transaction costs. However the strategies still remain profitable in many countries. Such mixed profitability further motivates the cross-country analysis.[52]

Third, Schmeling (2009) documents that, in addition to individualism, another of Hofstede's cultural dimensions— uncertainty avoidance—predicts cross-country differences in sentiment-based trading strategies' profitability in a sample of 18 industrialized countries for a period up to 20 years, from 1995 to 2005. I therefore examine whether the uncertainty avoidance dimension can explain the profitability of the technical trading strategies, but I do not note any significant results, even using an alternative measure of the GLOBE uncertainty avoidance index. Chui, Titman, and Wei (2010) also document that this dimension cannot explain the cross-county differences of their momentum profits.

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[52] To evaluate the profitability of technical trading strategies after transaction costs, Bajgrowicz and Scaillet (2012) use a one-way transaction cost of 12.5 bps from 1897 to 2011 in the US market, Ready (2002) uses a one-way transaction cost of 13 bps from 1962 to 1999, Bessembinder and Chan (1998) use a one-way transaction cost of 25 bps from 1926 to 1991. Allen and Karjalainen (1999) consider three different one-way transaction costs of 0.10%, 0.25% and 0.5% from 1928 to 1995. Sullivan, Timmermann, and White (1999) document a break-even transaction cost of 0.27% for the best-performing technical trading rule in their universe of 7846 rules during the period 1897 to 1996 on the DJIA. The authors also suggest that transaction costs are likely to have been higher than 0.27% at the beginning of the sample, but lower by the end of the sample. Although it is likely that transaction costs have declined over time (most of these studies are published around 2000), to keep my results comparable with previous studies I then use 10 bps and 25 bps as the rough benchmarks for one-way break-even transaction costs.

Fourth, as argued by studies including Bekaert, Harvey, Lundblad and Siegel (2007), nowadays the international stock markets are becoming more and more integrated especially since the 1980s (Henry, 2000). Investors are able to invest in foreign markets through the use of various techniques; therefore, is it possible that the cultural values of local investors play a less important role in explaining technical trading profits? To address this issue, I include stock market openness as a control variable in the main analysis. Following Bekaert, Harvey, Lundblad and Siegel (2007) and Chui, Titman and Wei (2010), I use the inevitability index in each country as a measure for stock market openness. The results are shown in Table 5.13. Overall, the results do not change. While the explanatory power of investor individualism and information uncertainty remains similar, interestingly the explanatory power of stock market development and integrity even increase after including stock market openness. Stock market openness also explain the profitability of seven strategies negatively, which is also consistent with the theory since, generally, more arbitrage opportunities exist in less-open markets. I also find that cultural values explain technical trading profits in two sample periods; the first 20 years of each market, and the period from 1994 to 2014. This has two implications for the relevance of market integration. First, if cultural values become less important over time, I should find that the explanatory power decreases over time. However, I find stronger predictive power of investor individualism in the later sample from 1994 to 2014. Also, during the period from 1994 to 2014, most markets in the sample, including many emerging markets, have become highly integrated into the world market; therefore, the explanatory power of cultural values discovered in this sample seems robust to world stock market integration.

Table 5.13: Cross-Country Analysis Controlled for Stock Market Openness

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50) and TRB (1, 50). I use the Hofstede's individualism index, the first principle components of the market development, and integrity proxies and information uncertainty proxies and stock openness as explanations. For each technical trading strategy, I report the parameter estimates and the associated *t*-statistics of the explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use a 10% significance level and the standard errors clustered by country.

Factors	VMA(1,50) *(10^{-3})	FMA(1,50) *(10^{-3})	TRB(1,50) *(10^{-3})	No. of significant results across all 26 Strategies
(1) idv (Hofstede)	-0.125	-0.042	-0.069	21 (-)
	(-3.4)	**(-2.19)**	**(-2.14)**	
(2) pc-market	2.219	0.488	2.383	21 (+)
	(3.37)	**(1.73)**	**(4.74)**	
(3) pc-uncertainty	2.957	0.152	1.992	13 (+)
	(2.64)	(0.35)	**(2.24)**	
(4) openness	-12.768	-2.904	-4.343	7 (-)
	(-1.62)	(-0.77)	(-1.36)	
no. of countries			32	

Fifth, cultural values measure human behavior; therefore, one may argue it has a greater impact on retail investors' trading. The relevant question could then be; if retail investors' trading only accounts for a small part of total market trading, would the explanatory power of investor individualism diminish? I include the total mutual fund size of a country against the total market capitalisation of all listed stocks of this country as a proxy to measure the weight of retail trading in the main regression; the results are shown in Table 5.14. The explanatory power of all three explanations remains robust, while the retail investors' weight does not seem to show much explanatory power.

Table 5.14: Cross-Country Analysis Controlled for Retail Investors' Weight

This table reports the results for the cross-country analysis of the technical trading profits using the technical indicators VMA (1, 50), FMA (1, 50) and TRB (1, 50). I use the Hofstede's individualism index, the first principle components of the market development, and integrity proxies and information uncertainty proxies and retail investors' weight as explanations. For each technical trading strategy, I report the parameter estimates and the associated *t*-statistics of the explanations. I also summarise the numbers of significant estimates and their signs for all 26 technical indicators in the last column. I use a 10% significance level and the standard errors are clustered by country.

Factors	**VMA(1,50) *(10^{-3})**	**FMA(1,50) *(10^{-3})**	**TRB(1,50) *(10^{-3})**	**No. of significant results across all 26 Strategies**
(1) idv (Hofstede)	-0.095	-0.041	-0.052	21 (-)
	(-3.53)	**(-2.42)**	**(-1.74)**	
(2) pc-market	1.943	0.378	2.111	16 (+)
	(3.08)	(1.31)	**(5)**	
(3) pc-uncertainty	2.660	-0.242	2.028	16 (+)
	(2.06)	(-0.54)	**(2.27)**	
(4) retail	0.081	-0.001	-0.150	3 (-)
	(0.6)	(-0.02)	**(-3.23)**	
no. of countries			29	

In addition, I include additional proxies for the market development and integrity explanation, including total private credits in a country, a corruption index, a law and order index, a political risk index, and an accounting disclosure index. Detailed descriptions of the variables are given in Appendix 3.2. I find the results are similar after including these proxies. I do not use these variables in the main analysis since they are available for smaller samples of countries and including them will significantly reduce the number of observations and thus the power of my main analysis. Moreover, both my main analysis in Section 5 and the orthogonalization tests in Section 6.4 are based on using the investor individualism explanation as my base variable, the market development and integrity explanation as the first additional variable, and the information uncertainty explanation as my second additional variable. I also replicate the analysis switching the roles of the first and the second additional variables, as well as starting with different explanations as the base variable. The results are similar after all these tests. Lastly, I employ formal tests for the possible multicollinearity problem; I check the variance inflation factors for all my regressions. All my variance inflation factors have values smaller than three, indicating a low degree of multicollinearity. Overall, the results still remain robust after these additional checks; the results are available upon request.

5.7 Conclusion

Technical analysis, one of the oldest forms of stock market analysis, dating back to as early as the 1700s,[53] has long been subject to academic scrutiny because it breaches the market efficiency hypothesis. Mixed results are documented in copious previous research and one of the reasons is that the results are from investing in different countries. While the debates continue, this study tries to reconcile the mixed findings by using several explanations to explain cross-country differences. Using a sample of 50 countries in a recent sample period from 1994 to 2014, I find these strategies actually generate significant profits in many countries, I also find profitability varies largely across countries and is related to several systematic factors, including investor individualism, overall stock market development and integrity, as well as information uncertainty. I add to the literature with the first piece of cross-country evidence in the technical analysis field and, overall, my evidence suggests technical analysis is more efficient in less

[53] Marshall, Young, and Rose (2006) document the oldest known form of technical analysis, candlestick charting, was originally applied to Japanese rice markets as early as the 1700s.

culturally individualistic, less developed/integrated, and more information-uncertain countries.

Chapter 6 Concluding Remarks

Overall, this thesis documents new evidence from both time-series and cross-sectional levels to shed some light on the efficiency of technical analysis in international stock markets. The first study highlights the importance of data-snooping bias in interpreting existing evidence on technical analysis, and the broader implication may be the need for constant out-of-sample checks on previous findings. The second study adds to the literature with a comprehensive review and examination on the widely used but less-examined technical market indicators, and provides more conclusive evidence when assessing the efficiency of technical analysis. The third study uses Bollinger Bands as an example to show how investors' usage can gradually eliminate any possible profitability of technical analysis over time, and more generally this warns of the danger of how all so-called "return predictability anomalies" can disappear over time. Lastly, despite the academic scrutiny it has received, my fourth study finds that technical analysis still possesses significant practical value in many international stock markets. Such value is dependent on three factors, namely investor's cultural individualism, market development and integrity, and information uncertainty.

To summarise, how useful is technical analysis? The answer depends on several conditions, including where the strategies are used, which strategies are chosen, and when the strategies are used. We must, of course, always keep in mind the danger of data-snooping and investors' overuse. However, at least it seems that there are some good reasons practitioners never give up on technical analysis.

References

Abbey, B. S., & Doukas, J. A. (2012). Is technical analysis profitable for individual currency traders? *Journal of Portfolio Management*, 39(1), 142.

Abraham, A., & Ikenberry, D. L. (1994). The individual investor and the weekend effect. *Journal of Financial and Quantitative Analysis, 29*(02), 263–277.

Achelis, S. B. (2001). *Technical Analysis from A to Z*. New York: McGraw Hill.

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

Allen, F., & Karjalainen, R. (1999). Using genetic algorithms to find technical trading rules. *Journal of Financial Economics*, *51*(2), 245–271.

Andrade, S. C., Chhaochharia, V., & Fuerst, M. E. (2013). “Sell in May and go away” just won't go away. *Financial Analysts Journal*, 69(4), 94–105.

Andrikopoulos, P., Daynes, A., Latimer, D., & Pagas, P. (2008). Size effect, methodological issues and ‘risk-to-default’: evidence from the UK stock market. *The European Journal of Finance*, *14*(4), 299–314.

Anscombe, F. J. (1967). Topics in the investigation of linear relations fitted by the method of least squares. *Journal of the Royal Statistical Society*. *Series B (Methodological), 29*(1), 1–52.

Bajgrowicz, P., & Scaillet, O. (2012). Technical trading revisited: False discoveries, persistence tests, and transaction costs. *Journal of Financial Economics*, 106(3), 473–491.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271–299.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645–1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–152.

Baker, M., B. Bradley, and J. Wurgler (2010). Benchmarks as limits to arbitrage: Understanding the low volatility anomaly, Working paper, Harvard University.

Ball, R. (1978). Anomalies in relationships between securities' yields and yield-surrogates. *Journal of Financial Economics*, *6*(2–3), 103–126.

Balsara, N. J., Chen, G., & Zheng, L. (2007). The Chinese stock market: An examination of the random walk model and technical trading rules. *Quarterly Journal of Business & Economics*, 46(2), 43–63.

Balsara, N., Chen, J., & Zheng, L. (2009). Profiting from a contrarian application of technical trading rules in the US stock market. *Journal of Asset Management*, 10(2), 97–123.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3–18.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2), 785–818.

Basu, S. (1977). Investment performance of common stocks in relation to their price - earnings ratios: A test of the efficient market hypothesis. *Journal of Finance, 32*(3), 663–682.

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics*, 12(1), 129–156.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2000). A new database on the structure and development of the financial sector. *World Bank Economic Review, 14*(3), 597–605.

Bekaert, G., Harvey, C. R., & Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies, 20*(6), 1783–1831.

Benartzi, S., Michaely, R., & Thaler, R. (1997). Do changes in dividends signal the future or the past? *Journal of Finance, 52*(3), 1007–1034.

Ben-Rephael, A., Kandel, S., & Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics, 104*(2), 363–382.

Bessembinder, H., & Chan, K. (1995). The profitability of technical trading rules in the Asian stock markets. *Pacific-Basin Finance Journal*, 3(2), 257–284.

Bessembinder, H., & Chan, K. (1998). Market efficiency and the returns to technical analysis. *Financial Management*, 5–17.

Biggs, B. M. (1966). The short interest: A false proverb. *Financial Analysts Journal*, *22*(4), 111–116.

Billingsley, R. S., & Chance, D. M. (1996). Benefits and limitations of diversification among commodity trading advisors. *Journal of Portfolio Management, 23*(1), 65–80.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business, 45*(3), 444–455.

Black, F. (1993). Estimating expected return. *Financial Analysts Journal*, *49*(5), 36–38.

Black, F., Jensen, M.C., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests, in M. Jensen, ed., *Studies in the Theory of Capital Markets,* Praeger, Westport.

Blume, L., Easley, D., & O'Hara, M. (1994). Market statistics and technical analysis: The role of volume. *Journal of Finance*, *49*(1), 153–181.

Bollerslev, T., Chou, R.Y., & Kroner, K.F. (1993). ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics, 52* (1–2), 5–59.

Bollinger, J. (2001). *Bollinger on Bollinger Bands*. McGraw Hill Professional.

Bouman, S., & Jacobsen, B. (2002). The Halloween indicator, "Sell in May and go away": Another puzzle. *American Economic Review*, 29(5), 1618–1635.

Boyd, J. H., Hu, J., & Jagannathan, R. (2005). The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *Journal of Finance, 60*(2), 649–672.

Branch, B. (1976). The predictive power of stock market indicators. *Journal of Financial and Quantitative Analysis, 11*(2), 269–285.

Brock, W., Lakonishok, J., & LeBaron, B. (1993). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance, 47*(5), 1731–1764.

Brown, D. P., & Jennings, R. H. (1989). On technical analysis. *Review of Financial Studies*, *2*(4), 527–551.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, *11*(1), 1–27.

Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. *Journal of Business*, *78*(2), 405–440.

Butler, M., & Kazakov, D. (2010). Particle swarm optimization of Bollinger Bands. In *Swarm Intelligence* (pp. 504–511), Springer, Berlin.

Camstra, A., & Boomsma, A. (1992). Cross-validation in regression and covariance structure analysis: An overview. *Sociological Methods & Research*, *21*(1), 89–115.

Chan, K., Covrig, V., & Ng, L. (2005). What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. *Journal of Finance*, *60*(3), 1495–1534.

Chatfield, C. (1995). Model uncertainty, data mining and statistical inference (with discussion), *Journal of the Royal Statistical Society, Series A (Statistics in Society), 158*(3), 419–466.

Chen, N., & Zhang, F. (1998). Risk and return of value stocks. *Journal of Business*, *71*(4), 501–535.

Chen, S., & Gu, A. Y. (2009). Margin debt balance vs stock market movements and expected GDP growth. *Academy of Accounting and Financial Studies*, *14*(2), 23.

Chiang, R., Gay, G., & Kolb, R. (1987). Commodity exchange seat prices. *Review of Futures Markets*, *6*, 1–10.

Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: do stocks overreact? *Journal of financial Economics*, *31*(2), 235–268.

Chordia, T., & Shivakumar, L. (2002). Momentum, business cycle, and time - varying expected returns. *Journal of Finance*, *57*(2), 985–1019.

Chui, A. CW., Titman, S., & Wei, KC. J. (2010). Individualism and momentum around the world. *Journal of Finance*, *65*(1), 361–392.

Ciana, P. (2011). *New Frontiers in Technical Analysis: Effective Tools and Strategies for Trading and Investing,* Bloomberg, New York.

Clarke, R. G., & Statman, M. (1998). Bullish or bearish? *Financial Analysts Journal*, *54*(3), 63–72.

Conrad, J., Cooper, M., & Kaul, G. (2003). Value versus glamour. *Journal of Finance*, *58*(5), 1969–1996.

Cooper, M., & Gulen, H. (2006). Is time series−based predictability evident in real time?. *Journal of Business*, *79*(3), 1263–1292.

Cortes, C., Mohri, M., Riley, M., & Rostamizadeh, A. (2008). Sample selection bias correction theory. In *Algorithmic Learning Theory* (pp. 38-53). Springer Berlin Heidelberg.

Dangl, T., & Halling, M. (2012). Predictive regressions with time-varying coefficients. *Journal of Financial Economics*, *106*(1), 157–181.

Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. *Journal of Finance, 56*(3), 921–965.

Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under - and overreactions. *Journal of Finance, 53*(6), 1839–1885.

Darrat, A. F., Li, B., Liu, B., & Su, J. J. (2011). A fresh look at seasonal anomalies: An international perspective. *International Journal of Business and Economics*, 10(2), 93–116.

Davis, J. L. (1994). The cross‐section of realized stock returns: The pre‐COMPUSTAT evidence. *Journal of Finance*, *49*(5), 1579–1593.

De Bondt, W. P. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of forecasting*, *9*(3), 355–371.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *Journal of finance*, *40*(3), 793–805.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, *45*(2), 379–395.

De Long, J., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1989). The size and incidence of the losses from noise trading. *Journal of Finance*, *44*(3), 681–696.

De Roon, F., Eiling, E., Gerard, B. & Hillion, P. (2011). Speculative profits or hedging benefits? Currency investing in global portfolios. Working Paper.

De Roon, F., Eiling, E., Gerard, B., & Hillion, P. (2012). Currency risk hedging: No free lunch. Available at SSRN: http://ssrn.com/abstract=1343644

DeFusco, A. R., McLeavey, W. D., Pinto, E. J., & Runkle E. D. (2007). *Quantitative Investment Analysis* (2nd ed). New Jersey, NJ: Wiley.

Denis, D. J., & Osobov, I. (2008). Why do firms pay dividends? International evidence on the determinants of dividend policy. *Journal of Financial Economics*, *89*(1), 62–82.

Dennis, P., & Mayhew, S. (2002). Risk-neutral skewness: Evidence from stock options. *Journal of Financial and Quantitative Analysis*, *37*(03), 471–493.

Denton, F. T. (1985). Data mining as an industry. *Review of Economics and Statistics*, *67*(1) 124–127.

Deshmukh, S., Goel, A. M., & Howe, K. M. (2013). CEO overconfidence and dividend policy. *Journal of Financial Intermediation*, *22*(3), 440–463.

Dimson, E., & Marsh, P. (1999). Murphy's law and market anomalies. *Journal of Portfolio Management*, 25(2), 53–69.

Driesprong, G., Jacobsen, B., & Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics*, *89*(2), 307–327.

Dyl, E. A., & Maberly, E. D. (1992). Odd-lot transactions around the turn of the year and the January effect. *Journal of Financial and Quantitative Analysis*, *27*(4), 591–604.

Edwards, F. R., & Zhang, X. (1998). Mutual funds and stock and bond market Stability. *Journal of Financial Services Research*, *13*(3), 257–282.

Edwards, R. D., Magee, J., & Bassetti, W. H. C. (2012). *Technical Analysis of Stock Trends*. CRC Press, Boca Raton, FL.

Elliott, G., & Timmermann, A. (2008). Economic forecasting. *Journal of Economic Literature*, *46*(1), 3–56.

Fama, E. F. (1965a). The behavior of stock-market prices. *Journal of Business*, *38*(1), 34–105.

Fama, E. F. (1965b). Random walks in stock market prices. *Financial Analyst Journal*, *21*(5), 55–59.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 25*(2), 383–417.

Fama, E. F. (1991). Efficient Capital Markets II. *Journal of Business, 46*(5), 1575–1617.

Fama, E. F., & Blume, M. E. (1966). Filter rules and stock-market trading. *Journal of Business, 39*(1), 226–241.

Fama, E. F., Fisher, L., Jensen, M. C. and Roll, R. (1969). The adjustment of stock prices to new information, *International Economic Review, 10*(1), 1–21.

Fama, E. F, & French, K. R. (1988). Permanent and temporary components of stock prices. *Journal of Political Economy, 96*(2), 246–274.

Fama, E. F, & French, K. R. (1995). Size and book - to - market factors in earnings and returns. *Journal of Finance, 50*(1), 131–155.

Fang, L., & Peress, J. (2009). Media coverage and the cross - section of stock returns. *Journal of Finance,* 64(5), 2023–2052.

Faraway, J. J. (1992). On the cost of data analysis. *Journal of Computational and Graphical Statistics, 1*(3), 213–229.

Feldman, T. (2010). A more predictive index of market sentiment. *Journal of Behavioral Finance, 11*(4), 211–223.

Fernandez, D. R., Carlson, D. S., Stepina, L. P., & Nicholson, J. D. (1997). Hofstede's country classification 25 years later. *Journal of Social Psychology, 137*(1), 43–54.

Fernandez-Rodrıguez, F., Gonzalez-Martel, C., & Sosvilla-Rivero, S. (2000). On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market. *Economics letters, 69*(1), 89–94.

Ferson, W. E., Sarkissian, S., & Simin, T. T. (2003). Spurious regressions in financial economics? *Journal of Finance*, *58*(4), 1393–1414.

Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal*, *56*(2), 16–23.

Fleming, J., Ostdiek, B., & Whaley, R. E. (1996). Trading costs and the relative rates of price discovery in stock, futures, and option markets. *Journal of Futures Markets*, *16*(4), 353–387.

Fortune, P. (2000). Margin requirements, margin loans, and margin rates: Practice and principles. *New England Economic Review*, 19–44.

Fosback, N. G. (1993). *Stock market logic: a sophisticated approach to profits on Wall Street.* Dearborn Financial Publishing, Chicago, IL.

Foster, F. D., Smith, T., & Whaley, R. E. (1997). Assessing goodness‐of‐fit of asset pricing models: The distribution of the maximal R^2. *Journal of Finance*, *52*(2), 591–607.

Fountas, S., & Segredakis, K. N. (2002). Emerging stock markets return seasonalities: The January effect and the tax-loss selling hypothesis. *Applied Financial Economics*, 12(4), 291–299.

Frankel, J. A., & Froot, K. A. (1990). Chartists, fundamentalists, and trading in the foreign exchange market. *American Economic Review*, 181–185.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, *88*(2), 299–322.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics,* 8(1), 55–69.

French, K. R. & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics*, *17*(1), 5–26.

Friesen, G. C., & Sapp, T. R. (2007). Mutual fund flows and investor returns: An empirical examination of fund investor timing ability. *Journal of Banking & Finance*, *31*(9), 2796–2816.

Friesen, G. C., Weller, P. A., & Dunham, L. M. (2009). Price trends and patterns in technical analysis: A theoretical and empirical examination. *Journal of Banking & Finance, 33*(6), 1089–1100.

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the street: Informational inefficiencies in a market with short‐term speculation. *Journal of Finance*, *47*(4), 1461–1484.

Fung, W., & Hsieh, D. A. (1997). Survivorship bias and investment style in the returns of CTAs. *Journal of Portfolio Management*, *24*(1), 30–41.

Gaumnitz, J. E., & Salabar, C. A. (1969). The Barron's confidence index: An examination of its value as a market indicator. *Financial Analysts Journal*, *25*(5), 16–70.

Gencay, R. (1996). Non-linear prediction of security returns with moving average rules. *Journal of Forecasting*, *15*(3), 165–174.

Gencay, R. (1998). The predictability of security returns with simple technical trading rules. *Journal of Empirical Finance*, *5*(4), 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.

Gencay, R., & Stengos, T. (1997). Technical trading rules and the size of the risk premium in security returns. *Studies in Nonlinear Dynamics and Econometrics*, *2*(2), 23–34.

Gencay, R., & Stengos, T. (1998). Moving average rules, volume and the predictability of security returns with feedforward networks. *Journal of Forecasting*, *17(5-6)*, 401–414.

Gençay, R., Ballocchi, G., Dacorogna, M., Olsen, R., & Pictet, O. (2002). Real-time trading models and the statistical properties of foreign exchange rates. *International Economic Review*, *43*(2), 463–492.

Gencay, R., Dacorogna, M., Olsen, R., & Pictet, O. (2003). Foreign exchange trading models and market behavior. *Journal of Economic Dynamics and Control*, *27*(6), 909–935.

Giot, P. (2003). The information content of implied volatility in agricultural commodity markets. *Journal of Futures Markets*, *23*(5), 441–454.

Glushkov, D. (2006). Sentiment beta. Available at SSRN: http://ssrn.com/abstract=862444

Goyal, A., & Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, *49*(5), 639–654.

Griffin, J. M., Ji, X., & Martin, J. S. (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *Journal of Finance*, *58*(6), 2515–2547.

Griffin, J. M., & Lemmon, M. L. (2002). Book–to–market equity, distress risk, and stock returns. *Journal of Finance, 57*(5), 2317–2336.

Grimes, A. (2012). *The Art & Science of Technical Analysis: Market Structure, Price Action & Trading Strategies.* Wiley.

Gu, A. Y. (2003). The declining January effect: Evidence from the US equity markets. *Quarterly Review of Economics and Finance*, 43(2), 395–404.

Gup, B. E. (1973). A note on stock market indicators and stock prices. *Journal of Financial and Quantitative Analysis*, *8*(04), 673–682.

Haggard, K. S., & Witte, H. D. (2010). The Halloween effect: trick or treat? *International Review of Financial Analysis*, 19(5), 379–387.

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, *48*(5), 1433–1461.

Hand, D. J., Mannila, H., & Smyth, P. (2001). *Principles of data mining*. MIT press.

Hanna, M. (1976). A stock price predictive model based on changes in ratios of short interest to trading volume. *Journal of Financial and Quantitative Analysis*, *11*(5), 857–872.

Hansen, P. R., & Timmermann, A. (2012). Choice of sample split in out-of-sample forecast evaluation. Working Paper.

Haugen, R. A., & Heins, A. J. (1975). Risk and the rate of return on financial assets: Some old wine in new bottles. *Journal of Financial and Quantitative Analysis,* 10(5), 775–784.

Hendricks, D., Patel, J., & Zeckhauser, R. (1993). Hot hands in mutual funds: Short‐run persistence of relative performance, 1974–1988. *Journal of Finance, 48*(1), 93–130.

Henkel, S. J., Martin, J. S., & Nardari, F. (2011). Time-varying short-horizon predictability. *Journal of Financial Economics*, *99*(3), 560–580.

Henriksson, R. D., & Merton, R. C. (1981). On market timing and investment performance II. statistical procedures for evaluating forecasting skills, *Journal of Business*, *54*(4), 513–533.

Henry, P. B. (2000). Stock market liberalization, economic reform, and emerging market equity prices. *Journal of Finance*, *55*(2), 529–564.

Hirose, T., Kato, H. K., & Bremer, M. (2009). Can margin traders predict future stock returns in Japan? *Pacific-Basin Finance Journal*, *17*(1), 41–57.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance, 56*(4), 1533–1597.

Hofstede, G. H. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations across Nations.* Sage, Thousand Oaks.

House, R. J., Hanges, P. J., Javidan, M., Dorfman, P. W., & Gupta, V. (2004). *Culture, Leadership, and Organizations: The GLOBE Study of 62 Societies*. Sage, Thousand Oaks.

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., 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.

Huber, P. J. (1973). Robust regression: asymptotics, conjectures and Monte Carlo. *The Annals of Statistics*, *1*(5), 799–821.

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.

Ikenberry, D., Lakonishok, J., & Vermaelen, T. (1995). Market underreaction to open market share repurchases. *Journal of Financial Economics*, 39(2), 181–208.

Ilmanen, A. (2011). Expected Returns: *An Investor's Guide to Harvesting Market Rewards*. Wiley.

Inoue, A., & Kilian, L. (2005). In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Reviews*, *23*(4), 371–402.

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), 283–330.

Jacobsen, B., & Dannenburg, D. (2003). Volatility clustering in monthly stock returns. *Journal of Empirical Finance*, *10*(4), 479–503.

Jacobsen, B., & Visaltanachoti, N. (2009). The Halloween effect in US sectors. *Financial Review, 44*(3), 437–459.

Jacobsen, B., Marshall, B., & Visaltanachoti, N. (2007). Return predictability revisited. Available from SSRN http://papers.ssrn.com/sol3/papers.cfm?abstract_id=965336.

Jacobsen, B., & Marquering, W. (2008). Is it the weather? *Journal of Banking & Finance*, *32*(4), 526–540.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance*, *45*(3), 881–898.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance, 48*(1), 65–91.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *Journal of Finance*, *23*(2), 389–416.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of Financial Economics*, *6*(2–3), 95–101.

Jensen, M. C., & Benington, G. A. (1970). Random walks and technical theories: Some additional evidence. *Journal of Finance*, *25*(2), 469–482.

Jiang, G., Lee, C. MC, & Zhang, Y. (2005). Information uncertainty and expected returns. *Review of Accounting Studies*, *10*(2–3), 185–221.

Kahn, M. N. (2010). Is technical analysis for investors really all technical? FT Press, New Jersey

Kaish, S. (1969). Odd lot profit and loss performance. *Financial Analysts Journal*, *25(*5), 83–89.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, 12(1), 13–32.

Keim, D. B., & Madhavan, A. (2000). The relation between stock market movements and NYSE seat prices. *Journal of Finance*, *55*(6), 2817–2840.

Kerrigan, T. J. (1974). The short interest ratio and its component parts. *Financial Analysts Journal*, *30*(6), 45–49.

Kewley, T. J., & Stevenson, R. A. (1967). The odd-lot theory as revealed by purchase and sale statistics for individual stocks. *Financial Analysts Journal*, 103–106.

Kim, T., & Ha, A. (2010, August). Investor sentiment and market anomalies. In *23rd Australasian Finance and Banking Conference*.

Kirkpatrick II, Charles D, & Dahlquist, Julie. (2010). *Technical Analysis: The Complete Resource for Financial Market Technicians*. FT Press, New Jersey.

Korajczyk, R. A. (1996). A measure of stock market integration for developed and emerging markets. *World Bank Economic Review, 10*(2), 267–289.

Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy. *Journal of Banking & Finance, 34*(1), 139–149.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. *Journal of Political Economy, 106*(6), 1113–1155.

Lakonishok, J., & Maberly, E. (1990). The weekend effect: Trading patterns of individual and institutional investors. *Journal of Finance*, *45*(1), 231–243.

Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies*, *1*(4), 403–425.

Lamont, O. A. and Stein, J. C., Aggregate short interest and market valuations (December 2003). Harvard Institute of Economic Research Discussion Paper No. 2027. Available at SSRN: http://ssrn.com/abstract=569876

Lee, C., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance, 55*(5), 2017–2069.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking & Finance*, *26*(12), 2277–2299.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics, 105*(1), 1–28.

Lento, C. (2009). Long-term dependencies and the profitability of technical analysis. *International Research Journal of Finance and Economics*, 269, 126–133.

Lento, C., & Gradojevic, N. (2011). The profitability of technical trading rules: A combined signal approach. *Journal of Applied Business Research*, 23(1), 13–28.

Lento, C., Gradojevic, N., & Wright, C. S. (2007). Investment information content in Bollinger Bands? *Applied Financial Economics Letters*, 3(4), 263–267.

Leung, J. M. J., & Chong, T. T. L. (2003). An empirical comparison of moving average envelopes and Bollinger Bands. *Applied Economics Letters*, 10(6), 339–341.

Lev, B., & Nissim, D. (2004). Taxable income, future earnings, and equity values. *Accounting Review*, 79(4), 1039–1074.

Levine, R., & Zervos, S. (1996). Stock market development and long-run growth. *World Bank Economic Review*, *10*(2), 323–339.

Levy, R. A. (1967). Relative strength as a criterion for investment selection. *Journal of Finance, 22*(4), 595–610.

Lo, A. W. (2002). The statistics of Sharpe ratios. *Financial Analyst Journal*, *58*(4), 36–52.

Lo, A. W. and MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies*, *1*(1), 41–66.

Lo, A. W, & MacKinlay, A. C. (1990a).When are contrarian profits due to stock market overreaction？ *Review of Financial Studies*, *3*(2), 175–206.

Lo, A. W., & MacKinlay, A. C. (1990b). Data-snooping biases in tests of financial asset pricing models. *Review of Financial Studies, 3*(3), 431–468.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, *55*(4), 1705–1770.

Low, C. (2004). The fear and exuberance from implied volatility of S&P 100 index options. *Journal of Business*, *77*(3), 527–546.

Lucey, B. M., & Whelan, S. (2004). Monthly and semi-annual seasonality in the Irish equity market 1934–2000. *Applied Financial Economics*, 14(3), 203–208.

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.

Malek, L. (2000). The role of TED spread and confidence index in explaining the behavior of stock prices. *American Business Review*, *18*(2).

Mandelbrot, B. (1963). The variation of certain speculative prices. *Journal of Business, 36*(4), 394–419.

Markus, H. R, & Kitayama, S. (1991). Culture and the self: Implications for cognition, emotion, and motivation. *Psychological review*, *98*(2), 224.

Marquering, W., Nisser, J., & Valla, T. (2006). Disappearing anomalies: A dynamic analysis of the persistence of anomalies. *Applied Financial Economics*, 16(4), 291–302.

Marshall, B. R., Young, M. R, & Rose, L. C. (2006). Candlestick technical trading strategies: Can they create value for investors? *Journal of Banking & Finance, 30*(8), 2303–2323.

Mayor, T. H. (1968). Short trading activities and the price of equities: Some simulation and regression results. *Journal of Financial and Quantitative Analysis*, *3*(3), 283–298.

McLean, R. D., & Pontiff, J. (2014). Does academic research destroy stock return predictability? Available at SSRN: http://ssrn.com/abstract=2156623.

McQueen, G., & Roley, V. V. (1993). Stock prices, news, and business conditions. *Review of financial studies, 6*(3), 683–707.

McQueen, G., & Thorley, S. (1999). Mining fool's gold. *Financial Analysts Journal, 55*(2) 61–72.

Mehdian, S., & Perry, M. J. (2002). Anomalies in US equity markets: A re-examination of the January effect. *Applied Financial Economics*, 12(2), 141–145.

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking and Finance, 34*(11), 2573–2586.

Merritt, A. (2000). Culture in the cockpit Do Hofstede's dimensions replicate? *Journal of Cross-Cultural Psychology*, *31*(3), 283–301.

Merton, R. C. (1985). On the current state of the stock market rationality hypothesis. Working Paper No. 1717-85, MIT, Sloan School of Management.

Michaely, R., Thaler, R. H., & Womack, K. L. (1995). Price reactions to dividend initiations and omissions: Overreaction or drift? *Journal of Finance*, *50*(2), 573–608.

Minton, B. A., & Schrand, C. (1999). The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing. *Journal of Financial Economics*, *54*(3), 423–460.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, *58*(1), 215–260.

Mühlhofer, T. (2009). They would if they could: Assessing the bindingness of the property holding constraint for REITs. Available at SSRN: http://ssrn.com/abstract=1129902.

Murphy, J. (1999). *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods And Applications*, Penguin, New York.

Neal, R., & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns? *Journal of Financial and Quantitative Analysis, 33*(4), 523–547.

Neely, C. J., & Weller, P. A. (2003). Intraday technical trading in the foreign exchange market. Journal of International Money and Finance, 22(2), 223–237.

Neely, C.J., Weller, P.A., 2012. Technical analysis in the foreign exchange market. In *Handbook of Exchange Rates.* Hoboken, NJ: Wiley.

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science, 60*(7), 1772–1791.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55* (3), 703–708.

Nissim, D., & Ziv, A. (2001). Dividend changes and future profitability. *Journal of Finance, 56*(6), 2111–2133.

Parisi, F., & Vasquez, A. (2000). Simple technical trading rules of stock returns: Evidence from 1987 to 1998 in Chile. *Emerging Markets Review*, *1*(2), 152–164.

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. (2004). The profitability of technical analysis: A review. *AgMAS Project Research Report 2004-2004*. Urbana, Il: University of Illinois at Urbana-Champaign.

Paulos, J.A. (2003). *A Mathematician Plays the Stock Market.* Basic Books, New York.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*(1), 435–480.

Peyer, U., & Vermaelen, T. (2009). The nature and persistence of buyback anomalies. *Review of Financial Studies*, 22(4), 1693–1745.

Pincus, M., Rajgopal, S., & Venkatachalam, M. (2007). The accrual anomaly: International evidence. *Accounting Review*, 82(1), 169–203.

Poterba, J. M., & Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics, 22*(1), 27–59.

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*, *38*(8), 2135–2158.

Raj, M., & Thurston, D. (1996). Effectiveness of simple technical trading rules in the Hong Kong futures markets. *Applied Economics Letters, 3*(1), 33–36.

Randall, M. R., Suk, D. Y., & Tully, S. W. (2003). Mutual fund cash flows and stock market performance. *Journal of Investing*, *12*(1), 78–80.

Rapach, D. E., & Wohar, M. E. (2006). In-sample vs. out-of-sample tests of stock return predictability in the context of data mining. *Journal of Empirical Finance*, *13*(2), 231–247.

Rapach, D., & Zhou, G. (2012). Forecasting stock returns. *Handbook of Economic Forecasting*. Elsevier, North Holland.

Ready, M. J. (2002). Profits from technical trading rules. *Financial Management*, 31(3), 43–61.

Reilly, F. K., & Whitford, D. T. (1982). A test of the specialists' short sale ratio. *Journal of Portfolio Management*, *8*(2), 12–18.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. *Journal of Financial Economics*, 12(1), 89–104.

Rhea, R. (1932). *The Dow Theory*, Barron's, New York.

Roberts, H. (1967). Statistical versus clinical prediction of the stock market, Unpublished manuscript.

Rozeff, M. S., & Kinney, Jr., W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics*, 3(4), 379–402.

Samuelson, P. A., (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review*, *6*(2), 41–49.

Sanders, D. R., Irwin, S. H., & Leuthold, R. M. (1997). Noise traders, market sentiment, and futures price behavior. Available at SSRN: http://ssrn.com/abstract=39932.

Scheinkman, J. A., & Xiong, W. (2003). Overconfidence and speculative bubbles. *Journal of political Economy, 111*(6), 1183–1220.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance, 16*(3), 394–408.

Schmidt, A. B. (2002). Why technical trading may be successful? A lesson from the agent-based modeling. *Physica A: Statistical Mechanics and its Applications, 303*(1), 185–188.

Scholes, M. S. (1972). The market for securities: Substitution versus price pressure and the effects of information on share prices, *Journal of Business, 45*(2), 179–211.

Schwert, G. W. (1977). Stock exchange seats as capital assets. *Journal of Financial Economics, 4*(1), 51–78.

Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance,* 1, 939–974.

Seneca, J. J. (1967). Short interest: Bearish or bullish? *Journal of Finance, 22*(1), 67–70.

Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *Journal of Psychology and Financial Markets, 1*(1), 49–60.

Shynkevich, A. (2012). Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking & Finance, 36*(1), 193–208.

Simon, D. P., & Wiggins, R. A. (2001). S&P futures returns and contrary sentiment indicators. *Journal of Futures Markets, 21*(5), 447–462.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review,* 71(3), 289–315.

Smith, R. D. (1968). Short interest and stock market prices. *Financial Analysts Journal*, 151–154.

Solnik, B. (1993). The performance of international asset allocation strategies using conditioning information. *Journal of Empirical Finance*, *1*(1), 33–35.

Solt, M. E., & Statman, M. (1988). How useful is the sentiment index? *Financial Analysts Journal*, *44*(5), 45–55.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302.

Stulz, R. M., & Williamson, R. (2003). Culture, openness, and finance. *Journal of Financial Economics*, *70*(3), 313–349.

Sullivan, R., Timmermann, A. & White, H. (1999). Data-snooping, technical trading, rule performance and the bootstrap. *Journal of Finance*, *54*(5), 1647–1691.

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.

Sullivan, R., Timmermann, A., & White, H. (2003). Forecast evaluation with shared data sets. *International Journal of Forecasting*, *19*(2), 217–227.

Summa, J. (2004). More mileage from margin. *Technical Analysis of Stocks and Commodities*, *22*(3), 48–51.

Swinkels, L., & van Vliet, P. (2012). An anatomy of calendar effects. *Journal of Asset Management*, 13(4), 271–286.

Tabell, E. W., & Tabell, A. W. (1964). The case for technical analysis. *Financial Analysts Journal*, *20*(2), 67–76.

Tang, L., & Koveos, P. E. (1998). A framework to update Hofstede's cultural value indices: economic dynamics and institutional stability. *Journal of International Business Studies*, *39*(6), 1045–1063.

Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of international Money and Finance*, *11*(3), 304–314.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics, 99*(1), 1–10.

Treynor, J. L., & Ferguson, R. (1985). In defense of technical analysis. *Journal of Finance*, *40*(3), 757–773.

Vasiliou, D., Eriotis, N. & Papathanasiou, S. (2008). Technical Trading Profitability in Greek Stock Market. *The Empirical Economics Letters*, *7*(7), 749–756.

Verardo, M. (2009). Heterogeneous beliefs and momentum profits. *Journal of Financial and Quantitative Analysis*, *44*(4), 795–822.

Vu, J. D., & Caster, P. (1987). Why all the interest in short interest? *Financial Analysts Journal*, *43*(4), 76–79.

Wang, C. (2002). Information, trading demand, and futures price volatility. *Financial Review*, *37*(2), 295–315.

Wang, Y. H., Keswani, A., & Taylor, S. J. (2006). The relationships between sentiment, returns and volatility. *International Journal of Forecasting*, *22*(1), 109–123.

Warther, V. A. (1995). Aggregate mutual fund flows and security returns. *Journal of Financial Economics*, *39*(2), 209–235.

Whaley, R. E. (1993). Derivatives on market volatility: Hedging tools long overdue. *Journal of Derivatives*, *1*(1), 71–84.

Whaley, R. E. (2000). The investor fear gauge. *Journal of Portfolio Management*, *26*(3), 12–17.

White, H. (1980). A heteroscedasticity consistent covariance matrix estimator and a direct test of heteroskedasticity. *Econometrica*, *48*(4), 817–838.

You, T., & Holder, M. E. (2008). Can exchange seat prices predict financial market volatility? *Journal of Futures Markets*, *28*(12), 1206–1221.

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean–variance relation. *Journal of Financial Economics*, *100*(2), 367–381.

Zakon, A. J., & Pennypacker, J. C. (1968). An analysis of the advance–decline line as a stock market indicator. *Journal of Financial and Quantitative Analysis*, *3*(3), 299–314.

Zhang, C. Y., & Jacobsen, B. (2013). Are monthly seasonals real? A three century perspective. *Review of Finance*, 17(5), 1743-1785.

Zhang, C. Y., & Jacobsen, B. (2014)."The Halloween indicator, “Sell in May and go away”: an even bigger puzzle". Available at SSRN: http://ssrn.com/abstract=2154873.

Zhang, X. (2006). Information uncertainty and stock returns. *Journal of Finance*, *61*(1), 105–137.

Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, *92*(3), 519–544.

Zweig, M. E. (1973). An investor expectations stock price predictive model using closed-end fund premiums. *Journal of Finance*, *28*(1), 67–78.

Appendices

A.1: Appendix to "Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test"

A.1.1 Sharpe Ratio Estimation 1987-2011

In this appendix I further evaluate the profitability of the technical trading strategies in comparison with a buy-and-hold strategy. For each trading strategy, I can either long on buy signals only, or otherwise invest in risk-free assets; or short sales on sell signals only, or otherwise invest in risk-free assets; or long on buy signals and short sales on sell signals and invest in risk-free assets when there is no trading signal.

Table A.1.1 gives the results comparing the Sharpe Ratios of the technical trading strategies and the buy-and-hold strategy on the DJIA from 1987 to 2011. The Sharpe Ratios are estimated by using:

$$\text{Sharpe Ratio} = (r_t^p - r_t^f)/\sigma_t^p \qquad \text{(A.1)}$$

in which r_t^p represents the returns of technical trading strategies, r_t^f represents the risk free rate which is set as the US 3-month Treasury Bill rates and σ^p represents the standard deviation of r_t^p. I also perform the significance test examining the differences between the Sharpe Ratios of the technical trading strategies and the Sharpe Ratio of the buy-and-hold strategy. The significance test are performed according to the methodology proposed by Lo (2002) and De Roon, Eiling, Gerard, and Hillion (2011), which assumes that the excess returns $r_t^p - r_t^f$ are *i.i.d.* normal.

[Insert Table A.1.1: Results for the Sharpe Ratio Estimation 1987-2011]

It is found that, for the variable-length moving average strategies, none of their Sharpe Ratios are significantly higher than the same period buy-and-hold Sharpe Ratio. For the Fixed-Length Moving Average strategies and the Trading Range Break strategies, which both have a 10 day holding period, I find most of the Sharpe Ratios are significantly lower than the buy-and-hold Sharpe Ratio. The Sharpe Ratio captures excess returns compensated for each unit of risk. My results in Table A show that none of my technical trading strategies pay more for extra risk than does the buy-and-hold strategy, whereas some of the technical trading rules even suffer a reduction in profit for taking each extra unit of risk. It makes no difference whether I invest on either buy, or sell signals only, or on both of them.

Table A.1.1: Results for the Sharpe Ratio Estimation 1987-2011

This table reports results for the Sharpe ratio estimation: Sharpe Ratio= $(r_t^p - r_t^f)/\sigma_t^p$ for the DJIA 1987-2011, where r_t^p represents the returns of technical trading strategies, r_t^f represents the risk free rates which is set as the US 3-month Treasury Bill rate and σ^p represents the standard deviation of r_t^p. Trading rules are written as (short, long, band), where short and long represent the short and long moving averages, respectively. A 1% price change is used as the band. The t-test results, which test the differences of the Sharpe ratios on technical trading strategies from the Sharpe ratios of the buy-and-hold strategy, are reported in the brackets, and are White standard error corrected and marked in bold if they are significant at the 10% significance level.

Period	**Trading Rules**	**$Sharpe_{Buy}$ ($*10^{-3}$)**	**$Sharpe_{sell}$ ($*10^{-3}$)**	**$Sharpe_{Buy\&Sell}$ ($*10^{-3}$)**	**$Sharpe_{Buy\&Hold}$ ($*10^{-3}$)**
			VMA Daily		
1987-2011	**(1,50,0)**	1.03	-1.72	-0.77	1.56
		(0.45)	(1.33)	(1.12)	
	(1,150,0)	1.07	-1.34	-0.43	1.56
		(0.42)	(1.17)	(0.95)	
	(5,150,0)	0.87	-1.50	-0.65	1.56
		(0.60)	(1.24)	(1.07)	
	(1,200,0)	1.61	-1.73	-0.34	1.56
		(0.03)	(1.33)	(0.93)	
	(2,200,0)	1.37	-1.92	-0.63	1.56
		(0.17)	(1.41)	(1.07)	
			VMA Daily Band=1%		
1987-2011	**(1,50,0.01)**	0.16	-1.49	-1.13	1.56
		(1.10)	(1.24)	(1.26)	
	(1,150,0.01)	1.30	-1.33	-0.29	1.56
		(0.21)	(1.17)	(0.88)	
	(5,150,0.01)	1.56	-1.32	-0.11	1.56
		(0.00)	(1.17)	(0.80)	
	(1,200,0.01)	1.84	-2.11	-0.52	1.56
		(0.23)	(1.50)	(1.01)	
	(2,200,0.01)	1.60	-2.00	-0.56	1.56
		(0.03)	(1.45)	(1.03)	
			FMA 10-days		
1987-2011	**(1,50,0)**	0.86	-2.42	-1.05	5.73
		(2.82)	**(4.24)**	**(3.71)**	
	(1,150,0)	-0.69	0.49	0.17	5.73
		(3.67)	**(2.68)**	**(2.96)**	
	(5,150,0)	-0.72	1.02	0.68	5.73
		(3.62)	**(2.45)**	**(2.70)**	
	(1,200,0)	-0.02	-2.49	-1.29	5.73
		(3.27)	**(4.27)**	**(3.82)**	
	(2,200,0)	-0.03	-3.02	-1.45	5.73
		(3.27)	**(4.58)**	**(3.94)**	

		FMA 10-days Band=1%			
1987-2011	**(1,50,0.01)**	-0.61	-2.98	-2.34	5.73
		(3.71)	**(4.54)**	**(4.49)**	
	(1,150,0.01)	-1.30	-1.22	-1.54	5.73
		(4.00)	**(3.56)**	**(3.85)**	
	(5,150,0.01)	0.18	-1.08	-0.43	5.73
		(3.10)	**(3.56)**	**(3.29)**	
	(1,200,0.01)	-1.11	-4.86	-3.39	5.73
		(3.92)	**(5.53)**	**(5.05)**	
	(2,200,0.01)	-1.49	-4.21	-3.50	5.73
		(4.08)	**(5.19)**	**(5.04)**	
		TRB 10-days			
1987-2011	**(1,50,0)**	-1.12	-1.70	-1.99	5.73
		(4.01)	**(3.74)**	**(4.07)**	
	(1,150,0)	-0.95	-3.10	-2.85	5.73
		(3.84)	**(4.50)**	**(4.56)**	
	(1,200,0)	-0.37	-2.81	-2.13	5.73
		(3.48)	**(4.35)**	**(4.17)**	
		TRB 10-days Band=1%			
1987-2011	**(1,50,0.01)**	0.58	-0.33	0.00	5.73
		(2.93)	**(3.07)**	**(2.96)**	
	(1,150,0.01)	-0.65	-1.76	-1.61	5.73
		(3.57)	**(3.86)**	**(3.85)**	
	(1,200,0.01)	-0.78	-2.46	-2.15	5.73
		(3.63)	**(4.19)**	**(4.12)**	

A.1.2 Henriksson & Merton Market Timing Ability Estimation 1987-2011

At the same time I conduct the Henriksson & Merton (1981) market timing ability test by running the regression:

$$r_t^p - r_t^f = \alpha + \beta\,(r_t^m - r_t^f) + c\,(r_t^m - r_t^f)\,D_{t-1} + \varepsilon_t \qquad \textbf{(A.2)}$$

in which r_t^p represents the returns of the technical trading strategies, r_t^f represents the risk free rate which is set as the US 3-month Treasury Bill rates and r_t^m represents the return on the DJIA index. D_{t-1} is a dummy variable that equals 1 when $r_t^m > r_t^f$ and 0 otherwise. c measures the market timing ability of the technical trading strategies, that is, if the technical trading strategies could correctly shift between risk-free assets and the market, depending on whether the market is expected to outperform the risk-free assets. A positive value of c indicates successful timing as the extra payoff when the market is up.

[Insert Table A.1.2: Results for the Henriksson & Merton Market Timing Ability Estimation 1987-2011]

The results are presented in Table A.1.2. I again cover all three ways of implementing a technical trading strategy: Invest on buy signals only; invest on sell signals only; or invest on both buy and sell signals. I find that none of the variable-length moving average trading strategies shows a positive significant timing coefficient c. There is one fixed-length moving average strategy (5, 150, 0) that is found to have a significant positive c value of 0.01 when investing on both buy and sell signals. Also, one trading range break strategy (5, 150, 0.01) is found to have the same significant positive c value of 0.01 while implementing buy signals only. These positive significant c values show some timing ability, while the rest of the Fixed-Length Moving Average and Trading Range Break strategies all have a non-significant c, or negative significant c. In general, I discover hardly any desirable market timing ability for these technical trading strategies.

Table A.1.2: Results for the Henriksson & Merton Market Timing Ability Estimation 1987-2011

This table reports the results for the regression model: $r_t^p - r_t^f = \alpha + \beta\,(r_t^m - r_t^f) + c\,(r_t^m - r_t^f)\,D_{t-1} + \varepsilon$ for the DJIA 1987-2011, where r_t^p represents the returns of the technical trading strategies, r_t^f represents the risk free rate which is set as the US 3-month Treasury Bill rate and r_t^m represents the return on the DJIA index. D is a dummy variable that equals 1 when $r_t^m > r_t^f$ and 0 otherwise. C measures the market timing ability of the technical trading strategies. Trading rules are written as (short, long, band) where short and long represent the short and long moving averages, respectively. A 1% price change is used as the band. The t-statistics are reported in brackets, which are White standard error corrected and marked in bold if they are significant at the 10% significance level.

Period	Trading Rules	C_{Buy}	C_{sell}	$C_{Buy\&Sell}$
		VMA Daily		
1987-2011	**(1,50,0)**	0.03	0.03	0.07
		(0.37)	(0.33)	(0.35)
	(1,150,0)	0.04	0.03	0.07
		(0.38)	(0.34)	(0.36)
	(5,150,0)	0.04	0.04	0.09
		(0.45)	(0.41)	(0.43)
	(1,200,0)	-0.06	-0.06	-0.12
		(-1.01)	(-1.08)	(-1.04)
	(2,200,0)	-0.06	-0.07	-0.13
		(-1.11)	(-1.18)	(-1.15)
		VMA Daily Band=1%		
1987-2011	**(1,50,0.01)**	0.02	0.04	0.07
		(0.29)	(0.40)	(0.36)
	(1,150,0.01)	0.03	0.04	0.08
		(0.36)	(0.42)	(0.39)
	(5,150,0.01)	0.05	0.04	0.09
		(0.51)	(0.40)	(0.45)
	(1,200,0.01)	-0.05	-0.08	-0.13
		(-0.87)	(-1.40)	(-1.17)
	(2,200,0.01)	-0.06	-0.08	-0.14
		(-1.09)	(-1.29)	(-1.21)
		FMA 10-days		
1987-2011	**(1,50,0)**	0.00	-0.01	-0.01
		(-0.54)	(-1.27)	(-1.15)
	(1,150,0)	-0.01	0.02	0.02
		(-0.67)	(0.8)	(0.57)
	(5,150,0)	0.00	0.01	0.01
		(1.13)	(1.52)	**(1.81)**
	(1,200,0)	0.00	0.00	0.00
		(0.04)	(-0.41)	(-0.22)
	(2,200,0)	-0.01	0.00	-0.01
		(-0.56)	(-1.39)	(-0.87)

		FMA 10-days Band=1%		
1987-2011	**(1,50,0.01)**	-0.01	-0.01	-0.02
		(-0.89)	**(-1.98)**	(-1.62)
	(1,150,0.01)	-0.01	0.03	0.02
		(-0.56)	(0.8)	(0.61)
	(5,150,0.01)	0.01	0.00	0.01
		(2.01)	(0.25)	(1.18)
	(1,200,0.01)	-0.01	-0.01	-0.02
		(-1.03)	**(-2.41)**	(-1.53)
	(2,200,0.01)	-0.01	-0.01	-0.01
		(-1.21)	**(-1.89)**	**(-1.92)**
		TRB 10-days		
1987-2011	**(1,50,0)**	0.00	-0.02	-0.02
		(0.34)	(-0.55)	(-0.5)
	(1,150,0)	0.00	-0.05	-0.05
		(-0.1)	**(-2.17)**	**(-2.14)**
	(1,200,0)	0.00	-0.04	-0.04
		(-1.06)	(-1.64)	**(-1.77)**
		TRB 10-days Band=1%		
1987-2011	**(1,50,0.01)**	0.01	0.02	0.03
		(1.5)	(0.59)	(0.73)
	(1,150,0.01)	0.00	-0.02	-0.02
		(0.91)	(-1.37)	(-1.25)
	(1,200,0.01)	0.00	-0.02	-0.02
		(0.16)	(-1.21)	(-1.18)

A.2: Appendix to "Technical Market Indicators: An Overview"

A.2.1 Summary Statistics

Market Indicators	Frequency	Sample Period	Type	N	Mean (*10⁻²)	Std Dev	Min	Max
Panel A: Market Sentiment Indicators								
Option Volumes:								
CBOE Calls Volume	Daily	1989 - 2011	Units	5617	3.88	0.41	-0.94	9.10
CBOE Puts Volume	Daily	1989 - 2011	Units	5621	6.12	1.08	-0.98	65.20
OEX Calls Volume	Daily	1989 - 2011	Units	5520	526.97	267.94	-1.00	19650.20
OEX Puts Volume	Daily	1989 - 2011	Units	5520	1200.18	614.78	-1.00	36312.00
CBOE Ratio of Traded Value of Puts to Calls	Daily	1986 - 2011	Ratio	6429	2.10	0.23	-0.88	6.03
Odd-lots Volumes:								
NYSE Odd Lot Purchases	Daily	1970 - 2011	Units	10472	13.39	11.05	-1.00	1130.84
NYSE Odd Lot Sales	Daily	1970 - 2011	Units	10472	3.40	0.40	-0.91	11.01
NYSE Odd Lot Shorts	Daily	1970 - 2011	Units	10472	108.67	27.82	-1.00	1300.57
Short Sales Volumes:								
NYSE Short Sales-Members	Weekly	1940 - 2008	Units	3570	4.66	0.36	-0.89	9.75
NYSE Short Sales-General Public	Weekly	1940 - 2008	Units	3570	5.68	0.40	-0.76	8.36
NYSE Short Sales-Specialists	Weekly	1940 - 2008	Units	3570	4.83	0.39	-0.91	12.09
NYSE Short Sales-Total	Weekly	1940 - 2008	Units	3570	4.18	0.32	-0.82	6.48
Short Interests:								
NYSE Short Interest Ratio	Monthly	1931 - 2010	Ratio	958	1.73	0.21	-0.73	2.70
NYSE Short Interest Shares	Monthly	1931 - 2010	Units	958	1.16	0.08	-0.33	0.44
AAII/II Sentiment Indices:								
AAII Bearish Index	Weekly	1989 - 2010	Index Number	1133	4.78	0.35	-0.76	3.10
AAII Bullish Index	Weekly	1989 - 2010	Index Number	1133	2.56	0.23	-0.67	1.70
AAII Neutral Index	Weekly	1989 - 2010	Index Number	1133	3.64	0.30	-0.74	2.42
Investors Intelligence Bearish Percentage	Weekly	1987 - 2010	Index Number	1227	0.34	0.08	-0.48	0.78
Investors Intelligence Bullish Percentage	Weekly	1987 - 2010	Index Number	1227	0.25	0.07	-0.31	0.44
Confidence Index:								
Barron's Confidence Index	Weekly	1932 - 2010	Index Number	4132	0.02	0.02	-0.16	0.21
Exchange Seat Prices:								
AMEX Seat Prices	Monthly	1921 - 1993	National Currency	861	2.27	0.24	-0.64	4.25
NYSE Annual Seat Price	Annual	1820 - 2003	National Currency	183	11.44	0.41	-0.43	3.00
Volatility Indices:								
CBOE S&P 500 Volatility Index	Daily	1986 - 2011	Index Number	6430	0.21	0.07	-0.47	3.13
CBOE NASDAQ Volatility Index	Daily	2001 - 2011	Index Number	2560	0.09	0.05	-0.27	0.44
CBOE S&P 100 Volatility Index	Daily	1986 - 2011	Index Number	6430	0.23	0.08	-0.47	3.13
AMEX NYSE Arca NASDAQ 100 Volatility Index	Daily	2001 - 2011	Index Number	2558	0.17	0.07	-0.47	0.92
CBOE DJIA Volatility Index	Daily	2005 - 2011	Index Number	1515	0.27	0.07	-0.28	0.70
Margin Account Balances:								
NYSE Margin Debt	Monthly	1918 - 2010	National Currency	1107	0.73	0.07	-0.34	0.95
NYSE Free Credit Balances	Monthly	1931 - 2010	National Currency	950	0.89	0.06	-0.37	0.33
NYSE Free Credit Balances on Cash Accounts	Monthly	1971 - 2010	National Currency	479	1.01	0.06	-0.18	0.30
NYSE Free Cash Balances in Margin Accounts	Monthly	1971 - 2010	National Currency	479	1.62	0.09	-0.65	0.97
Mutual Fund Balances:								
USA Mutual Fund Equity Funds Total Net Assets	Monthly	1984 - 2010	National Currency	324	1.47	0.05	-0.23	0.19
USA Mutual Fund Equity Funds Cash Percentage	Monthly	1968 - 2010	National Currency	516	0.11	0.07	-0.21	0.28
USA Mutual Fund Equity Funds Redemptions	Monthly	1984 - 2010	National Currency	324	5.91	0.58	-0.90	9.87
USA Mutual Fund Equity Funds New Sales	Monthly	1984 - 2010	National Currency	324	2.95	0.19	-0.49	1.10
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	1954 - 2010	National Currency	675	2.36	0.34	-0.90	8.81
USA Mutual Fund Equity and Bond Fund Cash Percent	Monthly	1954 - 2010	National Currency	675	0.17	0.07	-0.22	0.30
USA Mutual Fund Equity and Bond Fund Liquid Assets	Monthly	1954 - 2010	National Currency	671	1.24	0.06	-0.17	0.27
USA Mutual Fund Equity and Bond Fund Redemptions	Monthly	1954 - 2010	National Currency	675	2.73	0.17	-0.52	0.63
USA Mutual Fund Equity and Bond Fund New Sales	Monthly	1954 - 2010	National Currency	675	2.84	0.19	-0.48	0.96
Number of Dividend News:								
Moody's Monthly Decreased Dividends	Monthly	1956 - 2011	Units	659	0.31	0.07	-0.24	0.32

Market Indicators	Frequency	Sample Period	Type	N	Mean (*10⁻²)	Std Dev	Min	Max
Moody's Monthly Extra Dividends Declared	Monthly	1956 - 2011	Units	659	0.15	0.04	-0.25	0.39
Moody's Monthly Increased Dividends Declared	Monthly	1956 - 2011	Units	659	0.12	0.03	-0.13	0.12
Moody's Monthly Omitted Dividends	Monthly	1956 - 2011	Units	659	0.76	0.06	-0.18	0.24
Moody's Monthly Resumed Dividends	Monthly	1956 - 2011	Units	659	0.59	0.09	-0.38	1.27
S&P Monthly Dividend Decreases Declared	Monthly	1955 - 2010	Units	669	36.00	1.40	-0.95	13.00
S&P Monthly Extra Dividends Declared	Monthly	1955 - 2010	Units	673	20.66	0.74	-0.87	3.19
S&P Monthly Increased Dividends Declared	Monthly	1955 - 2010	Units	673	6.25	0.45	-0.91	7.09
S&P Monthly Omitted Dividends Declared	Monthly	1955 - 2010	Units	665	26.61	1.15	-0.95	14.00
S&P Monthly Resumed Dividends Declared	Monthly	1955 - 2010	Units	662	29.99	1.09	-0.90	9.00
Panel B: Market Sentiment Indicators								
Total Volume:								
NYSE Total Volume	Daily	1928 - 2011	Units	22055	6.51	1.19	-0.98	163.25
Total Volume Turnovers:								
NYSE Share Volume Turnover	Monthly	1925 - 2010	Ratio	1032	0.15	0.06	-0.37	0.57
NYSE Annual Share Value Turnover	Monthly	1934 - 2010	Ratio	915	0.30	0.04	-0.34	0.35
Short-term Trading Indices:								
NYSE Short-term Trading Index	Daily	1965-2011	Index Number	11667	15.44	0.74	-0.97	14.17
NASDAQ Short-term Trading Index	Daily	1972-2011	Index Number	9773	162.10	22.20	-1.00	1216.00
Daily Total Market Advances & Declines:								
NYSE Advances	Daily	1928 - 2011	Units	22050	15.79	0.90	-0.97	29.20
NYSE Declines	Daily	1928 - 2011	Units	22050	13.01	0.66	-0.93	22.17
NYSE Net Advances	Daily	1928 - 2011	Units	22022	-61.83	26.56	-893.00	1554.00
NYSE AD Line	Daily	1928 - 2011	Units	22050	-0.80	1.46	-192.00	43.80
NYSE Percentage Net Advances	Daily	1928 - 2011	Units	22022	-63.30	26.36	-881.20	1541.80
NASDAQ Advances	Daily	1972 - 2011	Units	9962	9.84	0.90	-0.96	64.18
NASDAQ Declines	Daily	1972 - 2011	Units	9962	8.77	2.48	-0.99	244.60
NASDAQ Net Advances	Daily	1972 - 2011	Units	9952	-38.01	24.64	-788.00	1144.00
NASDAQ AD Line	Daily	1972 - 2011	Units	9962	84.03	1.55	-38.13	114.24
NASDAQ Percentage Net Advances	Daily	1972 - 2011	Units	9952	-37.84	24.67	-789.41	1147.90
Alternext Advances	Daily	1959 - 2011	Units	13216	5.37	0.43	-0.94	17.80
Alternext Declines	Daily	1959 - 2011	Units	13216	4.25	0.43	-0.97	30.78
Alternext Net Advances	Daily	1959 - 2011	Units	13173	-52.41	11.24	-491.00	299.00
Alternext AD Line	Daily	1959 - 2011	Units	13216	-0.03	0.09	-6.79	3.92
Alternext Percentage Net Advances	Daily	1959 - 2011	Units	11909	-52.30	10.15	-151.72	280.57
Weekly Total Market Advances & Declines:								
NYSE Weekly Advances	Weekly	1940 - 2010	Units	3688	16.75	0.97	-0.94	29.18
NYSE Weekly Declines	Weekly	1940 - 2010	Units	3688	13.99	0.66	-0.92	10.87
NYSE Net Advances	Weekly	1940 - 2010	Units	3683	-129.71	22.92	-671.00	482.50
NYSE AD Line	Weekly	1940 - 2010	Units	3688	0.06	0.16	-6.89	4.03
Daily Total Maket New Highs & New Low:								
NYSE New Highs	Daily	1928 - 2011	Units	20614	19.16	3.01	-0.99	414.00
NYSE New Lows	Daily	1928 - 2011	Units	20558	20.50	1.15	-0.99	58.00
NYSE Net New Highs	Daily	1932 - 2011	Units	20369	3.37	4.05	-207.00	171.00
NYSE Cumulative Highs	Daily	1932 - 2011	Units	20694	0.06	0.02	-0.03	2.17
NYSE Percentage Net New Highs	Daily	1932 - 2011	Units	20281	2.35	3.80	-147.27	170.70
NASDAQ New Highs	Daily	1974 - 2011	Units	9206	7.59	0.46	-0.92	8.50
NASDAQ New Lows	Daily	1974 - 2011	Units	9203	10.11	0.61	-0.95	18.00
NASDAQ Net New Highs	Daily	1974 - 2011	Units	9171	-0.60	3.76	-105.00	65.00
NASDAQ Cumulative Highs	Daily	1974 - 2011	Units	9214	0.14	0.07	-1.33	6.00
NASDAQ Percentage Net New Highs	Daily	1974 - 2011	Units	9167	-0.61	3.76	-104.61	65.13
Alternext New Highs	Daily	1962 - 2011	Units	12219	14.83	1.19	-1.00	89.91
Alternext New Lows	Daily	1962 - 2011	Units	12222	16.50	1.20	-0.99	95.00
Alternext Net New Highs	Daily	1962 - 2011	Units	11929	-4.29	2.55	-82.00	92.00
Alternext Cumulative Highs	Daily	1962 - 2011	Units	12462	0.16	0.24	-9.80	15.00
Alternext Percentage Net New Highs	Daily	1963 - 2011	Units	11291	-2.48	2.57	-84.71	85.43
Weekly Total Maket New Highs & New Lows:								
NYSE Weekly New Highs	Weekly	1937 - 2010	Units	3869	17.32	0.94	-0.95	17.80
NYSE Weekly New Lows	Weekly	1937 - 2010	Units	3869	21.58	1.17	-0.95	27.20
NYSE Net New Highs	Weekly	1937 - 2010	Units	3860	2.08	7.06	-229.00	124.50
NYSE Cumulative Highs	Weekly	1937 - 2010	Units	3869	13.93	8.45	-10.72	525.00

A.2.2 GARCH (1,1) Specifications

In the previous OLS rolling window regression analysis, quite a few of my market indicators exhibit a widening of the confidence bounds problem. This may be a sign of volatility clustering. In fact, the volatility clustering problem in stock return data has been documented as early as 1963 (Mandelbrot (1963)). Many previous researchers argue a GARCH model can encounter such a problem. Bollerslev, Chou, and Kroner (1993) survey this strand of studies in depth and also note that small numbers of GARCH parameters seem sufficient to model variance dynamics over very long sample periods. Although I use White standard errors to correct for the heteroskedasticity problem in the OLS results, a robustness check using a GARCH (1, 1) model may provide further confidence in the results. The GARCH (1, 1) model specifies the same linear relation between market returns and the change of market indicators, but assumes normally distributed standard errors whose variance is restricted as

$$R_t = \alpha + \beta I_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid \phi_{t-1} \sim N(0, \sigma^2)$$

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2$$

I replicate my OLS analysis by using the GARCH (1, 1) model and present my results for the full sample and sub-samples below. In the full sample, I discover a total of 21 predictive market indicators at the 10% significance level, which is less than the 30 discovered in the OLS estimation. After the sub-sample analysis, 10 market indicators remain predictive; while most of them are the same as those found by the OLS regressions, the GARCH (1, 1) model picks up NYSE free credit balances and S&P

monthly extra dividends as market predictors, but drops the short interest ratio and NYSE cumulative highs featured in the OLS results. I then test the economic significance of the 10 indicators using the GARCH (1, 1) estimates. None of the market indicators beats the market under GARCH (1, 1) model either.

GARCH (1, 1) Results

This table reports the GARCH (1, 1) results of the regression model $R_t = \alpha_t + \beta I_{t-1} + \varepsilon_t$ for full samples and two equal length sub-samples. R_t represents S&P 500 periodic returns calculated as log differences of the S&P 500 Index values, I_{t-1} represents periodic percentage changes of market indicators. I obtain all data from the Global Financial Data. The t-statistics reported are White standard errors corrected and marked in bold if significant at 10% significance level. Panel A and Panel B report results for market sentiment and market strength indicators respectively.

	Full Sample			Sub-sample 1			Sub-sample 2		
Market Indicators	**Period**	**β (*10^{-3})**	**t value**	**Period 1**	**β (*10^{-3})**	**t value**	**Period 2**	**β (*10^{-3})**	**t value**
Panel A: Market Sentiment Indicators									
Option Volumes:									
CBOE Calls Volume	1989 - 2011	-0.24	-0.84	1989-1999	-0.20	-0.41	2000-2011	-0.24	-0.64
CBOE Puts Volume	1989 - 2011	0.04	0.19	1989-1999	0.01	0.04	2000-2011	0.27	0.67
OEX Calls Volume	1989 - 2011	0.00	0.08	1989-1999	0.00	-0.01	2000-2011	0.01	**11.47**
OEX Puts Volume	1989 - 2011	0.00	0.03	1989-1999	0.00	0.03	2000-2011	0.03	**11.63**
CBOE Ratio of Traded Value of Puts to Calls	1986 - 2011	0.76	1.51	1986-1998	0.81	1.07	1999-2011	0.83	1.19
Odd-lots Volumes:									
NYSE Odd Lot Purchases	1970 - 2011	0.00	-0.01	1970-1990	0.70	1.06	1991-2011	0.00	-0.01
NYSE Odd Lot Sales	1970 - 2011	0.18	0.89	1970-1990	0.80	**1.65**	1991-2011	0.00	-0.01
NYSE Odd Lot Shorts	1970 - 2011	0.00	0.19	1970-1990	-0.04	-0.67	1991-2011	0.00	0.19
Short Sales Volumes:									
NYSE Short Sales-Members	1940 - 2008	6.06	**6.62**	1940-1974	6.21	**5.36**	1975-2008	5.99	**4.06**
NYSE Short Sales-General Public	1940 - 2008	1.21	1.60	1940-1974	-0.14	-0.17	1975-2008	6.44	**4.27**
NYSE Short Sales-Specialists	1940 - 2008	6.05	**6.61**	1940-1974	6.47	**5.66**	1975-2008	5.73	**3.85**
NYSE Short Sales-Total	1940 - 2008	5.80	**6.10**	1940-1974	4.84	**3.97**	1975-2008	7.37	**4.61**
Short Interests:									
NYSE Short Interest Ratio	1931 - 2010	-10.20	-1.30	1931-1970	-10.20	-1.30	1971-2010	-10.20	-1.30
NYSE Short Interest Shares	1931 - 2010	11.10	0.77	1931-1970	10.90	0.76	1971-2010	11.10	0.77
AAII/II Sentiment Indices:									
AAII Bearish Index	1989 - 2010	1.04	0.59	1989-1999	0.54	0.21	2000-2010	0.77	0.31
AAII Bullish Index	1989 - 2010	0.57	0.22	1989-1999	0.98	0.29	2000-2010	0.73	0.18
AAII Neutral Index	1989 - 2010	-3.21	**-1.78**	1989-1999	-0.14	-0.05	2000-2010	-4.90	**-2.01**
Investors Intelligence Bearish Percentage	1987 - 2010	4.22	0.68	1987-1998	5.25	0.57	1999-2010	3.24	0.37
Investors Intelligence Bullish Percentage	1987 - 2010	-3.93	-0.46	1987-1998	-1.74	-0.17	1999-2010	-8.29	-0.57
Confidence Index:									
Barron's Confidence Index	1932 - 2010	-40.30	**-2.02**	1932-1970	-45.10	-1.41	1971-2010	-25.20	-0.95
Exchange Seat Prices:									
AMEX Seat Prices	1921 - 1993	0.76	0.09	1921-1958	15.10	1.15	1959-1993	-8.52	-0.97
NYSE Annual Seat Price	1820 - 2003	-7.86	-0.15	1820-1912	-12.60	-0.19	1913-2003	6.10	0.08
Volatility Indices:									
CBOE S&P 500 Volatility Index	1986 - 2011	-0.88	-0.42	1986-1998	-5.85	**-2.14**	1999-2011	6.25	**1.93**
CBOE NASDAQ Volatility Index	2001 - 2011	4.65	1.15	2001-2005	1.13	0.19	2006-2011	7.89	1.37
CBOE S&P 100 Volatility Index	1986 - 2011	0.77	0.39	1986-1998	-4.98	**-1.79**	1999-2011	7.45	**2.72**
AMEX NYSE Arca NASDAQ 100 Volatility Index	2001 - 2011	4.16	1.17	2001-2005	0.68	0.14	2006-2011	7.88	1.49
CBOE DJIA Volatility Index	2005 - 2011	6.40	1.55	2005-2007	4.42	0.93	2008-2011	11.90	1.61
Margin Account Balances:									
NYSE Margin Debt	1918 - 2010	-8.64	-0.47	1918-1963	1.60	0.07	1964-2010	-36.30	-0.85
NYSE Free Credit Balances	1931 - 2010	72.20	**3.21**	1931-1970	97.90	**2.40**	1971-2010	57.60	**2.00**
NYSE Free Credit Balances on Cash Accounts	1971 - 2010	31.50	1.13	1971-1990	9.48	0.22	1991-2010	63.30	1.60
NYSE Free Cash Balances in Margin Accounts	1971 - 2010	16.20	0.76	1971-1990	-12.60	-0.41	1991-2010	59.60	**1.91**
Mutual Fund Balances:									
USA Mutual Fund Equity Funds Total Net Assets	1984 - 2010	35.50	0.59	1984-1996	-33.40	-0.37	1997-2010	88.40	1.06

Market Indicators	Full Sample Period	β (*10⁻³)	t value	Sub-sample 1 Period 1	β (*10⁻³)	t value	Sub-sample 2 Period 2	β (*10⁻³)	t value
USA Mutual Fund Equity Funds Cash Percentage	1968 - 2010	6.99	0.26	1968-1988	8.42	0.19	1989-2010	-29.10	-0.74
USA Mutual Fund Equity Funds Redemptions	1984 - 2010	-4.45	-0.86	1984-1996	-5.48	-0.32	1997-2010	9.00	0.44
USA Mutual Fund Equity Funds New Sales	1984 - 2010	8.76	0.63	1984-1996	10.70	0.53	1997-2010	2.12	0.09
USA Mutual Fund Equity and Bond Fund Net Assets	1954 - 2010	10.60	0.55	1954-1981	102.60	**1.69**	1982-2010	9.67	0.26
USA Mutual Fund Equity and Bond Fund Cash Percent	1954 - 2010	11.00	0.49	1954-1981	13.90	0.45	1982-2010	9.96	0.30
USA Mutual Fund Equity and Bond Fund Liquid Assets	1954 - 2010	28.50	1.24	1954-1981	43.60	1.40	1982-2010	-6.90	-0.20
USA Mutual Fund Equity and Bond Fund Redemptions	1954 - 2010	-8.46	-1.04	1954-1981	-11.80	-1.03	1982-2010	-2.49	-0.20
USA Mutual Fund Equity and Bond Fund New Sales	1954 - 2010	8.26	1.04	1954-1981	5.60	0.53	1982-2010	12.00	0.91
Number of Dividend News:									
Moody's Monthly Decreased Dividends	1956 - 2008	55.70	**2.32**	1956-1984	79.10	**2.70**	1985-2011	19.30	0.47
Moody's Monthly Extra Dividends Declared	1956 - 2009	-62.90	-1.52	1956-1984	-125.60	-1.44	1985-2011	-55.40	-1.16
Moody's Monthly Increased Dividends Declared	1956 - 2009	-109.20	**-2.01**	1956-1984	-114.60	-1.62	1985-2011	-123.30	-1.63
Moody's Monthly Omitted Dividends	1956 - 2009	27.30	1.10	1956-1984	34.40	0.95	1985-2011	10.30	0.28
Moody's Monthly Resumed Dividends	1956 - 2009	26.00	1.41	1956-1984	83.40	**2.35**	1985-2011	6.24	0.31
S&P Monthly Dividend Decreases Declared	1955 - 2010	0.49	0.37	1955-1982	1.78	0.86	1983-2010	-1.18	-0.68
S&P Monthly Extra Dividends Declared	1955 - 2010	6.12	**2.81**	1955-1982	6.92	**2.36**	1983-2010	5.40	**1.69**
S&P Monthly Increased Dividends Declared	1955 - 2010	5.59	1.62	1955-1982	12.80	**2.13**	1983-2010	0.24	0.04
S&P Monthly Omitted Dividends Declared	1955 - 2010	0.94	0.87	1955-1982	0.55	0.34	1983-2010	0.96	0.63
S&P Monthly Resumed Dividends Declared	1955 - 2010	2.59	**1.80**	1955-1982	4.48	1.49	1983-2010	0.85	0.49
Panel B: Market Strength Indicators									
Total Volume:									
NYSE Total Volume	1928 - 2011	0.03	0.92	1928-1969	0.00	0.02	1970-2011	0.58	**1.98**
Total Volume Turnovers:									
NYSE Share Volume Turnover	1925 - 2010	-20.90	-1.20	1925-1967	31.90	0.72	1968-2010	-60.10	**-2.57**
NYSE Annual Share Value Turnover	1934 - 2010	18.50	0.49	1934-1971	-7.40	-0.12	1972-2010	-16.00	-0.15
Short-term Trading Indices:									
NYSE Short-term Trading Index	1965-2011	-0.66	**-5.57**	1965-1987	-1.21	-10.16	1988-2011	0.06	0.31
NASDAQ Short-term Trading Index	1972-2011	0.00	-0.26	1972-1991	-0.12	-1.03	1992-2011	0.00	-0.28
Daily Total Market Advances & Declines:									
NYSE Advances	1928 - 2011	1.05	**15.06**	1928-1969	1.15	**13.84**	1970-2011	0.88	**6.01**
NYSE Declines	1928 - 2011	-1.29	**-12.92**	1928-1969	-1.36	**-11.76**	1970-2011	-1.14	**-5.80**
NYSE Net Advances	1928 - 2011	0.00	-0.09	1928-1969	0.00	-0.13	1970-2011	0.00	-0.04
NYSE AD Line	1928 - 2011	0.00	-0.79	1928-1969	0.00	-1.28	1970-2011	0.00	-0.16
NYSE Percentage Net Advances	1940 - 2011	0.00	-0.19	1928-1969	0.00	-0.33	1970-2011	0.00	-0.03
NASDAQ Advances	1972 - 2011	0.42	**3.05**	1972-1991	0.55	**4.40**	1992-2011	0.12	0.56
NASDAQ Declines	1972 - 2011	-0.14	**-7.59**	1972-1991	-0.13	**-5.96**	1992-2011	-0.42	-1.17
NASDAQ Net Advances	1972 - 2011	0.00	-0.09	1972-1991	0.00	0.76	1992-2011	0.00	-0.40
NASDAQ AD Line	1972 - 2011	0.00	0.41	1972-1991	0.00	0.61	1992-2011	0.00	0.05
NASDAQ Percentage Net Advances	1972 - 2011	0.00	-0.09	1972-1991	0.00	0.76	1992-2011	0.00	-0.40
Alternext Advances	1959 - 2011	1.03	**9.39**	1959-1984	1.28	**12.22**	1985-2011	0.20	0.71
Alternext Declines	1959 - 2011	-0.76	**-12.51**	1959-1984	-0.77	**-13.32**	1985-2011	-0.64	**-1.77**
Alternext Net Advances	1959 - 2011	0.00	-0.36	1959-1984	0.00	0.67	1985-2011	-0.01	-1.37
Alternext AD Line	1959 - 2011	0.00	-0.78	1959-1984	0.00	-0.30	1985-2011	-0.02	-1.40
Alternext Percentage Net Advances	1959 - 2011	0.00	-0.88	1963-1986	0.00	0.21	1987-2011	-0.01	-1.17
Weekly Total Market Advances & Declines:									
NYSE Weekly Advances	1940 - 2010	-0.53	-1.19	1940-1974	0.46	0.82	1975-2010	-1.74	**-2.07**
NYSE Weekly Declines	1940 - 2010	0.42	0.80	1940-1974	-0.61	-0.92	1975-2010	1.94	**2.42**
NYSE Net Advances	1940 - 2010	0.00	0.10	1940-1974	-0.01	-0.51	1975-2010	0.00	0.20
NYSE AD Line	1940 - 2010	0.27	0.13	1940-1974	0.48	0.26	1975-2010	-97.80	-1.92
Daily Total Maket New Highs & New Lows:									
NYSE New Highs	1928 - 2011	0.14	**8.96**	1932-1971	0.46	**6.50**	1972-2011	0.11	**1.72**
NYSE New Lows	1932 - 2011	-0.30	**-6.78**	1932-1971	-0.34	**-7.50**	1972-2011	-0.15	-1.28
NYSE Net New Highs	1932 - 2011	0.01	1.00	1932-1971	0.01	0.63	1972-2011	0.01	0.63
NYSE Cumulative Highs	1932 - 2011	0.00	-0.07	1932-1971	0.01	0.35	1972-2011	0.01	0.35
NYSE Percentage Net New Highs	1932 - 2011	0.01	0.90	1932-1971	0.01	0.55	1972-2011	0.01	0.55
NASDAQ New Highs	1974 - 2011	0.41	**1.85**	1974-1992	0.68	**2.10**	1993-2011	0.15	0.49
NASDAQ New Lows	1974 - 2011	-0.10	-0.66	1974-1992	-0.26	-1.23	1993-2011	0.08	0.40
NASDAQ Net New Highs	1974 - 2011	-0.01	-0.48	1974-1992	-0.04	-1.23	1993-2011	-0.04	-1.23

Market Indicators	Full Sample Period	β (*10⁻³)	t value	Sub-sample 1 Period 1	β (*10⁻³)	t value	Sub-sample 2 Period 2	β (*10⁻³)	t value
NASDAQ Cumulative Highs	1974 – 2011	0.02	0.53	1974 – 1992	0.02	0.59	1993 – 2011	0.02	0.59
NASDAQ Percentage Net New Highs	1974 - 2011	-0.01	-0.50	1974-1992	-0.04	-1.24	1993-2011	-0.04	-1.24
Alternext New Highs	1962 - 2011	0.23	**3.10**	1962-1986	0.18	**1.98**	1987-2011	0.39	**1.97**
Alternext New Lows	1962 - 2011	-0.06	-0.66	1962-1986	-0.13	-1.19	1987-2011	0.04	0.31
Alternext Net New Highs	1962 - 2011	-0.01	-0.41	1962-1986	-0.02	-0.64	1987-2011	-0.02	-0.64
Alternext Cumulative Highs	1962 - 2011	-0.02	-0.48	1962-1986	0.03	0.79	1987-2011	0.03	0.79
Alternext Percentage Net New Highs	1962 - 2011	-0.01	-0.19	1963-1986	0.00	-0.07	1987-2011	0.00	-0.07
Weekly Total Maket New Highs & New Lows:									
NYSE Weekly New Highs	1937 - 2010	0.23	0.62	1937-1973	0.49	1.17	1974-2010	-0.67	-0.95
NYSE Weekly New Lows	1937 - 2010	-0.23	-1.08	1937-1973	-0.35	-1.60	1974-2010	0.24	0.35
NYSE Net New Highs	1937 - 2010	0.04	1.21	1937-1973	0.10	1.52	1974-2010	0.01	0.16
NYSE Cumulative Highs	1937 - 2010	-0.01	-0.01	1937-1973	0.56	0.18	1974-2010	-0.01	-0.01

GARCH (1, 1) Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability in both sub-samples under the GARCH (1, 1) regressions. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level.

			Buy & Hold Strategy			**Technical Strategy**							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Short Sales-Members	Weekly	1740	1.28	2.27	0.84	1.41	1.84	1.69	0.58	0.20	0.77	0.66	**21.94**
NYSE Short Sales-Specialists	Weekly	1738	1.28	2.27	0.84	1.24	1.78	0.81	0.01	0.04	0.14	0.62	**19.05**
NYSE Short Sales-Total	Weekly	1737	1.28	2.27	0.84	1.58	1.88	2.56	1.24	0.37	1.44	0.69	**24.48**
Panel B: Market Strength Indicators													
NYSE Advances	Daily	11024	0.24	1.06	0.85	-0.04	0.86	-2.15	**4.96**	-0.25	**-5.06**	0.64	**20.41**
NYSE Declines	Daily	11024	0.24	1.06	0.85	-0.07	0.91	-2.43	**6.36**	-0.30	**-6.52**	0.73	**38.54**
NASDAQ Advances	Daily	4981	0.25	1.18	1.34	0.19	1.17	0.83	**2.41**	-0.06	**-2.41**	0.98	**171.38**
Alternext Advances	Daily	6608	0.30	1.18	1.57	0.02	1.06	-0.90	**4.27**	-0.25	**-3.83**	0.79	**16.18**
Alternext Declines	Daily	6608	0.26	1.07	1.07	0.22	1.09	0.96	1.28	-0.05	**-0.94**	0.85	**16.26**
NYSE New Highs	Daily	10307	0.30	1.18	1.57	0.27	1.06	1.18	0.73	0.01	0.81	0.97	**303.42**
NYSE New Lows	Daily	10251	0.28	1.08	1.19	0.14	1.04	-0.07	**4.58**	-0.13	**-4.59**	0.93	**116.43**
Alternext New Highs	Daily	6109	0.26	1.20	1.24	0.26	1.20	1.24	N/A	0.00	**N/A**	1.00	**N/A**

A.2.3 Robust Regressions

Outliers can be another issue that causes instability of indication. I replicate my analysis using robust regressions to control the effect of potential outliers. Robust regressions limit the influence of outliers through estimating a scale parameter that downweights the observations that have large residuals. Robust regressions mainly control outliers on the dependent variable side. I follow the M-estimation method introduced by Huber (1973) to obtain my β estimates and I report the results below.

I have 32 indicators predict the full-sample returns, compared to the 30 under the OLS. The sub-sample analysis also gives me 10 indicators that provide relatively stable indication over time. Nine of these indicators are same as those under the OLS sub-sample analysis, while the robust regressions drop NYSE weekly cumulative highs but add the CBOE S&P 500 volatility index. The economic significance results for the 10 indicators use outlier robust estimates to calculate my portfolio returns and I largely do not discover any predictability of the market indicators, with one exception: Only NYSE total short sales seem to provide some profitability after controlling for risk and transaction costs; it has both a higher Sharpe ratio and Jensen's α than the buy and hold strategy. However, my main conclusion stays same.

Robust Regression Results

This table reports the robust regression results of the regression model $R_t = \alpha_t + \beta I_{t-1} + \varepsilon_t$ for full samples and two equal length sub-samples. R_t represents S&P 500 periodic returns calculated as log differences of the S&P 500 Index values, I_{t-1} represents periodic percentage changes of market indicators. I obtain all data from the Global Financial Data. The t-statistics reported are White standard errors corrected and marked in bold if significant at 10% significance level. Panel A and Panel B report results for market sentiment and market strength indicators respectively.

	Full Sample			Sub-sample 1			Sub-sample 2		
Market Indicators	**Period**	**β (*10⁻³)**	**Chi-stats**	**Period 1**	**β (*10⁻³)**	**Chi-stats**	**Period 2**	**β (*10⁻³)**	**Chi-stats**
Panel A: Market Sentiment Indicators									
Option Volumes:		0.00							
CBOE Calls Volume	1989 - 2011	-0.18	0.38	1989-1999	-0.53	1.32	2000-2011	0.00	0.00
CBOE Puts Volume	1989 - 2011	0.02	0.05	1989-1999	0.00	0.00	2000-2011	0.28	0.53
OEX Calls Volume	1989 - 2011	0.00	0.06	1989-1999	0.00	0.10	2000-2011	0.00	0.00
OEX Puts Volume	1989 - 2011	0.00	0.01	1989-1999	0.00	0.01	2000-2011	0.00	0.00
CBOE Ratio of Traded Value of Puts to Calls	1986 - 2011	0.95	**3.89**	1986-1998	-0.06	0.01	1999-2011	1.45	**3.88**
Odd-lots Volumes:									
NYSE Odd Lot Purchases	1970 - 2011	0.00	0.05	1970-1990	0.38	0.43	1991-2011	0.00	0.05
NYSE Odd Lot Sales	1970 - 2011	0.43	**4.28**	1970-1990	0.47	1.04	1991-2011	0.40	**2.84**
NYSE Odd Lot Shorts	1970 - 2011	0.00	0.26	1970-1990	-0.08	1.52	1991-2011	0.00	0.23
Short Sales Volumes:									
NYSE Short Sales-Members	1940 - 2008	6.80	**62.41**	1940-1974	6.40	**11.34**	1975-2008	7.74	**10.22**
NYSE Short Sales-General Public	1940 - 2008	1.78	**5.11**	1940-1974	-1.02	0.38	1975-2008	5.65	**5.91**
NYSE Short Sales-Specialists	1940 - 2008	6.67	**69.89**	1940-1974	6.80	**12.47**	1975-2008	5.53	**5.45**
NYSE Short Sales-Total	1940 - 2008	6.97	**51.78**	1940-1974	5.22	**6.70**	1975-2008	8.69	**11.66**
Short Interests:									
NYSE Short Interest Ratio	1931 - 2010	-13.53	**4.05**	1931-1970	-13.50	**4.03**	1971-2010	-13.53	**4.05**
NYSE Short Interest Shares	1931 - 2010	8.47	0.26	1931-1970	8.50	0.26	1971-2010	8.47	0.26
AAII/II Sentiment Indices:									
AAII Bearish Index	1989 - 2010	-0.14	0.01	1989-1999	-0.41	0.02	2000-2010	0.31	0.02
AAII Bullish Index	1989 - 2010	4.91	**3.69**	1989-1999	4.29	1.69	2000-2010	5.69	2.06
AAII Neutral Index	1989 - 2010	-5.03	**6.24**	1989-1999	-2.89	0.74	2000-2010	-6.41	**5.77**
Investors Intelligence Bearish Percentage	1987 - 2010	3.20	0.22	1987-1998	-1.15	0.01	1999-2010	6.78	0.51
Investors Intelligence Bullish Percentage	1987 - 2010	-2.39	0.08	1987-1998	8.18	0.64	1999-2010	-19.83	2.19
Confidence Index:									
Barron's Confidence Index	1932 - 2010	-35.57	**3.54**	1932-1970	-13.23	0.32	1971-2010	-65.22	**4.36**
Exchange Seat Prices:									
AMEX Seat Prices	1921 - 1993	1.35	0.05	1921-1958	11.17	1.08	1959-1993	-3.42	0.22
NYSE Annual Seat Price	1820 - 2003	-24.60	0.64	1820-1912	-14.60	0.25	1913-2003	-23.90	0.14
Volatility Indices:									
CBOE S&P 500 Volatility Index	1986 - 2011	2.93	**3.70**	1986-1998	-3.10	**3.67**	1999-2011	9.63	**10.11**
CBOE NASDAQ Volatility Index	2001 - 2011	7.81	**3.96**	2001-2005	2.76	0.18	2006-2011	10.97	**4.73**
CBOE S&P 100 Volatility Index	1986 - 2011	4.08	**7.70**	1986-1998	-2.62	2.62	1999-2011	10.21	**13.44**
AMEX NYSE Arca NASDAQ 100 Volatility Index	2001 - 2011	8.81	**8.58**	2001-2005	3.17	0.35	2006-2011	12.79	**11.47**
CBOE DJIA Volatility Index	2005 - 2011	9.34	**7.36**	2005-2007	5.22	1.89	2008-2011	17.06	**6.02**
Margin Account Balances:									
NYSE Margin Debt	1918 - 2010	-17.64	0.82	1918-1963	-12.14	0.27	1964-2010	-14.63	0.13
NYSE Free Credit Balances	1931 - 2010	37.82	2.61	1931-1970	80.49	**4.83**	1971-2010	8.22	0.07
NYSE Free Credit Balances on Cash Accounts	1971 - 2010	31.88	1.18	1971-1990	-14.45	0.13	1991-2010	78.14	**3.30**
NYSE Free Cash Balances in Margin Accounts	1971 - 2010	-24.39	1.38	1971-1990	-30.64	1.51	1991-2010	-13.34	0.12

Market Indicators	Full Sample Period	β (*10⁻³)	Chi-stats	Sub-sample 1 Period 1	β (*10⁻³)	Chi-stats	Sub-sample 2 Period 2	β (*10⁻³)	Chi-stats
USA Mutual Fund Equity Funds Total Net Assets	1984 - 2010	28.92	0.38	1984-1996	-58.41	0.86	1997-2010	65.00	0.84
USA Mutual Fund Equity Funds Cash Percentage	1968 - 2010	-0.93	0.00	1968-1988	4.63	0.02	1989-2010	-7.91	0.03
USA Mutual Fund Equity Funds Redemptions	1984 - 2010	-5.38	1.85	1984-1996	-6.13	**3.02**	1997-2010	10.35	0.24
USA Mutual Fund Equity Funds New Sales	1984 - 2010	0.80	0.00	1984-1996	-4.74	0.12	1997-2010	7.34	0.10
USA Mutual Fund Equity and Bond Fund Net Assets	1954 - 2010	9.40	**4.35**	1954-1981	90.72	2.63	1982-2010	8.66	**3.55**
USA Mutual Fund Equity and Bond Fund Cash Percent	1954 - 2010	-11.45	0.26	1954-1981	-7.15	0.06	1982-2010	-11.12	0.10
USA Mutual Fund Equity and Bond Fund Liquid Assets	1954 - 2010	1.80	0.01	1954-1981	18.18	0.33	1982-2010	-22.92	0.36
USA Mutual Fund Equity and Bond Fund Redemptions	1954 - 2010	-4.95	0.30	1954-1981	-8.58	0.46	1982-2010	-2.44	0.04
USA Mutual Fund Equity and Bond Fund New Sales	1954 - 2010	3.11	0.14	1954-1981	0.82	0.01	1982-2010	6.17	0.21
Number of Dividend News:									
Moody's Monthly Decreased Dividends	1956 - 2008	51.57	2.54	1956-1984	81.32	**3.13**	1985-2011	24.08	0.28
Moody's Monthly Extra Dividends Declared	1956 - 2009	-89.06	1.19	1956-1984	-250.92	**4.08**	1985-2011	0.73	0.00
Moody's Monthly Increased Dividends Declared	1956 - 2009	-108.17	2.14	1956-1984	-97.29	1.05	1985-2011	-109.76	0.90
Moody's Monthly Omitted Dividends	1956 - 2009	17.60	0.20	1956-1984	42.97	0.80	1985-2011	-35.42	0.29
Moody's Monthly Resumed Dividends	1956 - 2009	43.07	1.67	1956-1984	114.27	**6.17**	1985-2011	-22.79	0.23
S&P Monthly Dividend Decreases Declared	1955 - 2010	0.39	0.12	1955-1982	1.17	0.72	1983-2010	-1.26	0.45
S&P Monthly Extra Dividends Declared	1955 - 2010	4.66	**4.97**	1955-1982	5.52	**4.07**	1983-2010	3.86	1.44
S&P Monthly Increased Dividends Declared	1955 - 2010	1.02	0.09	1955-1982	8.27	1.82	1983-2010	-2.02	0.24
S&P Monthly Omitted Dividends Declared	1955 - 2010	1.09	0.63	1955-1982	0.37	0.03	1983-2010	1.30	0.53
S&P Monthly Resumed Dividends Declared	1955 - 2010	3.01	**4.47**	1955-1982	3.08	1.99	1983-2010	2.80	2.21
Panel B: Market Strength Indicators									
Total Volume:									
NYSE Total Volume	1928 - 2011	0.02	0.12	1928-1969	-0.01	0.07	1970-2011	0.55	**6.16**
Total Volume Turnovers:									
NYSE Share Volume Turnover	1925 - 2010	8.04	0.12	1925-1967	39.02	1.28	1968-2010	-27.24	0.79
NYSE Annual Share Value Turnover	1934 - 2010	38.72	1.14	1934-1971	36.44	0.87	1972-2010	50.18	0.27
Short-term Trading Indices:									
NYSE Short-term Trading Index	1965-2011	-0.46	**19.84**	1965-1987	-1.02	**52.78**	1988-2011	0.15	0.95
NASDAQ Short-term Trading Index	1972-2011	0.00	0.00	1972-1991	-0.17	1.67	1992-2011	0.00	0.00
Daily Total Market Advances & Declines:									
NYSE Advances	1928 - 2011	0.94	**237.72**	1928-1969	1.10	**269.05**	1970-2011	0.60	**22.86**
NYSE Declines	1928 - 2011	-0.87	**109.28**	1928-1969	-0.89	**91.82**	1970-2011	-0.92	**31.37**
NYSE Net Advances	1928 - 2011	0.00	0.43	1928-1969	0.00	0.50	1970-2011	0.00	0.14
NYSE AD Line	1928 - 2011	0.00	0.01	1928-1969	0.00	0.05	1970-2011	0.00	0.04
NYSE Percentage Net Advances	1940 - 2011	0.00	0.33	1928-1969	0.00	0.29	1970-2011	0.00	0.14
NASDAQ Advances	1972 - 2011	0.21	**4.72**	1972-1991	0.34	**8.74**	1992-2011	-0.26	2.28
NASDAQ Declines	1972 - 2011	-0.08	**5.71**	1972-1991	-0.08	**5.74**	1992-2011	-0.28	0.73
NASDAQ Net Advances	1972 - 2011	0.00	0.74	1972-1991	0.00	0.15	1992-2011	0.00	0.58
NASDAQ AD Line	1972 - 2011	0.00	0.01	1972-1991	0.00	0.21	1992-2011	0.00	0.14
NASDAQ Percentage Net Advances	1972 - 2011	0.00	0.74	1972-1991	0.00	0.15	1992-2011	0.00	0.58
Alternext Advances	1959 - 2011	1.06	**46.07**	1959-1984	1.52	**79.34**	1985-2011	0.07	0.06
Alternext Declines	1959 - 2011	-1.58	**102.73**	1959-1984	-3.03	**342.32**	1985-2011	-0.77	**5.49**
Alternext Net Advances	1959 - 2011	0.00	0.35	1959-1984	0.00	0.31	1985-2011	0.00	0.06
Alternext AD Line	1959 - 2011	0.00	0.00	1959-1984	0.00	0.05	1985-2011	0.00	0.12
Alternext Percentage Net Advances	1959 - 2011	0.00	0.07	1963-1986	0.00	0.08	1987-2011	0.00	0.08
Weekly Total Market Advances & Declines:									
NYSE Weekly Advances	1940 - 2010	-0.99	**9.93**	1940-1974	0.50	1.11	1975-2010	-1.95	**20.87**
NYSE Weekly Declines	1940 - 2010	0.67	2.09	1940-1974	-0.34	0.34	1975-2010	1.91	**6.82**
NYSE Net Advances	1940 - 2010	0.00	0.07	1940-1974	-0.01	0.03	1975-2010	0.00	0.10
NYSE AD Line	1940 - 2010	-1.07	0.32	1940-1974	-0.97	0.31	1975-2010	-54.26	1.33
Daily Total Maket New Highs & New Lows:									
NYSE New Highs	1928 - 2011	0.11	**36.67**	1932-1971	0.51	**49.34**	1972-2011	0.10	**22.02**
NYSE New Lows	1932 - 2011	-0.15	**9.75**	1932-1971	-0.20	**16.35**	1972-2011	-0.14	1.61
NYSE Net New Highs	1932 - 2011	0.02	2.01	1932-1971	0.03	**2.74**	1972-2011	0.02	0.54
NYSE Cumulative Highs	1932 - 2011	0.00	0.00	1932-1971	0.00	0.01	1972-2011	0.00	0.01
NYSE Percentage Net New Highs	1932 - 2011	0.02	1.31	1932-1971	0.02	1.19	1972-2011	0.02	0.54
NASDAQ New Highs	1974 - 2011	0.15	0.60	1974-1992	0.43	2.27	1993-2011	-0.14	0.26
NASDAQ New Lows	1974 - 2011	0.06	0.18	1974-1992	-0.23	1.27	1993-2011	0.37	**2.99**

Market Indicators	Full Sample Period	β (*10⁻³)	Chi-stats	Sub-sample 1 Period 1	β (*10⁻³)	Chi-stats	Sub-sample 2 Period 2	β (*10⁻³)	Chi-stats
NASDAQ Net New Highs	1974 - 2011	0.01	0.05	1974-1992	0.03	0.74	1993-2011	-0.01	0.11
NASDAQ Cumulative Highs	1974 - 2011	0.02	0.35	1974-1992	0.00	0.01	1993-2011	0.03	0.58
NASDAQ Percentage Net New Highs	1974 - 2011	0.00	0.04	1974-1992	0.03	0.70	1993-2011	-0.01	0.11
Alternext New Highs	1962 - 2011	0.18	**9.29**	1962-1986	0.10	**2.82**	1987-2011	0.47	**11.59**
Alternext New Lows	1962 - 2011	-0.12	**3.68**	1962-1986	-0.25	**5.85**	1987-2011	-0.06	0.51
Alternext Net New Highs	1962 - 2011	-0.01	0.07	1962-1986	-0.01	0.10	1987-2011	0.01	0.02
Alternext Cumulative Highs	1962 - 2011	-0.07	**5.25**	1962-1986	-0.01	0.09	1987-2011	-0.12	**7.37**
Alternext Percentage Net New Highs	1962 - 2011	0.00	0.00	1963-1986	-0.01	0.02	1987-2011	0.01	0.04
Weekly Total Maket New Highs & New Lows:									
NYSE Weekly New Highs	1937 - 2010	0.01	0.00	1937-1973	0.17	0.20	1974-2010	-0.32	0.33
NYSE Weekly New Lows	1937 - 2010	-0.27	1.09	1937-1973	-0.02	0.00	1974-2010	-0.91	1.86
NYSE Net New Highs	1937 - 2010	0.08	**3.74**	1937-1973	0.13	**3.51**	1974-2010	0.06	0.96
NYSE Cumulative Highs	1937 - 2010	-0.01	0.11	1937-1973	0.50	0.41	1974-2010	-0.01	0.12

Robust Regression Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability in both sub-samples under the robust regressions. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level.

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Short Sales-Members	Weekly	1791	1.06	2.29	-0.17	1.27	1.83	0.93	0.75	0.21	0.81	0.64	**21.46**
NYSE Short Sales-Specialists	Weekly	1789	1.06	2.29	-0.17	1.25	1.78	0.82	0.64	0.18	0.69	0.61	**19.12**
NYSE Short Sales-Total	Weekly	1788	1.06	2.29	-0.17	1.56	1.87	2.47	**1.89**	0.51	**1.99**	0.68	**23.91**
CBOE S&P 500 Volatility Index	Daily	3213	0.04	1.36	-0.23	0.04	1.36	-0.22	0.22	0.00	0.23	1.00	**2408.13**
NYSE Short Interest Ratio	Monthly	478	5.42	4.53	1.91	6.05	4.13	3.64	0.83	0.93	1.12	0.81	**23.54**
Panel B: Market Strength Indicators													
NYSE Advances	Daily	11025	0.24	1.06	0.85	-0.07	0.84	-2.57	**5.34**	-0.28	**-5.54**	0.61	**20.10**
NYSE Declines	Daily	11025	0.24	1.06	0.85	-0.01	0.94	-1.69	**5.46**	-0.24	**-5.58**	0.78	**45.92**
Alternext Declines	Daily	6607	0.30	1.18	1.58	-0.19	0.95	-3.21	**6.07**	-0.04	**-5.9**	0.64	**15.21**
NYSE New Highs	Daily	10306	0.26	1.07	1.07	0.27	1.06	1.20	0.80	0.02	0.9	0.97	**280.78**
Alternext New Highs	Daily	6108	0.26	1.20	1.24	0.18	1.18	0.59	**2.81**	-0.08	**-2.78**	0.97	**177.60**

A.2.4 Other Checks

I also perform several additional robustness checks. First, I only test the economic significance of the market indicators that show significant predictability in both sub-samples under several alternative models, namely, OLS, GARCH (1,1), and robust regression models. This may be too restrictive. I loosen my criteria and additionally test the economic significance of those indicators that show significant predictability in the full-sample analysis but not in the sub-sample analysis. I present results for the OLS, GARCH (1, 1), and robust regressions below. I find no additional predictability under the OLS and the GARCH (1, 1) models. However, I find NYSE weekly advances and NYSE net new highs have both higher Sharpe ratios than the market and a positive Jensen's α under the robust regression model. Although these two indicators may show some practical value, this does not alter my main conclusion that market indicators generally show very limited predictability.

Additional OLS Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with strategies based on market indicators that show significant predictability in full sample under the OLS regressions. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level.

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Odd Lot Purchases	Daily	5235	0.25	1.17	1.32	0.05	1.14	-0.34	**4.94**	-0.19	**-4.94**	0.94	**149.70**
NYSE Short Sales-General Public	Weekly	1741	1.28	2.26	0.85	1.28	1.75	1.08	0.16	0.08	0.30	0.61	**17.12**
AAII Bullish Index	Weekly	565	-0.21	2.66	-2.43	-0.50	2.44	-3.83	0.53	-0.38	-0.93	0.84	**26.23**
AAII Neutral Index	Weekly	565	-0.21	2.66	-2.43	0.33	2.29	-0.47	0.74	0.39	0.80	0.74	**15.96**
CBOE S&P 500 Volatility Index	Daily	3213	0.04	1.36	-0.23	-0.15	1.28	-1.71	**2.36**	-0.19	**-2.46**	0.88	**59.02**
CBOE NASDAQ Volatility Index	Daily	1278	0.01	1.57	-0.32	-0.55	1.12	-5.38	**2.28**	-0.57	**-2.63**	0.48	**10.43**
CBOE S&P 100 Volatility Index	Daily	3213	0.04	1.36	-0.23	-0.08	1.27	-1.21	1.49	-0.13	-1.56	0.87	**56.92**
CBOE DJIA Volatility Index	Daily	756	-0.03	1.87	-0.24	-0.31	1.31	-2.42	0.73	-0.29	-0.84	0.45	**8.22**
NYSE Free Credit Balances	Monthly	474	5.48	4.54	2.00	4.93	3.40	1.06	0.27	0.12	0.11	0.53	**9.24**
USA Mutual Fund Equity Funds Redemptions	Monthly	163	2.02	4.85	-0.98	2.02	4.85	-0.98	**N/A**	0.00	**N/A**	1	**N/A**
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	336	6.53	4.53	6.00	6.50	3.54	7.59	0.41	1.40	1.03	0.58	**7.46**
Moody's Monthly Increased Dividends Declared	Monthly	304	8.25	4.23	9.71	6.61	3.64	6.77	0.94	-0.63	-0.56	0.74	**13.39**
S&P Monthly Extra Dividends Declared	Monthly	335	6.24	4.52	5.43	5.89	3.67	5.75	0.09	0.79	0.60	0.63	**8.16**
S&P Monthly Resumed Dividends Declared	Monthly	330	8.00	4.40	9.42	6.97	3.51	8.89	0.14	0.76	0.55	0.61	**7.78**
Panel B: Market Strength Indicators													
NYSE Short-term Trading Index	Daily	5832	0.28	1.14	1.50	-0.38	0.95	-5.09	**8.34**	-0.60	**-8.55**	0.68	**31.14**
NASDAQ Declines	Daily	4980	0.25	1.18	1.32	0.27	1.17	1.57	1.36	0.03	1.34	0.98	**74.32**
Alternext Advances	Daily	6607	0.30	1.18	1.58	-0.33	0.86	-5.12	**7.14**	-0.54	**-7.24**	0.52	**14.20**
NYSE Weekly Advances	Weekly	1843	1.47	2.26	2.01	1.21	1.97	0.98	0.70	-0.15	-0.63	0.75	**32.10**
NYSE Net New Highs	Daily	10139	0.25	1.08	1.00	0.18	1.00	0.33	**1.78**	-0.06	**-1.67**	0.86	**78.72**
NYSE Net New Highs	Weekly	1929	1.61	2.32	2.52	1.56	1.86	2.86	0.24	0.16	0.62	0.64	**21.87**

Additional GARCH（1, 1) Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with strategies based on market indicators that show significant predictability in full sample under the GARCH(1,1) regressions. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level.

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
AAII Neutral Index	Weekly	565	-0.21	2.66	-2.43	0.09	2.55	-1.35	0.89	0.26	0.86	0.92	**38.75**
Barron's Confidence Index	Weekly	2065	1.24	2.31	0.92	1.47	2.12	2.06	1.27	0.26	1.41	0.84	**42.79**
Moody's Monthly Decreased Dividends	Monthly	326	6.24	4.45	4.50	4.70	3.83	1.23	1.07	-0.91	-0.80	0.73	**14.28**
Moody's Monthly Increased Dividends Declared	Monthly	304	8.25	4.23	9.71	6.77	3.69	7.11	0.87	-0.54	-0.50	0.76	**14.17**
S&P Monthly Resumed Dividends Declared	Monthly	330	8.00	4.40	9.42	7.37	3.56	9.87	0.12	1.09	0.79	0.63	**7.90**
Panel B: Market Strength Indicators													
NYSE Short-term Trading Index	Daily	5832	0.28	1.14	1.50	-0.38	0.95	-5.09	**8.34**	-0.60	**-8.55**	0.68	**31.14**
NASDAQ Advances	Daily	4980	0.25	1.18	1.32	0.13	1.16	0.35	**3.64**	-0.11	**-3.73**	0.97	**141.00**
NASDAQ Declines	Daily	4980	0.25	1.18	1.32	0.27	1.17	1.57	1.36	0.03	1.34	0.98	**74.32**
Alternext Advances	Daily	6607	0.30	1.18	1.58	-0.33	0.86	-5.12	**7.14**	-0.54	**-7.24**	0.52	**14.20**
NYSE New Lows	Daily	10278	0.27	1.08	1.12	0.15	1.02	0.02	**3.15**	-0.11	**-3.11**	0.88	**95.00**
NASDAQ New Highs	Daily	6708	0.16	0.01	2.05	0.08	0.92	-0.83	**4.94**	-0.25	**-4.81**	0.79	**35.13**

Additional Robust Regression Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with strategies based on market indicators that show significant predictability in full sample under the robust regressions. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level.

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
CBOE Ratio of Traded Value of Puts to Calls	Daily	3213	0.04	1.36	-0.23	0.03	1.36	-0.33	1.45	-0.01	-1.49	1.00	**1282.28**
NYSE Odd Lot Sales	Daily	5235	0.25	1.17	1.32	0.15	1.15	0.48	**2.95**	-0.09	**-2.93**	0.96	**153.56**
NYSE Short Sales-General Public	Weekly	1720	1.28	2.23	0.85	1.45	2.09	1.71	0.92	0.20	1.03	0.85	**51.83**
AAII Bullish Index	Weekly	565	-0.21	2.66	-2.43	-0.27	2.61	-2.72	0.33	-0.09	-0.39	0.96	**61.89**
AAII Neutral Index	Weekly	565	-0.21	2.66	-2.43	0.28	2.51	-0.63	1.27	0.43	1.24	0.89	**33.57**
Barron's Confidence Index	Weekly	2065	1.24	2.31	0.92	1.44	2.17	1.87	1.25	0.22	1.37	0.88	**48.95**
CBOE NASDAQ Volatility Index	Daily	1278	0.01	1.57	-0.32	-0.28	1.30	-2.56	1.30	-0.30	-1.43	0.67	**18.34**
CBOE S&P 100 Volatility Index	Daily	3213	0.04	1.36	-0.23	0.07	1.36	-0.05	1.61	0.02	1.65	1.00	**491.27**
AMEX NYSE Arca NASDAQ 100 Volatility Index	Daily	1277	0.00	1.57	-0.33	-0.42	1.26	-3.78	**1.88**	-0.44	**-2.10**	0.63	**15.89**
CBOE DJIA Volatility Index	Daily	756	-0.03	1.87	-0.24	-0.40	1.68	-2.47	1.27	-0.39	-1.38	0.79	**17.09**
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	336	6.53	4.53	6.00	7.04	3.86	8.35	0.75	1.53	1.16	0.71	**8.18**
S&P Monthly Extra Dividends Declared	Monthly	336	6.43	4.53	5.84	5.66	3.91	4.77	0.35	0.08	0.07	0.73	**9.00**
S&P Monthly Resumed Dividends Declared	Monthly	330	8.00	4.40	9.42	7.46	4.00	9.00	0.17	0.31	0.31	0.81	**20.55**
Panel B: Market Strength Indicators													
NASDAQ Advances	Daily	4980	0.25	1.18	1.32	0.21	1.17	0.98	**2.54**	-0.04	**-2.64**	0.99	**249.78**
NASDAQ Declines	Daily	4980	0.25	1.18	1.32	0.24	1.18	1.30	1.22	0.00	-1.26	1.00	**7474.20**
Alternext Advances	Daily	6607	0.30	1.18	1.58	-0.23	0.93	-3.72	**6.41**	-0.47	**-6.30**	0.61	**14.95**
NYSE Weekly Advances	Weekly	1843	1.02	2.26	2.01	1.78	2.16	3.54	**2.16**	0.35	**2.31**	0.91	**64.17**
NYSE New Lows	Daily	10278	0.27	1.08	1.12	0.17	1.06	0.25	**3.84**	-0.09	**-3.90**	0.95	**151.99**
Alternext New Lows	Daily	6110	0.25	1.20	1.17	0.08	1.13	-0.22	**3.00**	-0.15	**-2.64**	0.88	**16.08**
Alternext Cumulative Highs	Daily	5842	0.21	1.21	0.87	0.17	1.20	0.58	**1.81**	-0.03	**-1.78**	0.99	**255.18**
NYSE Net New Highs	Weekly	1929	1.61	2.32	2.52	1.98	2.19	4.35	**2.42**	0.43	**2.57**	0.89	**48.94**

Moreover, I use an alternative dataset to define the business cycles, the CFNAI[54] data, which start in 1967. I classify a period as a contraction period when the CFNAI-MA3 is less than -0.7 and an expansion period when the CFNAI-MA3 is greater than -0.7. Compared with the NBER data, the CFNAI data are published in real time and are thus free of hindsight bias. I follow the same steps as the NBER time-varying analysis and present my results below. The results remain similar and no indicator predicts the market significantly under either contractions or expansions. Last but not least, I check whether my results are sensitive to the 2008 financial crisis period. I also remove the top and bottom 5% extreme observations from the distribution of each market indicator to control for outliers from the predictive variable direction. My results remain robust; I do not present these results here to save space and they are available upon request.

[54] See http://www.chicagofed.org/webpages/publications/cfnai/.

CFNAI Business Cycle Time-Varying Results

This table reports the OLS results of the regression model $R_t = \alpha_t + \beta_1 D_{t-1} I_{t-1} + \beta_2 (1-D_{t-1}) I_{t-1} + \varepsilon_t$. R_t represents S&P 500 periodic returns calculated as log differences of the S&P 500 Index values, It-1 represents periodic percentage changes of market indicators. D_{t-1} is a dummy variable that equals 1(0) during CFNAI business cycle expansions (contractions). Therefore β_1 and β_2 measure the predictability of a market indicator during expansions and contractions respectively. I replicate the full sample OLS results for comparison in the first two columns, then I report β_1 and β_2 with associated t-statistics, and the last column reports chi-statistics testing the null hypothesis that β_1 and β_2 are equal. I obtain all data from the Global Financial Data. The t-statistics and chi-statistics reported are White standard errors corrected and marked in bold if significant at 10% significance level. Panel A and Panel B report results for market sentiment and market strength indicators respectively.

	Full Sample		Expansions		Contractions		
Market Indicators	**β (*10⁻³)**	**t value**	**β1 (*10⁻³)**	**t value**	**β2 (*10⁻³)**	**t value**	**Chi-statistic**
Panel A: Market Sentiment Indicators							
Option Volumes:							
CBOE Calls Volume	0.00	1.15	-0.32	-0.97	-2.29	-0.82	0.49
CBOE Puts Volume	-0.01	-0.12	0.00	0.04	-0.74	-0.31	0.10
OEX Calls Volume	0.00	-1.26	0.00	-1.26	-1.12	-1.04	1.07
OEX Puts Volume	0.00	0.25	0.00	0.25	1.52	1.17	1.38
CBOE Ratio of Traded Value of Puts to Calls	0.63	0.77	0.74	0.90	-0.21	-0.06	0.07
Odd-lots Volumes:							
NYSE Odd Lot Purchases	0.00	**-4.90**	0.00	**-6.24**	-0.33	-0.25	0.06
NYSE Odd Lot Sales	0.11	0.27	0.32	1.16	-0.41	-0.37	0.40
NYSE Odd Lot Shorts	0.00	1.14	0.00	0.14	0.01	1.58	2.02
Short Sales Volumes:							
NYSE Short Sales-Members	6.68	**7.15**	5.93	**3.64**	9.94	**4.28**	2.00
NYSE Short Sales-General Public	2.63	**2.58**	3.74	**1.99**	14.00	**3.91**	**6.42**
NYSE Short Sales-Specialists	5.90	**5.82**	5.21	**2.52**	7.22	**4.79**	0.61
NYSE Short Sales-Total	6.80	**5.59**	6.53	**3.59**	13.48	**4.66**	**4.13**
Short Interests:							
NYSE Short Interest Ratio	-23.19	**-2.22**	25.54	1.09	37.20	0.63	0.03
NYSE Short Interest Shares	-2.93	-0.12	6.02	0.17	51.82	0.69	0.31
AAII/II Sentiment Indices:							
AAII Bearish Index	0.02	0.01	0.57	0.31	3.47	-0.48	0.30
AAII Bullish Index	6.39	**2.26**	3.33	1.21	16.69	**2.10**	2.10
AAII Neutral Index	-8.70	**-2.83**	-6.85	**-2.22**	-18.89	**-1.85**	1.28
Investors Intelligence Bearish Percentage	-1.04	-0.11	4.46	0.48	-30.19	-0.87	0.93
Investors Intelligence Bullish Percentage	-0.36	-0.03	-4.30	-0.44	11.94	0.35	0.21
Confidence Index:							
Barron's Confidence Index	36.44	0.78	-63.15	-1.45	100.32	0.74	1.33
Exchange Seat Prices:							
AMEX Seat Prices	3.38	0.48	-2.91	-0.74	14.42	0.29	0.12
NYSE Annual Seat Price	-16.55	-0.73	78.17	0.81	-339.21	-1.11	1.58

Market Indicators	Full Sample β (*10⁻³)	t value	Expansions β1 (*10⁻³)	t value	Contractions β2 (*10⁻³)	t value	Chi-statistic
CBOE NASDAQ Volatility Index	13.28	**2.10**	14.90	**2.93**	8.68	0.44	0.09
CBOE S&P 100 Volatility Index	7.33	**1.96**	6.57	1.59	13.78	1.21	0.35
AMEX NYSE Arca NASDAQ 100 Volatility Index	4.00	0.61	10.68	**2.76**	-7.06	-0.45	1.22
CBOE DJIA Volatility Index	13.39	**1.90**	10.25	**2.32**	21.82	0.95	0.24
Margin Account Balances:							
NYSE Margin Debt	-0.72	-0.02	-32.88	-0.59	44.67	0.36	0.33
NYSE Free Credit Balances	80.49	**2.11**	3.60	0.09	149.82	1.05	0.98
NYSE Free Credit Balances on Cash Accounts	22.34	0.63	32.52	0.95	-41.55	-0.29	0.26
NYSE Free Cash Balances in Margin Accounts	1.66	0.04	-24.67	-0.83	133.67	1.28	2.16
Mutual Fund Balances:							
USA Mutual Fund Equity Funds Total Net Assets	92.74	1.44	-3.10	-0.04	311.35	**2.73**	**5.91**
USA Mutual Fund Equity Funds Cash Percentage	-20.76	-0.69	16.95	0.56	-260.10	**-2.56**	**6.82**
USA Mutual Fund Equity Funds Redemptions	-4.74	**-2.89**	-5.35	**-4.17**	29.78	0.56	0.44
USA Mutual Fund Equity Funds New Sales	6.59	0.54	-3.24	-0.27	67.98	**1.70**	**2.92**
USA Mutual Fund Equity and Bond Fund Net Assets	10.50	**6.14**	9.75	**10.51**	203.01	1.52	2.10
USA Mutual Fund Equity and Bond Fund Cash Percent	-17.87	-0.78	13.29	0.51	-206.80	**-2.01**	**4.30**
USA Mutual Fund Equity and Bond Fund Liquid Assets	13.26	0.51	32.62	1.11	-76.53	-0.69	0.93
USA Mutual Fund Equity and Bond Fund Redemptions	-10.50	-0.91	-15.98	-1.22	3.72	0.07	0.14
USA Mutual Fund Equity and Bond Fund New Sales	7.89	0.85	3.23	0.31	26.85	0.75	0.40
Number of Dividend News:							
Moody's Monthly Decreased Dividends	40.61	1.57	27.19	0.85	42.06	0.49	0.03
Moody's Monthly Extra Dividends Declared	-63.32	-1.38	12.32	0.28	-517.81	**-3.05**	**9.05**
Moody's Monthly Increased Dividends Declared	-97.86	**-1.97**	-74.67	-1.19	-190.32	-1.19	0.44
Moody's Monthly Omitted Dividends	7.60	0.24	-4.29	-0.11	2.62	0.02	0.00
Moody's Monthly Resumed Dividends	15.28	0.81	17.33	0.84	-18.23	-0.24	0.21
S&P Monthly Dividend Decreases Declared	0.43	0.45	-0.16	-0.11	9.41	0.98	0.97
S&P Monthly Extra Dividends Declared	4.48	**2.17**	5.36	**2.08**	-5.88	-0.65	1.45
S&P Monthly Increased Dividends Declared	2.11	0.57	4.01	0.60	0.60	0.14	0.19
S&P Monthly Omitted Dividends Declared	0.88	0.68	0.87	0.60	-6.08	-1.04	1.33
S&P Monthly Resumed Dividends Declared	2.85	**1.89**	3.50	**2.59**	-1.91	-0.38	1.09
Panel B: Market Strength Indicators							
Total Volume:							
NYSE Total Volume	0.09	0.83	0.51	**3.02**	3.73	**1.85**	2.52
Total Volume Turnovers:							
NYSE Share Volume Turnover	5.39	0.13	-72.86	**-2.18**	-65.27	-0.51	0.00
NYSE Annual Share Value Turnover	28.23	0.64	-11.06	-0.11	-59.14	-0.18	0.02
Short-term Trading Indices:							
NYSE Short-term Trading Index	-0.49	**-2.15**	-0.36	-1.49	-1.09	-1.59	1.00
NASDAQ Short-term Trading Index	-0.01	-1.16	0.00	-0.65	-0.02	-0.93	0.46
Daily Total Market Advances & Declines:							
NYSE Advances	0.51	**2.98**	0.84	**2.82**	0.71	0.99	0.03
NYSE Declines	-0.72	**-3.65**	-0.91	**-3.89**	-1.99	**-1.83**	0.95
NYSE Net Advances	0.00	0.49	0.00	0.31	0.02	**2.10**	**3.89**
NYSE AD Line	0.00	-0.35	0.00	-0.61	0.01	0.65	0.58
NYSE Percentage Net Advances	0.00	0.36	0.00	0.32	0.02	**2.10**	**3.88**
NASDAQ Advances	0.23	1.48	0.22	**1.93**	0.32	0.45	0.02
NASDAQ Declines	-0.10	**-3.41**	-0.08	**-5.22**	-1.80	-1.53	2.14
NASDAQ Net Advances	0.00	-0.50	0.00	-1.12	0.02	1.31	2.27
NASDAQ AD Line	0.00	-0.22	0.00	0.41	-0.01	-0.94	1.03
NASDAQ Percentage Net Advances	0.00	-0.51	0.00	-1.13	0.02	1.31	2.26

Market Indicators	Full Sample β (*10⁻³)	t value	Expansions β1 (*10⁻³)	t value	Contractions β2 (*10⁻³)	t value	Chi-statistic
Alternext Advances	1.18	**4.02**	0.90	**2.79**	2.16	**1.92**	1.16
Alternext Declines	-1.04	**-2.46**	-1.27	**-4.65**	-2.97	**-2.06**	1.35
Alternext Net Advances	0.01	0.80	0.00	0.28	0.02	0.64	0.29
Alternext AD Line	0.00	-0.03	-0.01	-1.21	0.04	**2.27**	**6.58**
Alternext Percentage Net Advances	0.01	0.60	0.00	0.14	0.02	0.67	0.38
Weekly Total Market Advances & Declines:							
NYSE Weekly Advances	-1.49	**-3.33**	-1.13	-1.62	-2.41	**-4.07**	2.02
NYSE Weekly Declines	0.65	1.21	0.53	0.64	1.79	0.92	0.35
NYSE Net Advances	0.00	0.22	0.00	0.23	0.01	0.11	0.01
NYSE AD Line	-1.20	-0.52	25.61	0.56	-156.05	-1.23	1.83
Daily Total Maket New Highs & New Lows:							
NYSE New Highs	0.14	**3.61**	0.10	**19.92**	0.60	1.03	0.74
NYSE New Lows	-0.13	-1.50	-0.22	-1.44	-0.06	-0.09	0.07
NYSE Net New Highs	0.04	**1.77**	0.02	1.00	0.01	0.16	0.01
NYSE Cumulative Highs	-0.01	-0.34	-0.01	-0.61	0.07	0.78	0.80
NYSE Percentage Net New Highs	0.04	1.60	0.02	1.00	0.01	0.15	0.01
NASDAQ New Highs	-0.16	-0.43	-0.02	-0.07	-0.42	-0.46	0.17
NASDAQ New Lows	0.25	1.26	0.11	0.57	0.76	1.44	1.31
NASDAQ Net New Highs	-0.01	-0.21	-0.01	-0.30	0.02	0.25	0.13
NASDAQ Cumulative Highs	0.03	0.98	0.02	0.69	0.16	1.18	1.01
NASDAQ Percentage Net New Highs	-0.01	-0.22	-0.01	-0.32	0.02	0.24	0.12
Alternext New Highs	0.20	**2.23**	0.24	**2.52**	1.08	1.60	1.51
Alternext New Lows	-0.06	-0.89	-0.04	-0.49	-0.13	-0.23	0.02
Alternext Net New Highs	0.00	0.11	0.00	-0.03	0.15	1.29	1.47
Alternext Cumulative Highs	-0.03	-0.88	-0.02	-0.41	-0.12	**-1.68**	1.52
Alternext Percentage Net New Highs	0.01	0.30	0.00	0.05	0.15	1.28	1.39
Weekly Total Maket New Highs & New Lows:							
NYSE Weekly New Highs	0.11	0.26	0.17	0.27	1.86	**1.67**	1.77
NYSE Weekly New Lows	-0.30	-0.74	-0.45	-0.71	0.51	0.12	0.05
NYSE Net New Highs	0.11	**1.88**	0.10	1.26	0.36	0.63	0.21
NYSE Cumulative Highs	-0.01	**-3.62**	-0.01	**-11.59**	-7.00	**-10.81**	**116.35**

CFNAI Expansions Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability during CFNAI expansion periods. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level. The estimations are based on the OLS regression results.

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Odd Lot Purchases	Daily	5218	0.25	1.17	1.32	0.09	0.86	-0.10	1.40	-0.08	-1.00	0.54	**22.68**
NYSE Short Sales-Members*	Weekly	1054	0.87	2.27	0.26	0.99	0.73	2.46	0.64	0.15	0.67	0.12	**4.03**
NYSE Short Sales-General Public	Weekly	1055	0.87	2.27	0.26	0.93	0.75	1.59	0.39	0.08	0.35	0.13	**4.21**
NYSE Short Sales-Specialists*	Weekly	1050	0.87	2.27	0.26	0.63	0.81	-2.29	0.76	-0.23	-0.97	0.15	**4.18**
NYSE Short Sales-Total	Weekly	1050	0.87	2.27	0.26	0.96	0.72	2.00	0.50	0.11	0.52	0.12	**3.83**
AAII Neutral Index	Weekly	525	-0.21	2.66	-2.43	0.14	0.81	-3.58	0.24	-0.28	-0.84	0.11	**2.27**
CBOE NASDAQ Volatility Index	Daily	1274	0.01	1.57	-0.32	-0.18	0.61	-3.85	1.13	-0.18	-1.14	0.15	**7.82**
AMEX NYSE Acra NASDAQ 100 Volatility Index	Daily	1273	0.00	1.57	-0.33	-0.09	0.62	-2.27	0.63	-0.08	-0.53	0.16	**7.90**
CBOE DJIA Average Volatility Index	Daily	752	-0.03	1.87	-0.24	0.00	0.67	-0.12	0.03	0.07	0.30	0.13	**6.22**
USA Mutual Fund Equity Funds Redemptions	Monthly	153	2.09	4.84	-0.79	4.79	3.95	5.85	1.33	1.32	0.69	0.67	**7.20**
USA Mutual Fund Equity and Bond Fund Net Assets	Monthly	207	5.56	4.39	5.45	4.60	2.40	5.98	0.09	0.74	0.52	0.28	**5.08**
S&P Monthly Extra Dividends Declared*	Monthly	200	5.54	4.38	5.44	3.80	1.95	3.32	0.31	0.37	0.32	0.17	**4.08**
S&P Monthly Resumed Dividends Declared*	Monthly	246	7.90	4.46	9.65	3.25	1.95	-1.73	**1.77**	-0.88	-0.79	0.16	**3.47**
Panel B: Market Strength Indicators													
NYSE Total Volume	Daily	5468	0.26	1.16	1.37	0.01	0.60	-1.55	**2.15**	-0.14	**-2.06**	0.25	**10.56**
NYSE Share Volume Turnover	Daily	240	5.56	4.39	5.45	4.14	2.92	3.34	0.40	-0.45	-0.30	0.44	**6.22**
NYSE Advances	Daily	5539	0.26	1.16	1.38	-0.25	0.65	-5.41	**5.31**	-0.39	**-5.33**	0.31	**17.06**
NYSE Declines	Daily	5466	0.26	1.16	1.38	0.03	0.56	-1.25	**1.88**	-0.11	**-1.77**	0.22	**10.43**
NASDAQ Advances	Daily	4971	0.25	1.18	1.32	0.04	0.84	-0.64	**1.83**	-0.12	-1.45	0.52	**21.41**
NASDAQ Declines	Daily	4971	0.25	1.18	1.32	0.30	0.90	2.31	1.02	0.13	1.56	0.59	**22.78**
Alternext Advances	Daily	5468	0.26	1.16	1.37	-0.05	0.53	-2.82	**2.91**	-0.19	**-3.05**	0.19	**9.34**
Alternext Declines	Daily	5468	0.26	1.16	1.37	0.01	0.58	-1.61	**2.17**	-0.14	**-2.10**	0.24	**10.34**
NYSE New Highs	Daily	5502	0.25	1.16	1.33	0.13	0.82	0.32	0.98	-0.04	-0.49	0.51	**22.40**
Alternext New Highs	Daily	5453	0.25	1.16	1.30	-0.04	0.76	-1.84	**2.77**	-0.19	**-2.45**	0.43	**20.64**
NYSE Cumulative Highs	Weekly	1138	1.54	2.34	3.58	0.62	1.43	-0.59	1.60	-0.40	-1.15	0.37	**7.47**

CFNAI Contractions Economic Significance Test

This table compares risk and return characteristics of buy and hold strategies with technical strategies based on market indicators that show significant predictability during CFNAI contraction periods. I report means, standard deviations and Sharpe ratios for buy and hold strategies and technical strategies consequently, and then I report t-statistics testing the null hypothesis that the Sharpe ratios of the two strategies are equal. I then report Jensen's α estimation results for technical strategies in the last four columns. α values indicate excess returns generated by the technical strategies at given risk level β over market returns. I also present associated t-statistics testing their differences from zero for α and β values. All t-statistics are White standard errors corrected and marked in bold if significant at 10% significance level. The estimations are based on the OLS regression results.

			Buy & Hold Strategy			Technical Strategy							
Market Indicators	**Frequency**	**N**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**Mean ($*10^{-3}$)**	**Std. Dev. ($*10^{-2}$)**	**Sharpe Ratio ($*10^{-2}$)**	**t-stats**	**α ($*10^{-3}$)**	**t-stats**	**β**	**t-stats**
Panel A: Market Sentiment Indicators													
NYSE Short Sales-Members	Weekly	1054	0.87	2.27	0.26	0.99	0.73	2.46	0.64	0.15	0.67	0.12	**4.03**
NYSE Short Sales-General Public	Weekly	1055	0.87	2.27	0.26	0.93	0.75	1.59	0.39	0.08	0.35	0.13	**4.21**
NYSE Short Sales-Specialists	Weekly	1050	0.87	2.27	0.26	0.63	0.81	-2.29	0.76	-0.23	-0.97	0.15	**4.18**
NYSE Short Sales-Total	Weekly	1050	0.87	2.27	0.26	0.96	0.72	2.00	0.50	0.11	0.52	0.12	**3.83**
AAII Bullish Index	Weekly	524	-0.21	2.66	-2.43	0.57	0.69	1.92	0.86	0.14	0.49	0.07	**1.93**
AAII Neutral Index	Weekly	525	-0.21	2.66	-2.43	0.14	0.81	-3.58	0.24	-0.28	-0.84	0.11	**2.27**
USA Mutual Fund Equity Funds Total Net Assets	Monthly	141	2.09	4.84	-0.79	0.61	1.79	-10.46	0.98	-1.44	-1.26	0.09	**2.15**
USA Mutual Fund Equity Funds Cash Percentage	Monthly	241	5.15	4.39	4.65	3.13	2.37	0.08	0.71	-0.32	-0.24	0.25	**3.33**
USA Mutual Fund Equity Funds New Sales	Monthly	141	2.09	4.84	-0.79	0.59	1.50	-12.64	1.11	-0.92	-1.36	0.03	1.14
USA Mutual Fund Equity and Bond Fund Cash Percent	Monthly	243	5.56	4.39	5.45	2.22	2.36	-4.01	1.44	-0.82	-0.62	0.23	**3.07**
Moody's Monthly Extra Dividends Declared	Monthly	252	5.67	4.37	5.67	2.98	1.48	-1.41	0.94	0.14	0.20	0.07	**2.54**
Panel B: Market Strength Indicators													
NYSE Total Volume	Daily	5468	0.26	1.16	1.37	0.01	0.60	-1.55	**2.15**	-0.14	**-2.06**	0.25	**10.56**
NYSE Declines	Daily	5466	0.26	1.16	1.38	0.03	0.56	-1.25	**1.88**	-0.11	**-1.77**	0.22	**10.43**
NYSE Net Advances	Daily	10287	0.31	1.08	1.48	0.16	0.58	0.20	1.34	-0.04	-0.86	0.28	**13.77**
NYSE Percentage Net Advances	Daily	10286	0.31	1.08	1.47	0.16	0.58	0.15	1.38	-0.04	-0.91	0.28	**13.80**
Alternext Advances	Daily	5468	0.26	1.16	1.37	-0.05	0.53	-2.82	**2.91**	-0.19	**-3.05**	0.19	**9.34**
Alternext Declines	Daily	5468	0.26	1.16	1.37	0.01	0.58	-1.61	**2.17**	-0.14	**-2.10**	0.24	**10.34**
Alternext AD Line	Daily	5447	0.30	1.16	1.70	0.07	0.72	-0.41	**1.75**	-0.11	-1.50	0.37	**14.72**
NYSE Weekly Advances	Weekly	1119	1.26	2.35	2.37	0.57	1.22	-1.04	1.20	-0.28	-0.88	0.28	**4.66**
Alternext Cumulative Highs	Daily	4957	0.34	1.17	2.11	0.02	0.74	-0.95	**2.45**	-0.17	**-2.15**	0.38	**14.35**
NYSE Weekly New Highs	Weekly	1126	1.26	2.35	2.37	0.23	1.19	-3.92	**2.16**	-0.62	**-1.92**	0.26	**4.48**
NYSE Cumulative Highs	Weekly	1138	1.54	2.34	3.58	0.62	1.43	-0.59	1.60	-0.40	-1.15	0.37	**7.47**

A.3: Appendix to "Technical Analysis: A Cross-Country Analysis"

A.3.1: Stock Market Data

Country	Stock Market Index	R_m (%)	Risk-free Rates
Argentina	Buenos Aires SE General Index	0.058	Argentina Time Deposit Rate (before Sep 2012), Argentina 3-month BCRA Treasury Auction Yield
Australia	Australia ASX All-Ordinaries	0.018	Australia 3-month Treasury Bill Yield
Austria	Austria Wiener Boersekammer Share Index	0.015	Austria 3-month Time Deposit Rate
Bangladesh	Dhaka SE General Index	0.085	Bangladesh 3-month Treasury Bill Yield
Belgium	Brussels All-Share Price Index	0.020	Belgium 3-month Treasury Bill Yield
Brazil	Dow Jones Brazil Stock Index	0.072	Brazil 3-month Treasury Bill Yield
Canada	Canada S&P/TSX 300 Composite	0.023	Canada 3-month Treasury Bill Yield
Chile	Santiago SE Indice General de Precios de Acciones	0.030	Chile 3-month Inflation Adjusted T-bill Yield (before July 1997), Chile 3-month Nominal T-bill Auction Yield
China	Shanghai SE Composite	0.023	China Time Deposit Rate (before Jan 2002), China 3 Month Repo on Treasury Bills
Colombia	Colombia IGBC General Index	0.051	Colombia 3-month Time Deposit Rate (before Jan 1998), Colombia 3-month Treasury Bill Yield
Czech	Prague SE PX Index	-0.008	Czech Republic 3-month Treasury Bill Yield
Denmark	OMX Copenhagen All-Share Price Index	0.033	Denmark 3-month Treasury Bill Yield
Ecuador	Ecuador Bolsa de Valores de Guayaquil	0.010	Ecuador Sucre Time Deposit Rate (before Feb 2000), Ecuador Dollar Deposit Rate
Finland	OMX Helsinki Capped Price Index	0.028	Finland Household Deposit Rate
France	France CAC All-Tradable Index	0.015	France 3-month Treasury Bill Yield
Germany	Germany CDAX Composite Index	0.016	Germany 3-month Treasury Bill Yield
Greece	Athens SE General Index	0.001	Greece 3-month Treasury Bill Yield
Hong Kong	Hong Kong Hang Seng Composite Index	0.014	Hong Kong 3-month Treasury Bill Yield
India	Bombay SE Sensitive Index	0.033	India 3-month Treasury Bill Yield
Indonesia	Jakarta SE Composite Index	0.049	Indonesia 3-month Time Deposits
Ireland	Ireland ISEQ Overall Price Index	0.016	Ireland 3-month Treasury Bill Yield
Israel	Tel Aviv All-Share Index	0.042	Israel 3-month Treasury Bill Yield
Italy	Banca Commerciale Italiana Index	0.028	Italy 3-month Treasury Bill Yield
Jamaica	Jamaica Stock Exchange All-Share Composite Index	0.033	Jamaica 3-month Treasury Bill Yield
Japan	Nikkei 225 Stock Average	-0.017	Japan 3-month Treasury Bill Yield
Korea	Korea SE Stock Price Index	0.015	South Korea 12-month Monetary Stabilization Bill
Luxembourg	Luxembourg SE LUXX Index	0.016	Luxembourg Sight Deposit Rate
Malaysia	Malaysia KLSE Composite	0.005	Malaysia 3-month T-bill Discount Rate
Mexico	Mexico SE Indice de Precios y Cotizaciones	0.052	Mexico 3-month Cetes Yield (before June 2012), Mexico 9-month Treasury Bond Yield
New Zealand	New Zealand SE All-Share Capital Index	0.006	New Zealand 3-month Treasury Bill Yield
Netherlands	Netherlands All-Share Price Index	0.015	Netherlands 3-month Treasury Bill Yield
Norway	Oslo SE All-Share Index	0.040	Norway 3-month Treasury Bill Yield
Pakistan	Pakistan Karachi SE-100 Index	0.041	Pakistan 3-month Treasury Bill Rate
Panama	Panama Stock Exchange Index	0.065	Panama 3-month Time Deposit Rate
Peru	Lima SE General Index	0.051	Peru Time Deposit Rate
Philippines	Manila SE Composite Index	0.019	Philippines 3-month Treasury Bill Yield
Portugal	Oporto PSI-20 Index	0.007	Portugal 3-month Treasury Bill Yield
South Africa	FTSE/JSE All-Share Index	0.045	South Africa 3-month Treasury Bill Yield
Singapore	Singapore FTSE Straits-Times Index	0.001	Singapore 3-month Treasury Yield
Slovak	Bratislava SE SAX Index	-0.007	Slovakia Average Deposit Rate (after Jan 2008), Slovakia 3-month T-bill Yield
Slovenia	Slovenia Bourse Index	0.023	Slovenia Demand Deposit Rate to 1 Year
Spain	Madrid SE General Index	0.024	Spain 3-month T-Bill Yield
Sweden	Sweden OMX Affärsvärldens General Index	0.031	Sweden 3-month Treasury Bill Yield
Switzerland	Switzerland Price Index	0.018	Switzerland 3-month Treasury-Bill Yield
Taiwan	Taiwan SE Capitalisation Weighted Index	0.005	Taiwan 3-month Treasury-bill Yield
Thailand	Thailand SET General Index	-0.005	Thailand 3-month Treasury Bill Yield
Turkey	Istanbul SE IMKB-100 Price Index	0.134	Turkey 3-month Treasury Bond Yield
UK	UK FTSE All-Share Index	0.015	United Kingdom 3-month Treasury Bill Yield
US	S&P 500 Composite Price Index	0.026	USA Government 90-day T-Bills Secondary Market
Venezuela	Caracas SE General Index	0.157	Venezuela 1-month Time Deposit Rate

A.3.2: Description of Variables

Variable	Type	Sample Period	No. of Countries	Source	Description
Factor 1: Herding Behavior					
(1) Hofstede Individualism Index (idv)	cross-sectional		50	Hofstede (2001)	A higher value indicates a higher degree of individualism (lower degree of collectivism).
Factor 2: Market Development and Market Integrity					
(1) Stock Market Size (size)	cross-sectional & annual	1994 - 2012	48	World Bank	Stock market size is measured by total market capitalisation of listed companies as percentage of this countries' GDP.
(2) Stock Market Age (age)	cross-sectional		50	Global Financial Data	Global Financial Data provides historically extensive stock market data, I use the year when the stock market data becomes available in this database as a proxy for stock market age for each country.
(3) Transaction Costs (tran)	cross-sectional		40	Chan, Covrig, and Ng (2005)	A higher value indicates higher transaction costs.
(4) Investor Protection (creditor)	cross-sectional		47	La Porta et al.(2006)	A higher value indicates better investor protection.
(5) Anti-director Rights (ant_dir)	cross-sectional		49	La Porta et al.(2006)	A higher value indicates better investor protection.
(6) Concentration of Ownership (ownership)	cross-sectional		45	La Porta et al.(2006)	A higher value indicates more concentration.
(7) Insider Trading (sh_vo)	cross-sectional		49	La Porta et al.(2006)	A higher value indicates insider trading is less likely.
(8) pc-market	cross-sectional & annual	1994 - 2012	36		pc-market is the first principle component of the seven proxies for stock market development/integrity above, it explains 40.74% of the total variations. To construct pc-market, I multiply original values of size, creditor, ant_dir and sh_vo by -1 so that a greater value of pc-market indicates less stock market development/integrity.
Factor 3: Information Uncertainty					
(1) Stock Market Turnover (turnover)	cross-sectional & monthly	1994:03 - 2014:03	41	Datastream	Market turnover of country j in month t is measured as the market dollar trading volume of the Datastream Global Index of this country divided by this index's market capitalisation in month t.
(2) Volatility of Cash Flow Growth Rates(cf_vol)	cross-sectional & monthly	1994:03 - 2014:03	41	Datastream	cfvol of country j in year y is the standard deviation of this country's monthly cash flow growth rate in the sixty-month period prior to year y. The cash flow of country j in month t is the ratio between the price index of this country's Global Index and the price-to-cash flow index of the same Global Index. The growth rate in month t is computed as ln (cf_{jt}/cf_{jt-12}).
(3) Book-to-Market Ratio (b/m)	cross-sectional & monthly	1994:03 - 2014:03	41	Datastream	Book to price ratio of the Datastream Global Index of a country.
(4) pc-uncertainty	cross-sectional & monthly	1994:03 - 2014:03	41		pc-uncertainty is the first principle component of the three proxies for information uncertainty above, it explains 31.03% of the total variations. A higher value of pc-market indicates greater information uncertainty.
Macroeconomic Variables					
(1) NBER Business Cycles (cycle)	monthly	1994:03 - 2014:03		NBER	I include a dummy variable that equals 1(0) during economic contractions (expansions).
(2) January dummy (jan)	monthly	1994:03 - 2014:04			I include a dummy variable that equals 1(0) in January (other months).
(3) MSCI World Index Return (world)	monthly	1994:03 - 2014:03		Global Financial Data	

A.3.2 (continued)

Variable	Type	Sample Period	No. of Countries	Source	Description
(4) GDP per capita Growth Rate (gdp_gw)	cross-sectional & annual	1994 - 2013	48	World Bank: World Development Index	GDP per capita is in the constant 2005 U.S. dollar for all countries. Gdp_gw in year y in country j is calculated as the average real GDP per capita growth rate of country j over the years from y-5 to y-1.
(5) Change of Exchange Rate (cfx)	cross-sectional & annual	1996 - 2014	40	Datastream	cfx in year y in country j is the average change of the exchange rate(local currency against U.S. dollar) in the 60-month period before year y. The cfx for the U.S. is zero.
(6) Dividend Yield (dy)	cross-sectional & monthly	1994:03 - 2014:03	45	Datastream	dy is the dividend yield of the Datastream global index of a country.
(7) Developed vs. Developing Economy (hdi)	cross - sectional		50	United Nation: Human Development Index	I include a dummy variable that equals 1(0) for developed (developing) economies.
Additional Variables					
(1) GLOBE Individualism Index(idv_g)	cross-sectional		38	House et al. (2004)	This index equals GLOBE's institutional collectivism index multiplied by -1. A higher value indicates a higher degree of individualism (lower degree of collectivism).
(2) Tang and Koveos (2008) Individualism Index (idv_tk)	cross-sectional		46	Tang and Koveos (2008)	A higher value indicates a higher degree of individualism (lower degree of collectivism).
(3) Uncertainty Avoidance Index (uai)	cross-sectional		50	Hofstede (2001)	A higher value indicates a higher degree of uncertainty avoidance.
(4) GLOBE Uncertainty Avoidance Index (uai_g)	cross-sectional		39	House et al. (2004)	A higher value indicates a higher degree of uncertainty avoidance.
(5) Total Private Credits (private_cr)	cross-sectional & annual	1994 - 2011	47	World Bank	Total private credit by deposit money banks and other financial institutions as percentage of this countries' GDP.
(6) Corruption Index (corrp)	cross-sectional & annual	1996 - 2012	50	International Country Risk Guide (ICRG)	A higher value indicates a lower corruption level.
(7) Law and Order Index (law)	cross-sectional & annual	1996 - 2012	50	International Country Risk Guide (ICRG)	A higher value indicates a better law and order system.
(8) Political Risk Index (political)	cross-sectional & annual	1996 - 2012	50	International Country Risk Guide (ICRG)	A higher value indicates a lower political risk.
(9) Disclosure (acctg)	cross-sectional		41	La Porta et al.(2006)	A higher value indicates better accounting disclosures.
(10) Stock Market Openness (open)	cross-sectional & monthly	1994 - 2008	32	S&P Emerging Markets Data Base	Stock market openness is measured by an investability index. The index is calculated by dividing the market capitalisation of the constituent forms comprising the Standard & Poor's/International Finance Corporation Investable index of a country to those comprising the Standard & Poor's/International Finance Corporation global index of this country. The index equals one for developed markets.
(11) Retail Investors' Weight	cross-sectional & annual	1994 - 2012	29	Morningstar, World Bank	I measure retail investors' weight by using the total mutual fund size of a country divided by the total market capitalisation of listed companies in this country.

A.3.3: Predictive Abilities of Technical Indictors in International Stock Markets

Country	VMA(1,50)		VMA(1,150)		VMA(5,150)		VMA(1,200)		VMA(2,200)	
	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats
Argentina	1.64	**2.93**	0.72	1.21	0.26	0.43	1.09	**1.79**	0.82	1.34
Australia	0.34	1.11	0.14	0.41	0.11	0.32	0.22	0.60	0.09	0.26
Austria	1.41	**3.83**	0.87	**2.35**	0.97	**2.65**	0.61	1.62	0.37	0.99
Bangladesh	2.69	**5.50**	2.00	**4.11**	1.77	**3.66**	1.70	**3.51**	1.67	**3.45**
Belgium	0.78	**2.17**	1.02	**2.68**	0.94	**2.47**	0.83	**2.19**	0.52	1.39
Brazil	-12.34	**-3.48**	-13.20	**-3.53**	0.83	0.22	-12.14	**-3.03**	-5.09	-1.49
Canada	0.63	**1.74**	0.45	1.16	0.37	0.94	0.26	0.65	0.19	0.48
Chile	1.47	**6.01**	0.78	**3.18**	0.54	**2.20**	0.79	**3.16**	0.47	**1.88**
China	1.90	**3.31**	0.83	1.43	0.75	1.30	0.38	0.66	0.44	0.76
Colombia	2.15	**5.31**	1.11	**2.69**	0.78	**1.88**	0.99	**2.34**	0.70	**1.66**
Czech	1.55	**3.69**	1.11	**2.53**	0.99	**2.27**	0.69	1.57	0.56	1.28
Denmark	1.14	**3.19**	1.47	**3.81**	1.38	**3.58**	1.35	**3.46**	1.30	**3.35**
Ecuador	0.56	1.31	0.89	**1.98**	1.18	**2.60**	1.06	**2.30**	1.18	**2.55**
Finland	1.11	**1.96**	0.76	1.29	0.94	1.61	0.52	0.88	0.41	0.68
France	0.37	0.87	0.75	**1.74**	0.87	**2.04**	0.57	1.29	0.65	1.46
Germany	0.90	**2.01**	0.43	0.94	0.44	0.99	0.71	1.47	0.66	1.37
Greece	2.29	**4.53**	2.07	**4.11**	1.41	**2.80**	1.83	**3.61**	1.52	**2.98**
Hong Kong	1.07	**2.08**	0.66	1.26	0.58	1.11	0.47	0.86	0.57	1.03
India	1.24	**2.59**	0.61	1.22	0.46	0.93	0.48	0.95	0.20	0.40
Indonesia	2.33	**4.56**	0.93	**1.69**	0.60	1.11	0.75	1.33	0.63	1.12
Ireland	1.37	**3.20**	0.95	**2.03**	1.16	**2.53**	1.14	**2.33**	1.08	**2.24**
Israel	0.98	**2.06**	0.99	**2.12**	1.06	**2.29**	0.97	**2.09**	0.84	**1.82**
Italy	1.13	**3.06**	1.05	**2.78**	0.76	**2.03**	0.85	**2.25**	0.54	1.42
Jamaica	1.78	**5.86**	1.13	**3.80**	0.72	**2.40**	0.76	**2.54**	0.51	**1.70**
Japan	0.48	1.10	0.62	1.44	0.80	**1.86**	0.56	1.28	0.51	1.18
Korea	1.38	**2.75**	1.10	**2.11**	0.88	**1.70**	0.92	**1.76**	0.97	**1.86**
Luxembourg	1.62	**4.35**	1.19	**3.06**	1.18	**3.06**	1.09	**2.74**	1.13	**2.84**
Malaysia	1.58	**3.75**	1.05	**2.28**	0.62	1.35	0.95	**1.87**	0.77	1.51
Mexico	1.11	**2.20**	0.26	0.48	-0.10	-0.19	0.35	0.61	0.05	0.10
New Zealand	0.31	1.36	0.27	1.11	0.16	0.67	0.20	0.84	0.13	0.53
Netherlands	0.50	1.11	0.74	1.49	0.73	1.46	0.56	1.11	0.57	1.13
Norway	1.53	**3.32**	1.00	**1.91**	1.16	**2.23**	0.92	**1.71**	0.98	**1.83**
Pakistan	2.02	**4.08**	1.53	**2.88**	1.31	**2.49**	1.56	**2.85**	1.36	**2.51**
Panama	1.51	**8.21**	1.53	**7.80**	1.48	**7.52**	1.52	**7.58**	1.43	**6.93**
Peru	2.67	**6.18**	1.79	**3.96**	0.99	**2.23**	1.43	**3.21**	1.33	**3.01**
Philippines	1.61	**3.70**	1.04	**2.29**	1.00	**2.22**	0.67	1.42	0.56	1.17
Portugal	1.70	**4.95**	1.29	**3.84**	1.20	**3.56**	1.30	**3.85**	1.17	**3.48**
South Africa	0.57	1.35	0.11	0.22	0.01	0.02	0.24	0.46	-0.34	-0.68
Singapore	0.92	**2.32**	1.05	**2.65**	0.88	**2.21**	0.61	1.48	0.48	1.16
Slovak	0.55	1.45	0.34	0.90	0.61	1.62	0.99	**2.72**	0.94	**2.56**
Slovenia	2.36	**6.16**	1.57	**3.91**	1.41	**3.60**	1.22	**3.02**	0.95	**2.39**
Spain	0.65	1.49	0.53	1.16	0.48	1.06	0.61	1.33	0.60	1.29
Sweden	0.96	**2.04**	0.75	1.48	0.91	**1.83**	0.69	1.29	0.38	0.73
Switzerland	0.54	1.42	0.93	**2.39**	0.74	**1.93**	0.75	**1.92**	0.73	**1.89**
Taiwan	1.40	**3.34**	0.54	1.27	0.49	1.14	0.49	1.12	0.57	1.32
Thailand	1.85	**3.93**	0.66	1.39	0.57	1.19	0.41	0.85	0.38	0.79
Turkey	0.92	1.19	1.92	**2.27**	1.08	1.29	0.84	0.96	0.93	1.08
UK	-0.11	-0.29	0.07	0.19	0.26	0.68	0.12	0.29	0.26	0.65
US	-0.13	-0.32	0.11	0.24	0.33	0.72	0.31	0.64	0.43	0.89
Venezuela	3.01	**5.84**	2.73	**4.85**	2.22	**3.73**	2.61	**4.38**	2.18	**3.59**

A.3.3 (continued)

Country	VMA(1,50,0.01) R_{buy}-R_{sell} (*10^{-3})	VMA(1,50,0.01) t-stats	VMA(1,150,0.01) R_{buy}-R_{sell} (*10^{-3})	VMA(1,150,0.01) t-stats	VMA(5,150,0.01) R_{buy}-R_{sell} (*10^{-3})	VMA(5,150,0.01) t-stats	VMA(1,200,0.01) R_{buy}-R_{sell} (*10^{-3})	VMA(1,200,0.01) t-stats	VMA(2,200,0.01) R_{buy}-R_{sell} (*10^{-3})	VMA(2,200,0.01) t-stats
Argentina	1.87	**3.04**	0.84	1.30	0.48	0.76	0.98	1.52	0.80	1.25
Australia	0.32	0.85	0.18	0.48	0.14	0.38	0.22	0.55	0.12	0.30
Austria	1.65	**3.84**	0.88	**2.19**	0.94	**2.35**	0.46	1.12	0.49	1.20
Bangladesh	2.94	**5.35**	2.12	**4.13**	1.87	**3.64**	1.81	**3.60**	1.76	**3.50**
Belgium	0.92	**2.12**	0.93	**2.29**	0.90	**2.23**	0.82	**2.03**	0.76	**1.87**
Brazil	-13.98	**-3.42**	-14.61	**-3.54**	1.00	0.25	-14.66	**-3.51**	-3.62	-1.06
Canada	0.60	1.39	0.40	0.90	0.36	0.80	0.38	0.85	0.29	0.63
Chile	1.58	**5.55**	0.95	**3.52**	0.57	**2.10**	0.83	**3.04**	0.60	**2.17**
China	1.75	**2.83**	0.95	1.56	0.68	1.11	0.38	0.63	0.42	0.71
Colombia	2.31	**5.00**	1.22	**2.80**	0.79	**1.79**	0.95	**2.15**	0.68	1.54
Czech	1.66	**3.53**	1.07	**2.30**	0.95	**2.05**	0.73	1.56	0.61	1.30
Denmark	1.23	**2.98**	1.45	**3.50**	1.40	**3.40**	1.33	**3.27**	1.34	**3.29**
Ecuador	0.47	0.93	0.90	**1.78**	1.33	**2.63**	1.12	**2.22**	1.27	**2.51**
Finland	1.24	**1.98**	0.87	1.43	1.13	**1.84**	0.54	0.86	0.58	0.92
France	0.36	0.74	0.83	**1.81**	0.81	**1.78**	0.68	1.44	0.66	1.42
Germany	0.89	**1.78**	0.55	1.10	0.60	1.20	0.79	1.53	0.71	1.37
Greece	2.48	**4.54**	2.02	**3.91**	1.44	**2.78**	1.94	**3.74**	1.61	**3.11**
HK	1.16	**2.01**	0.73	1.31	0.52	0.93	0.52	0.90	0.63	1.10
India	1.40	**2.68**	0.67	1.29	0.45	0.87	0.41	0.78	0.16	0.31
Indonesia	2.50	**4.41**	0.82	1.41	0.79	1.40	0.82	1.40	0.58	1.01
Ireland	1.47	**2.98**	1.16	**2.28**	1.18	**2.32**	1.14	**2.18**	1.00	**1.92**
Israel	1.14	**2.14**	1.01	**2.06**	0.99	**2.07**	0.95	**1.97**	0.86	**1.80**
Italy	1.34	**3.25**	1.13	**2.85**	0.72	**1.82**	0.87	**2.19**	0.72	**1.81**
Jamaica	2.08	**5.97**	1.20	**3.84**	0.78	**2.44**	0.93	**2.95**	0.60	**1.89**
Japan	0.46	0.93	0.73	1.62	0.78	**1.73**	0.57	1.27	0.60	1.32
Korea	1.48	**2.66**	1.20	**2.18**	1.08	**1.96**	0.98	**1.81**	0.90	1.64
Luxembourg	2.08	**4.85**	1.25	**2.98**	1.32	**3.17**	1.08	**2.52**	1.18	**2.77**
Malaysia	1.74	**3.56**	1.02	**2.02**	0.74	1.47	1.21	**2.18**	1.08	**1.94**
Mexico	1.14	**2.03**	0.24	0.42	-0.06	-0.10	0.16	0.26	0.16	0.28
NZ	0.57	**1.94**	0.14	0.53	0.15	0.58	0.13	0.50	0.17	0.65
Netherlands	0.54	1.01	0.67	1.22	0.86	1.57	0.65	1.17	0.70	1.27
Norway	1.57	**3.00**	1.08	**1.93**	1.12	**2.02**	0.93	1.63	0.90	1.59
Pakistan	2.24	**4.07**	1.65	**2.96**	1.41	**2.56**	1.50	**2.66**	1.33	**2.38**
Panama	1.85	**7.68**	1.61	**7.82**	1.62	**7.86**	1.56	**7.58**	1.58	**7.77**
Peru	2.98	**6.20**	1.77	**3.74**	1.27	**2.74**	1.50	**3.25**	1.45	**3.16**
Philippines	1.94	**4.08**	1.14	**2.44**	0.89	**1.90**	0.90	**1.83**	0.47	0.96
Portugal	1.94	**4.91**	1.34	**3.74**	1.34	**3.71**	1.32	**3.78**	1.17	**3.34**
SA	0.67	1.35	0.15	0.29	0.14	0.28	0.12	0.21	-0.19	-0.34
Singapore	1.19	**2.60**	1.12	**2.61**	0.86	**1.98**	0.71	1.59	0.62	1.41
Slovak	0.71	**1.65**	0.53	1.36	0.93	**2.37**	0.86	**2.27**	1.11	**2.93**
Slovenia	2.71	**6.21**	1.67	**4.11**	1.41	**3.37**	1.26	**2.85**	1.21	**2.80**
Spain	0.56	1.12	0.57	1.18	0.45	0.93	0.61	1.26	0.63	1.32
Sweden	0.97	**1.82**	0.88	1.62	1.00	**1.88**	0.68	1.20	0.77	1.36
Switzerland	0.66	1.43	0.84	**2.02**	0.91	**2.20**	0.66	1.58	0.59	1.41
Taiwan	1.53	**3.30**	0.68	1.48	0.49	1.08	0.66	1.44	0.70	1.51
Thailand	2.19	**4.29**	0.75	1.49	0.73	1.43	0.51	1.00	0.53	1.04
Turkey	0.82	1.00	1.76	**2.03**	1.33	1.55	0.97	1.08	0.95	1.06
UK	0.14	0.31	0.10	0.22	0.27	0.63	0.05	0.11	0.20	0.45
US	-0.10	-0.20	0.09	0.18	0.24	0.46	0.25	0.47	0.46	0.86
Venezuela	3.39	**5.80**	2.74	**4.63**	2.53	**4.03**	2.67	**4.29**	2.31	**3.68**

A.3.3 (continued)

Country	FMA(1,50)		FMA(1,150)		FMA(5,150)		FMA(1,200)		FMA(2,200)	
	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats
Argentina	10.34	1.08	14.21	1.15	-0.09	-0.01	18.85	1.07	-1.04	-0.05
Australia	7.31	1.44	2.45	0.40	-2.46	-0.38	0.39	0.05	-1.36	-0.15
Austria	3.49	0.55	15.24	**1.85**	38.54	**4.27**	5.32	0.62	1.95	0.23
Bangladesh	19.30	**1.97**	13.30	1.33	20.55	**1.96**	10.73	0.75	33.34	1.54
Belgium	1.71	0.35	-10.67	-1.41	9.48	0.78	1.51	0.15	-13.71	-1.10
Brazil	-88.08	**-1.87**	-154.97	-1.56	37.52	0.39	-114.63	-1.52	-67.28	-1.05
Canada	0.64	0.12	1.37	0.20	0.78	0.10	-14.35	**-1.74**	-12.08	-1.40
Chile	16.51	**3.04**	3.00	0.43	11.64	1.23	12.27	**2.48**	-0.05	-0.01
China	30.98	**2.91**	3.99	0.32	9.19	0.64	-5.86	-0.42	-2.24	-0.16
Colombia	27.05	**2.60**	21.72	**2.02**	11.27	0.93	26.81	1.40	-2.48	-0.14
Czech	10.16	1.49	10.86	1.21	12.82	1.30	-2.86	-0.30	-14.51	-1.25
Denmark	2.41	0.35	8.93	0.79	12.97	1.21	6.16	0.70	-1.88	-0.15
Ecuador	-25.66	**-2.48**	-27.20	**-3.40**	-10.71	-1.62	-11.75	-0.90	3.55	0.40
Finland	0.67	0.07	-15.55	-1.17	-4.20	-0.29	-2.04	-0.18	-7.77	-0.63
France	-3.19	-0.51	-22.78	**-2.63**	-6.60	-0.59	-15.37	**-1.75**	-12.60	-1.35
Germany	7.38	1.10	-5.68	-0.64	-29.35	**-2.55**	-13.01	-1.39	-4.87	-0.44
Greece	23.04	**2.07**	31.14	**1.77**	20.48	1.19	44.88	**2.22**	17.24	0.90
HK	-3.70	-0.41	20.07	1.58	16.37	1.17	17.92	1.00	21.67	1.52
India	6.85	0.70	17.02	1.34	8.37	0.75	12.07	0.96	3.12	0.22
Indonesia	37.61	**3.68**	5.24	0.30	20.42	1.34	15.81	0.94	10.96	0.69
Ireland	-4.13	-0.51	-18.09	**-2.10**	3.40	0.37	-0.62	-0.05	3.24	0.24
Israel	10.23	0.97	25.70	**1.91**	30.17	**1.83**	31.58	**2.02**	33.85	**2.09**
Italy	0.75	0.10	20.19	**2.05**	20.91	**2.21**	5.78	0.65	2.46	0.25
Jamaica	12.15	1.21	32.50	**1.98**	31.01	**2.09**	26.71	**1.70**	21.49	1.39
Japan	10.23	1.54	-7.72	-0.73	-0.23	-0.02	6.02	0.63	-11.75	-1.19
Korea	17.60	**1.91**	21.40	1.61	6.29	0.52	30.22	**2.58**	31.48	**2.85**
Luxembourg	7.15	1.08	13.84	1.52	14.33	1.36	-3.07	-0.33	-3.51	-0.38
Malaysia	9.67	1.22	18.22	**2.17**	10.24	1.09	7.16	0.76	5.14	0.53
Mexico	9.34	1.11	0.16	0.02	-3.40	-0.27	-18.54	-1.14	-28.78	**-1.80**
NZ	4.98	1.08	-1.27	-0.17	10.43	1.29	6.09	0.70	6.51	0.90
Netherlands	8.06	1.22	1.91	0.23	4.46	0.49	0.88	0.12	-4.88	-0.56
Norway	1.05	0.12	12.10	1.07	19.65	1.40	13.61	1.24	39.47	**3.05**
Pakistan	29.49	**3.05**	6.60	0.47	19.75	1.11	2.86	0.17	13.59	0.79
Panama	-1.43	-0.33	6.05	0.94	11.88	1.62	21.01	**2.28**	15.29	**2.01**
Peru	23.54	**2.34**	18.90	1.31	-3.61	-0.22	19.23	1.39	17.92	1.08
Philippines	11.43	1.24	13.45	0.98	28.54	**2.10**	15.46	1.30	22.52	1.39
Portugal	15.41	**2.18**	-5.42	-0.56	3.68	0.32	6.43	0.56	12.73	0.88
SA	-1.33	-0.21	2.45	0.28	-1.73	-0.16	19.39	**1.96**	8.35	0.83
Singapore	7.03	1.06	11.20	1.38	14.50	1.54	-0.23	-0.03	-11.31	-1.13
Slovak	0.94	0.14	8.44	0.65	4.60	0.37	4.66	0.41	14.11	1.19
Slovenia	21.47	**1.94**	29.18	1.46	30.16	**2.30**	-2.77	-0.23	-6.09	-0.51
Spain	4.23	0.59	3.01	0.29	0.79	0.07	0.87	0.08	6.23	0.54
Sweden	-5.63	-0.78	-11.39	-1.30	-5.63	-0.42	-11.82	-1.34	-13.30	-1.27
Switzerland	-5.61	-1.02	-3.07	-0.33	4.15	0.46	0.96	0.11	4.48	0.44
Taiwan	11.34	1.45	-12.04	-1.08	3.81	0.29	-8.34	-0.74	-7.16	-0.58
Thailand	10.00	0.93	15.24	1.38	34.97	**3.00**	7.66	0.70	4.24	0.43
Turkey	26.24	**1.74**	41.61	**2.08**	26.96	1.14	34.94	1.61	29.94	1.37
UK	1.07	0.24	-9.28	-1.19	0.25	0.03	-3.71	-0.51	9.73	1.35
US	-4.85	-0.96	-17.10	**-2.50**	7.54	0.98	-17.95	**-2.05**	-7.45	-0.80
Venezuela	24.16	**2.27**	47.82	**2.07**	18.77	0.79	5.90	0.20	11.92	0.37

A.3.3 (continued)

Country	FMA(1,50,0.01)		FMA(1,150,0.01)		FMA(5,150,0.01)		FMA(1,200,0.01)		FMA(2,200,0.01)	
	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats
Argentina	10.47	0.83	25.85	**2.08**	3.81	0.23	22.43	1.19	1.46	0.08
Australia	12.53	1.50	4.00	0.59	-0.27	-0.04	4.52	0.59	-3.55	-0.38
Austria	3.74	0.36	19.32	**2.26**	33.38	**3.17**	11.55	1.09	4.16	0.49
Bangladesh	16.16	0.64	12.01	1.15	18.12	1.58	6.97	0.44	31.80	1.46
Belgium	-18.32	**-1.97**	-6.00	-0.77	-1.44	-0.11	3.20	0.30	-6.03	-0.48
Brazil	-133.12	**-1.75**	-166.49	-1.60	52.19	0.49	-114.91	-1.49	-69.22	-1.02
Canada	13.95	1.43	2.68	0.40	-1.91	-0.22	-8.65	-1.02	-8.45	-0.93
Chile	-35.59	**-1.91**	-5.77	-0.76	13.69	1.24	12.16	**2.45**	-3.88	-0.53
China	36.47	**2.49**	-1.44	-0.11	1.89	0.12	-8.69	-0.61	-5.54	-0.38
Colombia	22.82	1.44	28.72	**2.50**	12.27	0.86	25.79	1.40	-9.21	-0.44
Czech	-0.41	-0.04	12.58	1.37	15.05	1.54	1.15	0.10	-12.86	-1.10
Denmark	5.02	0.37	-1.87	-0.14	13.06	1.12	8.78	1.01	-3.42	-0.27
Ecuador	-54.64	**-3.76**	-40.50	**-4.20**	-17.18	**-1.75**	-12.88	-0.90	-1.02	-0.10
Finland	11.71	0.75	-8.99	-0.65	-6.08	-0.39	1.99	0.17	-4.42	-0.31
France	-17.36	**-1.74**	-18.44	**-2.06**	-6.17	-0.53	-10.88	-1.19	-15.68	-1.56
Germany	8.04	0.68	-17.96	**-1.97**	-15.78	-1.61	-13.05	-1.41	-5.88	-0.46
Greece	9.68	0.61	29.86	1.58	22.54	1.29	55.43	**2.75**	17.49	0.91
Hong Kong	-14.87	-1.16	16.64	1.19	17.36	1.13	23.10	1.25	36.02	**2.52**
India	38.61	**3.00**	18.80	1.40	24.75	**2.19**	20.45	1.62	5.54	0.36
Indonesia	42.76	**2.64**	10.22	0.56	24.08	1.63	15.22	0.82	12.70	0.75
Ireland	-1.33	-0.11	-12.24	-1.49	4.10	0.43	4.38	0.34	6.11	0.44
Israel	-13.03	-0.75	27.56	**1.86**	25.88	1.48	38.42	**2.60**	34.31	**2.06**
Italy	8.16	0.66	16.62	1.54	19.79	**1.98**	1.45	0.14	-2.28	-0.22
Jamaica	29.62	1.33	40.33	**2.02**	32.88	**1.97**	28.85	**1.83**	31.27	**1.99**
Japan	9.61	1.07	-2.71	-0.25	-2.17	-0.17	3.76	0.37	-9.21	-0.85
Korea	-5.34	-0.36	18.30	1.32	14.28	1.11	29.67	**2.44**	37.58	**3.19**
Luxembourg	-7.58	-0.57	21.31	**2.33**	14.24	1.33	-4.95	-0.52	-2.13	-0.22
Malaysia	24.65	1.13	21.73	**2.26**	9.25	0.90	9.27	0.91	4.97	0.48
Mexico	0.68	0.05	-0.96	-0.08	-3.22	-0.23	-7.93	-0.46	-26.74	-1.62
New Zealand	16.06	1.57	3.54	0.46	9.18	1.11	8.38	0.92	9.38	1.27
Netherlands	-2.02	-0.16	-10.73	-1.50	4.66	0.45	-0.49	-0.06	-9.31	-0.96
Norway	7.25	0.55	15.50	1.49	20.57	1.41	10.25	0.89	35.31	**2.75**
Pakistan	34.22	**1.96**	-0.14	-0.01	18.80	0.96	-7.41	-0.41	11.36	0.61
Panama	-9.87	**-2.38**	0.72	0.06	15.79	**2.23**	12.85	**2.18**	16.10	**1.79**
Peru	50.73	**2.29**	18.25	1.17	5.29	0.29	16.36	1.18	11.98	0.70
Philippines	27.66	**1.87**	11.68	0.75	33.51	**2.47**	15.57	1.27	13.93	0.90
Portugal	23.81	**1.95**	-4.69	-0.46	10.08	0.93	12.66	1.17	19.84	1.24
South Africa	-3.85	-0.33	7.52	0.76	-8.15	-0.66	19.97	**1.96**	9.01	0.88
Singapore	-9.12	-0.77	9.64	1.18	14.07	1.13	0.03	0.00	-15.57	-1.43
Slovak	5.71	0.57	0.78	0.06	8.79	0.65	-5.02	-0.43	6.56	0.55
Slovenia	68.13	1.34	29.33	1.33	36.83	**3.02**	-4.57	-0.34	-1.43	-0.11
Spain	3.62	0.28	7.18	0.66	1.14	0.10	2.06	0.19	5.39	0.41
Sweden	-2.39	-0.20	-7.74	-0.90	-1.09	-0.08	-15.50	-1.58	-13.24	-1.23
Switzerland	3.32	0.37	-5.48	-0.50	8.78	0.88	0.00	0.00	5.83	0.52
Taiwan	-3.63	-0.31	-9.81	-0.79	7.63	0.56	-6.00	-0.51	-0.27	-0.02
Thailand	13.17	0.89	18.27	1.60	40.91	**3.23**	4.10	0.37	2.85	0.29
Turkey	-7.81	-0.44	37.26	**1.81**	14.61	0.63	24.62	1.08	33.95	1.42
UK	-12.10	-1.51	-8.78	-0.98	-3.97	-0.46	1.93	0.25	10.74	1.52
US	-7.51	-0.96	-23.51	**-3.06**	6.66	0.75	-19.88	**-2.16**	-3.91	-0.37
Venezuela	20.68	1.19	41.20	**1.94**	22.13	0.79	-2.40	-0.07	1.73	0.05

A.3.3 (continued)

Country	TRB(1,50)		TRB(1,150)		TRB(1,200)		TRB(1,50,0.01)		TRB(1,150,0.01)		TRB(1,200,0.01)	
	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats	R_{buy}-R_{sell} (*10^{-3})	t-stats
Argentina	25.74	**2.56**	35.16	**1.85**	28.81	1.38	34.78	**2.84**	39.74	**1.72**	29.87	1.22
Australia	1.50	0.36	-2.84	-0.43	-6.81	-0.84	-6.70	-1.12	-7.05	-0.72	-7.45	-0.56
Austria	11.62	**2.09**	9.91	1.09	9.88	0.85	20.23	**2.59**	21.59	**1.91**	25.42	**1.85**
Bangladesh	45.44	**5.16**	46.50	**3.55**	40.29	**2.49**	43.97	**3.65**	41.43	**2.26**	29.54	1.44
Belgium	9.31	1.39	8.40	0.76	8.14	0.65	13.70	1.25	9.74	0.65	9.27	0.59
Brazil	-37.65	-0.93	-114.87	-1.20	-151.96	-1.18	-51.71	-1.01	-132.17	-1.18	-160.84	-1.15
Canada	1.06	0.19	-4.03	-0.33	-2.05	-0.13	-1.80	-0.24	-3.60	-0.25	-4.83	-0.28
Chile	19.84	**4.39**	26.95	**3.23**	28.23	**3.46**	21.63	**2.36**	36.66	**1.99**	30.49	**1.87**
China	16.08	1.60	19.26	1.19	11.40	0.61	22.66	**1.74**	19.89	0.87	8.62	0.34
Colombia	24.22	**3.13**	26.16	**2.48**	21.73	1.61	27.00	**2.88**	27.80	**1.88**	14.79	0.80
Czech	29.58	**3.35**	32.27	**2.51**	32.43	**2.23**	23.69	**2.35**	43.58	**2.53**	42.12	**2.15**
Denmark	12.77	**2.10**	15.83	**1.83**	17.24	1.43	19.22	**2.14**	21.05	1.64	30.11	**1.97**
Ecuador	16.66	**2.33**	26.59	**2.80**	26.37	**2.54**	22.73	**2.10**	32.96	**3.17**	31.05	**2.98**
Finland	8.04	0.92	17.90	1.43	21.06	1.41	7.28	0.76	7.56	0.58	6.04	0.37
France	-5.98	-1.01	-2.24	-0.22	-0.71	-0.06	-7.17	-0.88	-2.76	-0.21	-2.78	-0.18
Germany	0.46	0.07	12.39	1.07	5.21	0.41	-7.07	-0.80	4.01	0.28	-3.06	-0.19
Greece	23.13	**2.89**	15.74	1.58	18.06	**1.66**	28.49	**2.66**	19.15	1.39	14.42	0.99
Hong Kong	2.75	0.37	7.46	0.65	11.99	0.90	3.69	0.43	11.84	0.83	13.85	0.87
India	11.93	**1.78**	-0.68	-0.06	-2.71	-0.21	11.18	1.22	-11.08	-0.84	-14.53	-0.96
Indonesia	33.52	**4.34**	38.57	**2.79**	32.41	**2.49**	34.78	**3.62**	37.63	**2.22**	20.09	1.25
Ireland	11.69	**1.83**	11.30	1.00	11.16	0.87	6.93	0.82	-0.33	-0.03	2.96	0.20
Israel	17.98	**1.97**	22.64	1.60	36.56	**2.32**	19.23	**1.78**	19.24	1.11	28.76	1.45
Italy	7.48	1.12	16.22	1.60	13.91	1.22	12.00	1.25	27.91	**1.89**	28.46	**1.70**
Jamaica	35.78	**5.67**	39.06	**4.44**	39.23	**3.88**	45.83	**4.54**	54.75	**3.54**	55.66	**3.17**
Japan	-3.19	-0.52	-5.47	-0.51	-13.31	-1.20	1.10	0.14	-3.39	-0.27	-14.47	-1.11
Korea	-0.59	-0.08	-11.97	-1.22	-12.39	-1.07	-1.04	-0.11	-9.86	-0.77	-9.15	-0.65
Luxembourg	29.08	**4.29**	31.86	**2.36**	30.52	**2.04**	37.94	**3.96**	52.03	**2.70**	47.16	**2.28**
Malaysia	22.50	**3.41**	25.84	**2.31**	21.78	**1.68**	20.70	**2.01**	13.97	0.92	13.01	0.74
Mexico	11.86	1.36	19.06	0.92	6.32	0.23	12.62	1.37	16.57	0.77	1.37	0.05
New Zealand	5.26	1.37	6.32	0.97	7.04	1.01	2.65	0.32	-0.04	0.00	-7.34	-0.64
Netherlands	3.55	0.52	18.29	1.23	17.85	1.08	1.47	0.15	14.17	0.84	9.88	0.52
Norway	18.10	**2.44**	20.17	1.48	29.52	**2.16**	12.96	1.37	28.05	1.62	37.03	**2.07**
Pakistan	35.52	**3.26**	62.92	**3.07**	73.87	**2.92**	41.06	**3.18**	62.91	**2.21**	72.59	**2.23**
Panama	-20.44	-0.54	-21.79	-0.52	-23.65	-0.53	22.86	**3.40**	28.43	**3.40**	30.68	**3.73**
Peru	37.78	**5.01**	39.23	**3.04**	40.62	**2.93**	42.88	**4.72**	41.08	**2.86**	44.18	**2.96**
Philippines	21.47	**2.83**	14.90	1.27	18.12	1.36	16.29	**1.71**	7.92	0.59	8.90	0.59
Portugal	22.77	**4.05**	31.88	**3.59**	20.23	**1.96**	29.07	**3.77**	34.82	**3.26**	18.80	1.48
South Africa	4.31	0.68	-5.58	-0.38	-23.58	-1.45	-4.08	-0.47	-17.49	-0.94	-32.61	**-1.68**
Singapore	20.24	**3.50**	27.66	**2.72**	29.75	**2.68**	14.32	**1.72**	15.39	1.41	12.58	1.04
Slovak	14.25	**2.19**	21.44	**2.83**	26.88	**3.37**	16.83	**1.80**	29.42	**2.80**	33.25	**3.06**
Slovenia	27.87	**3.84**	33.78	**3.73**	35.08	**3.81**	25.57	**2.21**	34.54	**2.60**	35.54	**2.68**
Spain	-3.25	-0.46	-4.75	-0.45	-3.47	-0.29	4.67	0.51	16.58	1.15	18.91	1.22
Sweden	-6.46	-0.95	9.99	0.83	3.93	0.28	-4.30	-0.49	11.26	0.76	1.67	0.10
Switzerland	4.40	0.74	10.68	1.01	8.90	0.73	-0.49	-0.06	7.50	0.58	6.86	0.46
Taiwan	-0.99	-0.15	1.63	0.16	7.09	0.60	2.86	0.34	6.49	0.53	14.18	1.02
Thailand	26.53	**3.44**	26.50	**2.04**	29.73	**2.00**	25.37	**2.74**	23.50	1.63	33.86	**2.15**
Turkey	21.31	**1.94**	21.44	1.31	14.24	0.77	30.43	**2.39**	32.00	**2.01**	22.43	1.28
UK	-6.01	-1.09	-8.95	-0.82	-13.11	-1.00	-9.20	-1.18	-14.55	-1.13	-14.29	-0.95
US	-5.54	-0.93	-9.41	-0.66	-9.86	-0.64	-10.71	-1.31	-5.94	-0.43	0.89	0.05
Venezuela	54.89	**4.92**	62.87	**3.66**	69.60	**3.90**	64.30	**4.16**	72.22	**2.80**	85.25	**2.90**

A.3.4: Risk-Adjusted Profits of 26 Technical Trading Strategies

Country	VMA (1,50) (%)	VMA (1,150) (%)	VMA (5,150) (%)	VMA (1,200) (%)	VMA (2,200) (%)	VMA (1,50,0.01) (%)	VMA (1,150,0.01) (%)	VMA (5,150,0.01) (%)	VMA (1,200,0.01) (%)	VMA (2,200,0.01) (%)
Argentina	1.198	1.199	1.190	1.194	1.191	1.289	1.291	1.281	1.286	1.283
Australia	0.144	0.152	0.144	0.145	0.137	0.118	0.126	0.118	0.119	0.112
Austria	1.459	1.438	1.454	1.439	1.427	1.418	1.396	1.413	1.397	1.385
Bangladesh	2.294	2.294	2.294	2.295	2.295	2.213	2.213	2.213	2.214	2.214
Belgium	0.787	0.764	0.766	0.763	0.767	0.749	0.726	0.728	0.725	0.729
Brazil	-16.804	-16.794	-16.194	-16.483	-16.696	-16.486	-16.476	-15.876	-16.165	-16.378
Canada	0.581	0.596	0.600	0.608	0.607	0.503	0.518	0.522	0.530	0.529
Chile	1.289	1.292	1.293	1.292	1.292	1.163	1.166	1.167	1.166	1.166
China	1.684	1.678	1.658	1.686	1.688	1.383	1.377	1.357	1.385	1.387
Colombia	1.548	1.498	1.507	1.489	1.493	1.496	1.446	1.455	1.438	1.441
Czech	1.391	1.391	1.401	1.410	1.416	1.294	1.294	1.303	1.312	1.318
Denmark	1.114	1.119	1.120	1.123	1.125	0.990	0.996	0.996	1.000	1.002
Ecuador	-0.023	-0.020	-0.031	-0.020	-0.030	-0.140	-0.137	-0.148	-0.137	-0.147
Finland	1.031	1.071	1.083	1.079	1.076	1.084	1.124	1.136	1.132	1.129
France	0.356	0.362	0.363	0.354	0.361	0.327	0.333	0.334	0.326	0.332
Germany	0.929	0.930	0.922	0.915	0.923	0.795	0.796	0.788	0.781	0.789
Greece	1.848	1.846	1.843	1.847	1.841	1.818	1.816	1.813	1.817	1.812
Hong Kong	1.047	1.067	1.044	1.049	1.045	0.978	0.997	0.974	0.979	0.976
India	0.920	0.920	0.919	0.919	0.920	0.984	0.983	0.983	0.982	0.984
Indonesia	1.709	1.704	1.730	1.712	1.702	1.660	1.654	1.680	1.663	1.653
Ireland	1.300	1.310	1.320	1.310	1.328	1.194	1.205	1.214	1.205	1.222
Israel	0.653	0.655	0.655	0.656	0.657	0.736	0.739	0.739	0.740	0.741
Italy	1.028	1.050	1.053	1.050	1.056	1.050	1.072	1.076	1.073	1.079
Jamaica	0.871	0.861	0.853	0.847	0.842	0.927	0.918	0.909	0.903	0.898
Japan	0.645	0.618	0.618	0.637	0.636	0.549	0.521	0.521	0.541	0.539
Korea	1.112	1.115	1.115	1.116	1.115	1.081	1.085	1.084	1.086	1.085
Luxembourg	1.650	1.693	1.698	1.685	1.698	1.761	1.803	1.809	1.796	1.809
Malaysia	1.393	1.394	1.397	1.397	1.390	1.262	1.263	1.266	1.266	1.259
Mexico	0.642	0.660	0.648	0.654	0.656	0.608	0.626	0.614	0.620	0.622
New Zealand	0.120	0.133	0.130	0.125	0.124	0.295	0.308	0.305	0.301	0.300
Netherlands	0.484	0.474	0.476	0.470	0.487	0.439	0.428	0.431	0.425	0.441
Norway	1.414	1.412	1.413	1.412	1.417	1.265	1.263	1.264	1.263	1.269
Pakistan	1.620	1.616	1.618	1.620	1.621	1.664	1.660	1.661	1.663	1.664
Panama	1.305	1.304	1.303	1.306	1.305	1.161	1.161	1.160	1.163	1.162
Peru	2.470	2.470	2.470	2.470	2.470	2.479	2.480	2.480	2.480	2.480
Philippines	1.290	1.297	1.295	1.298	1.296	1.405	1.412	1.410	1.413	1.411
Portugal	1.646	1.656	1.663	1.654	1.653	1.611	1.621	1.629	1.619	1.618
South Africa	0.788	0.794	0.786	0.762	0.755	0.767	0.774	0.765	0.741	0.734
Singapore	0.739	0.752	0.748	0.754	0.758	0.853	0.866	0.862	0.868	0.872
Slovak	0.148	0.149	0.149	0.147	0.149	0.272	0.272	0.272	0.271	0.272
Slovenia	1.842	1.837	1.839	1.844	1.841	1.877	1.872	1.875	1.879	1.876
Spain	0.619	0.646	0.641	0.643	0.643	0.471	0.498	0.493	0.495	0.495
Sweden	0.957	0.952	0.959	0.957	0.964	0.862	0.857	0.864	0.862	0.869
Switzerland	0.619	0.622	0.616	0.595	0.599	0.595	0.598	0.592	0.571	0.575
Taiwan	1.407	1.414	1.416	1.398	1.394	1.361	1.368	1.370	1.352	1.348
Thailand	1.773	1.792	1.783	1.804	1.801	1.838	1.857	1.848	1.870	1.866
Turkey	-0.545	-0.657	-0.522	-0.557	-0.713	-0.504	-0.615	-0.480	-0.515	-0.671
UK	-0.236	-0.218	-0.217	-0.233	-0.225	-0.014	0.004	0.006	-0.010	-0.002
US	-0.094	-0.098	-0.081	-0.088	-0.100	-0.036	-0.040	-0.023	-0.030	-0.043
Venezuela	2.901	2.913	2.934	2.908	2.938	2.996	3.008	3.029	3.003	3.033
Average	0.701	0.702	0.718	0.709	0.703	0.689	0.690	0.706	0.697	0.691

A.3.4 (continued)

Country	FMA (1,50) (%)	FMA (1,150) (%)	FMA (5,150) (%)	FMA (1,200) (%)	FMA (2,200) (%)	FMA (1,50,0.01) (%)	FMA (1,150,0.01) (%)	FMA (5,150,0.01) (%)	FMA (1,200,0.01) (%)	FMA (2,200,0.01) (%)
Argentina	0.054	0.047	0.054	0.049	0.053	-0.001	-0.008	0.000	-0.006	-0.002
Australia	0.115	0.129	0.128	0.128	0.129	0.054	0.068	0.067	0.067	0.068
Austria	0.080	0.087	0.081	0.082	0.070	0.057	0.063	0.058	0.059	0.046
Bangladesh	0.338	0.336	0.337	0.337	0.337	0.032	0.030	0.031	0.031	0.031
Belgium	-0.005	-0.012	0.001	-0.006	-0.007	-0.153	-0.160	-0.147	-0.155	-0.155
Brazil	-3.615	-3.608	-3.537	-3.505	-3.604	-3.298	-3.290	-3.219	-3.188	-3.287
Canada	-0.036	-0.027	-0.023	-0.031	-0.033	0.094	0.103	0.106	0.099	0.096
Chile	0.309	0.307	0.309	0.310	0.308	-0.094	-0.096	-0.094	-0.093	-0.095
China	0.670	0.661	0.652	0.647	0.650	0.425	0.416	0.407	0.402	0.405
Colombia	0.465	0.469	0.474	0.466	0.493	0.123	0.127	0.133	0.124	0.151
Czech	0.158	0.157	0.168	0.159	0.151	-0.048	-0.049	-0.039	-0.047	-0.056
Denmark	-0.028	-0.008	-0.007	-0.009	-0.006	0.019	0.040	0.040	0.039	0.041
Ecuador	-0.576	-0.578	-0.582	-0.571	-0.578	-0.541	-0.544	-0.547	-0.537	-0.544
Finland	-0.060	-0.030	-0.021	-0.018	-0.021	0.114	0.143	0.152	0.155	0.152
France	-0.138	-0.118	-0.119	-0.124	-0.123	-0.266	-0.246	-0.247	-0.252	-0.251
Germany	0.168	0.197	0.178	0.176	0.181	0.062	0.090	0.072	0.070	0.075
Greece	0.473	0.476	0.476	0.478	0.473	0.016	0.018	0.018	0.021	0.016
Hong Kong	-0.146	-0.135	-0.141	-0.134	-0.140	-0.242	-0.230	-0.236	-0.230	-0.235
India	0.057	0.057	0.058	0.057	0.057	0.540	0.540	0.541	0.540	0.541
Indonesia	0.647	0.647	0.645	0.663	0.654	0.443	0.443	0.441	0.459	0.450
Ireland	-0.167	-0.150	-0.146	-0.144	-0.135	-0.043	-0.026	-0.022	-0.019	-0.010
Israel	0.148	0.147	0.147	0.147	0.147	-0.113	-0.114	-0.114	-0.114	-0.113
Italy	-0.015	-0.010	-0.011	-0.008	-0.006	0.035	0.040	0.039	0.042	0.044
Jamaica	0.047	0.046	0.053	0.050	0.049	0.144	0.143	0.150	0.146	0.146
Japan	0.326	0.315	0.303	0.317	0.314	0.228	0.217	0.204	0.219	0.216
Korea	0.396	0.396	0.396	0.397	0.397	-0.134	-0.133	-0.133	-0.133	-0.133
Luxembourg	0.123	0.132	0.129	0.123	0.128	-0.071	-0.061	-0.064	-0.071	-0.066
Malaysia	0.214	0.210	0.208	0.218	0.214	0.181	0.177	0.176	0.185	0.181
Mexico	0.042	0.071	0.066	0.060	0.073	-0.103	-0.073	-0.079	-0.084	-0.072
New Zealand	0.074	0.080	0.086	0.084	0.078	0.070	0.076	0.081	0.080	0.073
Netherlands	0.185	0.195	0.204	0.188	0.201	-0.043	-0.033	-0.024	-0.039	-0.027
Norway	-0.044	-0.040	-0.037	-0.042	-0.034	0.016	0.020	0.023	0.018	0.026
Pakistan	0.585	0.584	0.581	0.575	0.577	0.354	0.354	0.351	0.344	0.347
Panama	-0.034	-0.036	-0.035	-0.033	-0.033	-0.013	-0.015	-0.014	-0.012	-0.012
Peru	0.418	0.418	0.418	0.418	0.418	0.338	0.338	0.338	0.338	0.338
Philippines	0.137	0.142	0.145	0.144	0.146	0.233	0.238	0.241	0.239	0.241
Portugal	0.333	0.320	0.327	0.322	0.327	0.169	0.155	0.162	0.158	0.163
South Africa	-0.070	-0.063	-0.067	-0.050	-0.053	-0.068	-0.061	-0.065	-0.048	-0.051
Singapore	0.143	0.136	0.131	0.128	0.130	-0.146	-0.153	-0.158	-0.161	-0.159
Slovak	-0.073	-0.073	-0.073	-0.072	-0.072	0.029	0.029	0.029	0.030	0.030
Slovenia	0.311	0.302	0.300	0.295	0.296	0.087	0.078	0.076	0.071	0.072
Spain	0.089	0.091	0.089	0.094	0.097	-0.032	-0.030	-0.032	-0.027	-0.024
Sweden	-0.194	-0.215	-0.217	-0.210	-0.209	-0.036	-0.057	-0.059	-0.052	-0.050
Switzerland	-0.203	-0.192	-0.196	-0.191	-0.195	0.009	0.020	0.016	0.021	0.017
Taiwan	0.217	0.219	0.221	0.217	0.217	-0.132	-0.130	-0.128	-0.132	-0.132
Thailand	0.314	0.317	0.316	0.325	0.318	0.248	0.251	0.250	0.258	0.252
Turkey	0.109	0.118	0.042	0.146	0.066	-0.611	-0.603	-0.678	-0.574	-0.654
UK	-0.056	-0.062	-0.054	-0.054	-0.053	-0.175	-0.182	-0.174	-0.174	-0.173
US	-0.234	-0.231	-0.227	-0.220	-0.215	-0.162	-0.159	-0.154	-0.148	-0.143
Venezuela	0.299	0.288	0.293	0.313	0.316	0.138	0.127	0.132	0.153	0.155
Average	0.047	0.050	0.050	0.054	0.051	-0.045	-0.042	-0.042	-0.039	-0.041

A.3.4 (continued)

Country	TRB(1,50) (%)	TRB(1,150) (%)	TRB(1,200) (%)	TRB(1,50,0.01) (%)	TRB(1,150,0.01) (%)	TRB(1,200,0.01) (%)
Argentina	0.916	0.897	0.904	0.964	0.945	0.952
Australia	-0.038	-0.038	-0.040	-0.152	-0.152	-0.154
Austria	0.634	0.610	0.603	0.506	0.482	0.475
Bangladesh	1.926	1.927	1.927	1.145	1.146	1.146
Belgium	0.496	0.479	0.474	0.265	0.248	0.244
Brazil	-1.858	-1.846	-1.845	-2.109	-2.098	-2.097
Canada	0.125	0.112	0.106	-0.047	-0.060	-0.066
Chile	0.890	0.886	0.878	0.324	0.320	0.313
China	0.699	0.684	0.678	0.645	0.630	0.624
Colombia	0.945	0.928	0.922	0.748	0.731	0.725
Czech	1.013	1.008	1.011	0.527	0.523	0.525
Denmark	0.630	0.637	0.634	0.401	0.408	0.405
Ecuador	0.424	0.410	0.414	0.316	0.302	0.306
Finland	0.488	0.476	0.473	0.250	0.239	0.236
France	-0.256	-0.259	-0.263	-0.209	-0.213	-0.217
Germany	0.119	0.115	0.115	-0.169	-0.173	-0.172
Greece	0.894	0.885	0.886	0.790	0.781	0.783
Hong Kong	0.206	0.198	0.202	0.118	0.110	0.114
India	0.518	0.516	0.516	0.244	0.241	0.241
Indonesia	1.218	1.206	1.212	0.914	0.901	0.907
Ireland	0.541	0.522	0.523	0.184	0.165	0.166
Israel	0.685	0.688	0.689	0.453	0.457	0.457
Italy	0.333	0.333	0.328	0.209	0.209	0.204
Jamaica	1.185	1.168	1.170	0.884	0.867	0.869
Japan	-0.038	-0.034	-0.034	0.041	0.045	0.045
Korea	-0.106	-0.106	-0.105	-0.123	-0.123	-0.122
Luxembourg	1.397	1.389	1.386	1.013	1.005	1.002
Malaysia	0.972	0.980	0.981	0.501	0.509	0.510
Mexico	0.430	0.429	0.433	0.298	0.298	0.302
New Zealand	0.150	0.149	0.147	0.011	0.010	0.008
Netherlands	0.227	0.221	0.223	0.029	0.023	0.025
Norway	0.760	0.754	0.750	0.315	0.310	0.306
Pakistan	1.515	1.519	1.512	1.175	1.180	1.172
Panama	0.911	0.906	0.905	0.304	0.300	0.299
Peru	1.760	1.761	1.761	1.365	1.366	1.366
Philippines	0.829	0.830	0.830	0.413	0.414	0.414
Portugal	1.023	1.024	1.034	0.676	0.677	0.687
South Africa	0.329	0.330	0.338	-0.061	-0.060	-0.052
Singapore	0.754	0.779	0.779	0.284	0.309	0.309
Slovak	0.495	0.496	0.495	0.344	0.345	0.344
Slovenia	1.187	1.196	1.189	0.569	0.577	0.571
Spain	-0.100	-0.110	-0.114	0.111	0.102	0.098
Sweden	-0.062	-0.060	-0.060	-0.123	-0.121	-0.121
Switzerland	0.302	0.298	0.297	0.009	0.006	0.004
Taiwan	-0.036	-0.041	-0.042	0.049	0.045	0.044
Thailand	1.104	1.097	1.096	0.708	0.701	0.700
Turkey	0.520	0.656	0.662	0.659	0.795	0.801
UK	-0.279	-0.274	-0.279	-0.215	-0.210	-0.214
US	-0.160	-0.148	-0.155	-0.239	-0.226	-0.233
Venezuela	2.768	2.758	2.757	2.378	2.368	2.367
Average	0.588	0.587	0.586	0.354	0.353	0.352

A. 4: Statement of Contribution to Doctoral Thesis Containing Publications to Chapter 2

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Jiali(Jasmine) Fang

Name/Title of Principal Supervisor: Dr. Yafeng Qin

Name of Published Research Output and full reference:

Name: Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test
Reference: 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.

In which Chapter is the Published Work: Chapter 2

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate:

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Jasmine Fang is the main author of this paper and while her supervisors have made substantial contributions - which is reflected by co-authorship - the papers are essentially the work of Jasmine.

Jiali Fang — 03/11/2014
Candidate's Signature — Date

Yafeng Qin — 07/11/2014
Principal Supervisor's signature — Date

GRS Version 3– 16 September 2011

A. 5: Statement of Contribution to Doctoral Thesis Containing Publications to Chapter 3

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Jiali(Jasmine) Fang

Name/Title of Principal Supervisor: Dr. Yafeng Qin

Name of Published Research Output and full reference:

Name: Technical Market Indicators: An Overview
Reference: Fang, J., Qin, Y., & Jacobsen, B. (2014). Technical Market Indicators: An Overview. Forthcoming in Journal of Behavioral and Experimental Finance

In which Chapter is the Published Work: Chapter 3

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate:

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Jasmine Fang is the main author of this paper and while her supervisors have made substantial contributions - which is reflected by co-authorship - the papers are essentially the work of Jasmine.

Jiali Fang Digitally signed by Jiali Fang
Candidate's Signature

03/11/2013
Date

Yafeng Qin Digitally signed by Yafeng Qin
Principal Supervisor's signature

07/11/2014
Date

GRS Version 3– 16 September 2011