High-Low Price Prediction and Technical Analysis

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Abstract

High and low prices convey additional information beyond closing prices, based on the fact that the improved high-low volatility estimator enjoys higher efficiency than the standard close-to-close variance. Empirical results show that a positive risk-return relationship is exhibited more frequently when predicted high-low prices are applied rather than historical data by taking advantage of the new volatility estimator in 48 countries. In this study, models using historical data contain (1) historical closing prices, (2) historical high-low prices, and (3) the Risk Aversion method, while the three high-low prices prediction approaches include (1) Engle and Granger two-step linear model, (2) Engle and Granger non-linear model, and (3) MIDAS technique. Corporate governance variables, associated with laws and enforcement, have weak explanatory power over investors' perception of risk. This study also contributes to the validity of technical analysis by showing that high and low prices forecasts are able to generate valuable trading signals and positive returns based on range-based strategy and midpoint strategy. The superior investment performance benefits investors in trading both stock indices and options in U.S. financial markets.

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Table of Contents

Abstract i

Acknowledgements ii

Table of Contents iii

Chapter 1 Introduction 1

1.1 Background 1

1.2 Contribution 5

1.3 Preliminary results 6

1.4 Outlines of the thesis 6

Chapter 2 Literature Review 7

2.1 Advantages of high-low prices 7

2.2 Variance construction based on high-low prices 7

2.3 High-low prices' prediction models 9

2.3.1 Engle and Granger ordinary least squares model 9

2.3.2 Engle and Granger non-linear least squares model 11

2.3.3 MIDAS 12

2.4 Corporate governance 13

2.5 Technical analysis 15

2.5.1 Trading stock indices 15

2.5.2 Trading options 19

2.6 Hypotheses Development 20

Chapter 3 Data 22

Chapter 4 Methodology 24

4.1 Historical data 24

4.2 High-low prices' forecasting models 25
4.2.1 Engle and Granger ordinary least squares model 25
4.2.2 Engle and Granger non-linear least squares model 30
4.2.3 MIDAS 31
4.3 Risk aversion method 34
4.4 Technical analysis 35
4.4.1 Trading stock indices 35
4.4.2 Trading options: 36
Chapter 5 Empirical Results 39
5.1 Risk and return relationship 39
5.1.1 Historical data 39
5.1.2 Forecast high-low prices 42
5.2 Corporate governance 47
5.3 Technical analysis 53
5.3.1 Trading stock indices 53
5.3.2 Trading options 67
Chapter 6 Conclusions 70
References 72
Appendix A: 79
Appendix B: 81

List of Tables

Table 5.1 Summary Risk Aversion Coefficients Using Historical Data 39

Table 5.2 Summary Risk Aversion Coefficients Using Historical Closing Prices 41

Table 5.3 Summary Risk Aversion Coefficients Using Forecasted High-low Prices ... 43

Table 5.4 Summary Risk Aversion Coefficients For Countries With Strong Persistence 46

Table 5.5 Results Summary for Four Legal Origins 48

Table 5.6 Results Summary for Investor Protection and Law Enforcement 50

Table 5.7 Results Summary for Securities Law Factors 51

Table 5.8 Summary Statistics for Monthly and Daily Returns 54

Table 5.9 Results for Co-integration Relationship Pre-test 55

Table 5.10 Results for Simple Technical Trading Strategies from Two Estimation Periods 58

Table 5.11 Summary Results for Range-based Strategy 61

Table 5.12 Summary Results for Midpoint Strategy 64

Table 5.13 Results Summary for Trading Options 69

Appendix

Appendix A 79

Appendix B 81

Chapter 1 Introduction

1.1 Background

Under market efficiency, closing prices should provide all necessary information and thus studies on stock returns and volatility usually start with the basic close-to-close returns, even though data on opening, high, low and closing prices are widely available. While extant studies place much greater weight on the explanatory power of closing prices than other prices, both historical and predicted high-low price dynamics draw limited attention. A few works that extend the analysis to high and low prices point out such two prices series provide valuable information not reflected by closing prices. Therefore, the motivation to evaluate the properties of high and low prices is quite obvious.

Particularly, the benefits of the high and low prices are not only embedded in their universal accessibility, but also in them being a rich source of information in relation to market liquidity and transaction cost. To illustrate, the bid-ask spread, which typically represents the cost paid by financial traders, could be approached in a simple way from high-low prices (Corwin & Schultz, 2012). That is to say, the high-low prices indirectly control trading volume, which implies it controls the market liquidity, for the reason that higher transaction cost will depress investors' trading demand. Besides, the price range, given by the difference between the high and the low price, is regarded as a better approximation of truly unobserved volatility in that the wider the range is, the more volatile the market is likely to be (Cheung, Cheung, & Wan, 2009). Following are several reasons studying the high and low prices of securities is essential.

First, it has been proved that a novel approach to assess risk, which is based on high-low equity prices, gives a better indication of which direction future volatility is likely to move towards (Beckers, 1983). Initially, Parkinson (1980) introduces the idea to incorporate high-low prices into volatility measurement so as to more accurately capture the underlying price volatility. Under certain assumptions, the efficiency of such a risk estimator is 5.2 times higher than the traditional close-to-close variance, which indicates the new volatility estimator contains a greater amount of information that is relevant. Subsequently, modifications and improvements under dynamic price models have been proposed continuously, including Garman and Klass (1980), Kunitomo (1992) and Buescu, Taksar, and KonÉ (2013). Given that, it is natural to take advantage of new volatility estimators, which may offer some incremental explanatory power over the variations in risk and return trade-off. However, researchers who look backwards by investigating past price patterns may find the general principle “higher risk and higher return” unreasonable, since it may not occur during the time intervals they pick or due to the different models they use. Only investors who look forwards will expect higher returns if they choose to bear more risk. As a result, volatility estimators based on the forecasting of high-low prices, rather than historical data, might better explain the mysterious risk and return relationship.

In addition to exploring the information content embedded in past prices, an increasing body of literature has focused on the predictability of high-low prices. Mok, Lam, and Li (2000) analyse the behaviour of high-low stock prices and they find that the high and low futures prices of the S&P 500 and Hang Seng index are actually governed by a random walk process, while the price ranges have integration of order zero. Given the so-called co-integration relationship, Engle and Granger (1987) initiate the formulation of the correlation in the econometrics sense by introducing a two-step linear model, while Cheung (2007) attests to the co-integration relationship between the highs and the lows in terms of three major U.S. stock indices and carries the findings one step further by developing the co-integration related vector error correction model (VECM). Later on, Cheung, Cheung, and Wan (2009) complement the previous study by successfully forecasting the high-low price series and price ranges for eight countries’ stock indices with the help of VECM, which proves it is an effective prediction mechanism. Such a successful co-integration framework that passes several empirical tests has become a cornerstone in fully investigating common patterns and properties controlling price ranges. As a result, Caporin, Ranaldo, and de Magistris (2013) extend the existing VECM by proposing and implementing a fractional vector autoregressive model with error correction (FVECM), which reinforces the usefulness of the co-integration concept.

Alternatively, high and low prices prediction models could be derived from Engle and Ganger's method using non-linear least squares, following the same co-integration logic. The problem with conventional linear regressions, or the Engle-Granger two-step ordinary least squares co-integration model in this case, lies in the absence of a standard asymptotic distribution, which will limit the use of linear models to some extent. In comparison to the traditional linear least squares regressions, the Engle and Granger non-linear model is asymptotically unbiased as well as normally distributed. That it fits well with finite samples is another advantage that leads to more effective profitability assessment (Liu, Margaritis, & Tourani-Rad, 2008). On account of the outstanding features mentioned above, it is necessary to apply the Engle and Granger non-linear least squares model to capture the consistent co-integration relationship between the high and the low prices with greater accuracy.

On the other hand, a new method to predict high and low equity prices, which is based on mixed data sampling, named MIDAS, is introduced by Ghysels, Santa-Clara, and Valkanov (2004). The conventional wisdom with reference to ordinary least squares is regressions requiring contemporaneous data. What if the dependent and independent variables are in different frequencies? In particular, examining data with different frequencies may offer some unique information since analysing only low-frequency data and totally ignoring high-frequency data will possibly miss useful information. Implementing MIDAS as a model to estimate conditional variance, Ghysels, Santa-Clara, and Valkanov (2005) reach a robust conclusion that the positive relationship between risk and return is significant. In this paper, with the help of Engle and Granger linear and non-linear models and the MIDAS technique, new volatility estimators calculated from several approaches to the prediction of high-low prices will supplement the explanation of the risk and return puzzle.

Second, the high and low prices are also two key components in forming technical trading strategies. Although the worth of technical analysis lacks plausibility, Caporin, Ranaldo, and de Magistris (2013) find favourable empirical results to support simple technical trading rules with respect to the prediction of high-low prices. Filter rules such as support and resistance level strategy, price channel strategy and contrarian strategy are in particular linked to high-low equity prices. For instance, trading signals are initiated when stock prices penetrate local high or low prices, which resemble upper and lower bands. Also, the high-low price ranges help establish the width of the band, based on which violation strategy determines the trading signals and in turn, the profits. The two simple trading rules adopted in this paper are generally in line with the notion of contrarian strategy illustrated by Caporin, Ranaldo, and de Magistris (2013), without considering money management techniques such as stop loss or taking profits. In essence, the value of the economic signals derived from predicted high-low prices will be evaluated by their ability to provide a superior performance in investing.

Third, based on the fact that price range is able to better model volatility behaviour than the predictor only using closing prices, high and low equity prices play critical roles in pricing derivatives, especially options. An early example of the direct application of high-low prices as an input in options pricing for American puts is given by Parkinson (1977) while the famous Black-Scholes options-pricing formula for European options is one of the indirect implications, since the high-low stock prices are related to an options variance parameter. Complementary to options valuation, various types of exotic options contracts are constructed based on the highest or lowest prices during an agreed-upon period. To illustrate, Cheung, Cheung, He, and Wan (2010) successfully derive a profitable trading strategy once the callable bull/bear contract has been launched in Hong Kong. Trigger points, depending on the high-low prices rather than the opening and closing prices, are defined to carry out trading signals and execute transactions. In this paper, buying and selling indications, which are determined by the two technical trading strategies adopted, are processed in the trade of index options, accompanying both dollar returns and the rate of returns are used to judge profitability.

1.2 Contribution

In brief, this report contributes to the previous literature on the applications of both historical and anticipated high-low prices via novel volatility estimators. To explore this idea, new ways to assess volatility, corresponding to historical prices and several high-low prices' forecasting methods, provide alternative ways to examine of the puzzle of risk-return trade-off. At the same time, simple trading strategies for stock indices and options are investigated in order to exemplify the superior investing performance of technical analysis than the naïve buy and hold strategy in terms of valuable trading signals and positive profits. The technical investment strategies that are implemented are based on Engle and Granger's co-integration linear model to forecast high and low prices. In other words, this paper assesses whether predicted high-low prices based on a co-integration concept are able to better evaluate the risk and return relationship and such prices' potential implications by means of profitable trading strategies and options transactions. In addition, legal factors are applied in order to explain the variations in risk aversion coefficients, which are the risk parameters generated from risk-return regressions.

With reference to volatility approximation and risk-return relationship interpretation, 48 countries around the world are considered, whereas the discussion of the technical trading strategies regarding stock indices and options concentrates on U.S. data only. This is because the former allows the comparison of different risk-return patterns that exist in different countries and permits the use of corporate governance factors as explanatory variables, while the U.S. data provides an ideal opportunity to investigate abnormal returns due to the United States having the longest available data and the most efficient financial market.

1.3 Preliminary results

To anticipate the results, high-low prices of stocks are capable of conveying useful information that closing prices fail to reflect in terms of more convincing evidence in explaining positive risk-return trade-off and the generation of positive profits from technical trading strategies. In order to successfully model and forecast high-low stock indices prices in 48 countries, three prediction models are used: (1) Engle and Granger two-step linear model, (2) Engle and Granger non-linear model, and (3) MIDAS technique. The first two corroborate notions related to the co-integration concept and MIDAS mixes data with different frequencies. Then, the predicted high-low prices that are extended to the application of volatility as an explanatory variable in the risk-return trade-off in the presence of two estimation periods should yield a significant positive relationship. Corporate governance factors, especially legal factors, are expected to explain what changes risk aversion coefficients derived from previous risk and return regressions, grounded in the perception that good protection increases investors' willingness to invest. Since the two technical trading strategies adopted, relying on the Engle and Granger co-integration linear prediction model, should be able to better capture the moving patterns of stock indices' high and low prices, trading signals should indicate the right time to enter or exit the financial markets. Given those signals, simple technical trading rules would not only provide profitable investment opportunities to stock index traders, but also to options-trading participants.

1.4 Outline of the thesis

The remained of this paper is organized as follows. Section II includes a review of related literature and hypotheses development. Section III describes the data, while Section IV discusses in detail the methodology in relation to the models applied. Section V presents the empirical results, which are sub-divided into several subsections, corresponding to each model mentioned in the methodology. Section VI concludes and summarizes the results.

Chapter 2 Literature Review

2.1 Advantages of high-low prices

Generally speaking, the empirical value of the high and the low price series lies in their wide accessibility, low acquisition costs and a great robustness to microstructure effects (Fiszeder & Perczak, 2013). In comparison to frequently examined closing prices, it is clear that data on high-low stock prices do have merit in several areas. Recently, Corwin and Schultz (2012) develop a bid-ask spread valuation technique based on daily high and low prices because the high-low prices' ratio estimator performs better than the widely-used covariance estimator, which relies only on closing prices, in easy calculating and various applications. Even when the previous bid-ask spread technique is under consideration, Deuskar, Gupta, and Subrahmanyam (2011) have already implemented the procedure so as to better measure transaction cost.

Also, the fact that the bid-ask spread is able to extract differential behaviour for active and infrequently traded stocks indicates information asymmetry is another source of information about high-low prices that goes beyond the simple closing prices (Easley, Kiefer, O'Hara, & Paperman, 1996). Existing studies emphasize that the high-low price range is extensively utilized by financial traders because it is a key ingredient in earning returns (Taylor & Allen, 1992). Therefore, high and low prices consistently deliver advantageous information we seldom pay attention to. On the other hand, several volatility estimation methods for high-low prices, which show superiority over the classic close-to-close variance estimator, are worth discussing.

2.2 Variance construction based on high-low prices

Volatility measurement is an inevitable issue in many financial applications such as portfolio analysis, assets valuation and risk management. Although the issue of volatility estimation is subject to extensive analysis, the vast majority of the studies concentrate on closing prices. However, Andersen and Bollerslev (1998) provide evidence that despite the absence of bias in the standard volatility estimator, it is generally too noisy to be regarded as efficient. In order to increase efficiency, Parkinson (1980) first introduces a more sophisticated volatility estimator by taking additional information into account, including high and low equity prices. He develops the extreme value method on the assumption that the logarithm of prices' movements are governed by geometric Brownian motion with no drift, while Kunitomo (1992) proposes an improved model acquiring non-zero drift prices.

In the same year when the new volatility estimator is introduced, Garman and Klass (1980) prove that simply using daily high and low stock prices, as Parkinson directed, yields a better volatility estimator with 5.2 times higher efficiency than the traditional close-to-close estimator. Empirical tests conducted by Beckers (1983) demonstrate the validity and accuracy of the new Parkinson high-low prices' risk estimator. Based on all available price series (opening, high, low and closing prices), Garman and Klass (1980) further derive a "best" variance estimator, which is unbiased and has minimum variance with an even higher efficiency of 7.4 times, while Beckers (1983) suggests an alternative optimal estimator with a major difference from Garman-Klass's best practical estimator in considering the stocks' relationships with each other. These two estimators, which incorporate all four price series, inspire researchers to realize ignoring other price dynamics will have a substantial cost for accuracy.

Rogers and Satchell (1991) find putting high, low, opening and closing prices together achieves an even better representation of variance than does using only high-low prices in two different ways: first, the variance is smaller and second is the variance is independent of drift. To carry the findings one step forward, Dennis and Qiang (2000) point out that zero drift tends to overestimate risk while there being no price jump at the opening of the trading day results in risk underestimation. Therefore, they present a modified volatility estimator accompanied by nice properties, which are consistent in dealing with the opening price jump and remain un-biased irrespective of drift. Alternatively, a slightly different solution to the problem of the opening price jump is to treat it as an unobserved evolution of after-hours effects, in addition to using true price range data instead of normalized high-low spreads. This makes the method addressed by Buescu, Taksar, and KonÉ (2013) more practical when investigating a smaller number of data points.

Recently, Fiszeder and Perczak (2013) analytically evaluate and confirm the properties of the popular Parkinson, Garman-Klass and Rogers-Satchell volatility estimators. They also process the aforementioned models and derive the expected values and mean square errors of those models under both zero drift and non-zero-drift assumptions. The fact that high-low equity prices are characterized by a persistent correlation with each other enables the formulation of the new volatility estimators mentioned earlier, which sheds light on testing whether high-low prices' prediction models could still retain the consistent long-run relationship. Therefore, it is worthwhile to examine the properties of new volatility estimators based on different high-low prediction models in explaining the risk-return relationship.

2.3 High-low prices' prediction models

2.3.1 Engle and Granger ordinary least squares model

The starting point of high-low prices' forecasting models is the analysis of the co-integration concept. From the perspective of econometrics, whether a long-term equilibrium relationship between two integrated variables of the same order exists is the key property of co-integration (Wooldridge, 2009). Earlier, with the purpose of making spurious regressions involving variables governed by a unit root process possibly meaningful, Engle and Granger (1987), Johansen (1988) and Johansen and Juselius (1990) each give different formal treatments to the notion of co-integration but all are connected with an error-correcting mechanism. Given that, Cheung (2007) develops the so-called vector error correction model (VECM) assuming no price drift.

Empirical tests performed in the United States prove that the high and low prices of three major stock indices, the S&P 500 Index, the Dow Jones Industrial Index and the

NASDAQ Index, exhibit a co-integration relationship, while each of the high and low prices evolves as a random walk in time (Cheung, 2007). In reality, not only in the United States, but also in the national stock prices of the other three of the world's four largest stock markets – the U.K., Japan and Germany – also include a unit root process (Lee & Jeon, 1995). The fact that eight more country indices' pass the VECM co-integration tests demonstrates co-integration between the highs and lows is not a minor phenomenon (Cheung, Cheung, & Wan, 2009). Furthermore, Mok, Lam, and Li (2000) have proved that daily high-low prices in the Hang Seng and S&P 500 index futures wander randomly over time.

With reference to error correction mechanisms, Engle and Granger (1987) find price range is a proper instrument to express such an error correction term, which guarantees their two-step co-integration model captures the fundamental correlation embodied in the high and low prices. Building upon such clever way to circumvent the direct estimation of the error correction term, Cheung, Cheung, and Wan (2009) further find the co-integration concept is also supportive to forecast high-low prices and ranges of stock indices by using VECM. Grounded in Cheung's findings, the superiority of VECM forecasts is also confirmed in high-low exchange rate application (He & Wan, 2009).

Nevertheless, the investigation of high-low prices prediction is not limited to using VECM. When Caporin, Ranaldo, and de Magistris (2013) implement a fractional vector autoregressive model with error correction (FVECM), a more precise model candidate is put forward. This alternative model's flexibility fits well not only with the prediction of high-low prices but also with technical trading performance, since the analysis is in a fractional context, which is a wider sense. In this paper, the simplified Engle-Granger Ordinary Least Squares (EG-OLS) approach has been chosen to forecast high-low prices and price ranges, with the primary objective of explaining the risk and return relationship. In the subsequent section, the practical relevance of using high-low prices' forecasts based on EG-OLS will also be examined in the context of technical analysis, that is to say, simple technical trading strategies and options transactions.

2.3.2 Engle and Granger non-linear least squares model

Since the Engle-Granger Ordinary Least Squares (EG-OLS) procedure mentioned above is able to provide super-consistent coefficients, it is widely observed that many time series of analytical interest follow this two-step model when the long-term relationship between variables of interest could be expressed by a co-integration relationship (Stock, 1987). However, there has been considerable debate about the appropriate test statistics for the EG-OLS regression model, though ordinary least squares (OLS) estimates are generally believed to be reliable.

The major concern with EG-OLS is that the test statistics obtained from linear estimates lack standard asymptotic distributions (Liu, Margaritis, & Tourani-Rad, 2008; Stock, 1987), which will limit the capacity for testing long-term estimates and thus, will hurt the model’s efficiency. In other words, the difficulty in drawing meaningful critical values lies in the distribution of OLS coefficients, which is neither normal nor unbiased even in large samples. This will further complicate the task of applying the EG-OLS technique, as exemplified by Hamilton (1994). Complementary to the absence of a readily available hypothesis-testing technique, the fact that error embedded in coefficient estimates will not decay with the enlarged sample size, but will persist, will naturally lead to incorrect assessment by the model (Kao & Chiang, 2001). In general, EG-OLS should be implemented carefully before the underlying drawbacks have been remedied thoroughly. In order to improve the predictability of high-low prices, a modified Engle-Granger method using non-linear least squares will be illustrated below.

Phillips and Loretan (1991) re-examine the co-integration correlation and propose a model using a non-linear specification, which performs substantially better than the conventional OLS model. Contrary to EG-OLS, the Engle and Granger non-linear least squares model (EG-NLS) rectified both problems previously listed by keeping error away from simultaneous bias and producing useful statistical inferences on regression estimates, which are strongly supported by Barnhart, McNown, and Wallace (1999). Furthermore, the improved EG-NLS model is also applicable when taking into account past and future changes in the senses of adding leads and lags terms. In order to better capture the dynamics of the co-integration relationship, the modified EG-NLS model is flexible enough to incorporate all prior knowledge related to unit root process (Gonzalo, 1994). Overall, estimates obtained from the EG-NLS model might better evaluate the long-term economic equilibrium between integrated high and low prices than does the EG-OLS.

2.3.3 MIDAS

For financial analysts, the intuition concerning typical time series regressions involving factors of interest is to start their research with contemporary data. In practice, a situation often encountered is that utilizing only data with the same frequency might not fully take advantage of all the useful information available. Researchers are presented with challenges if some information is at a high-frequency level while other information is available on a low-frequency basis. The common solution is to ensure that the factors on each side of the equation have the same data frequencies. Potentially, regression models with dependent and independent regressors under the same time period tend to eliminate useful information content while instead, if the time frames on the two sides of the regression are different, they are likely to provide more information. For instance, applying monthly data alone makes it possible to ignore the details contained in daily data.

To conquer these problems, Ghysels, Santa-Clara, and Valkanov (2004) address a new way to construct regression frameworks, which is the so-called mix data sampling (MIDAS) approach. The MIDAS technique is a novel approach that estimates and forecasts conditional variances at low frequency from the weighted average of lagged squared returns from high-frequency data, the validity of which is confirmed by Miller (2011). For instance, monthly variance forecasts could be derived from weighted averages of lagged daily squared returns, with the weights given to each returns parameterized in a flexible form. As the introducers of the MIDAS approach, Ghysels, Santa-Clara, and Valkanov (2006) have also attested to the satisfactory performance of the MIDAS framework specified in empirical volatility forecasting with data sampled at different frequencies.

In comparison to the generalized autoregressive conditional heteroskedasticity (GARCH) model, the explanatory power of MIDAS is more favourable towards positive risk and return trade-off (Ghysels, Santa-Clara, & Valkanov, 2005). Later, Ghysels, Sinko, and Valkanov (2007) provide additional convincing evidence to supplement their previous studies on the positive risk-return relationship and meanwhile, several new extensions of the MIDAS technique have been proposed to demonstrate the value of the MIDAS approach regarding microstructure noise and volatility forecasting in more detail. In addition to concentrating on the financial area, the MIDAS mechanism has wide applications in economics and other areas. To illustrate, Clements and Galvão (2008) successfully adapt the MIDAS model to generate U.S. output growth forecasts, which is a crucial macroeconomic factor. In the context of empirical economic growth, the superiority of MIDAS nonlinear least squares compared to the traditional least squares has been verified (Andreou, Ghysels, & Kourtellos, 2010).

2.4 Corporate governance

It has been taken for granted that positive risk-return trade-off, which is stated as ‘higher risk predicts higher return’, could be described as the fundamental principle in finance. In other words, investors will punish risky investments more by requiring higher returns in order to avoid uncertainty. Such a relationship, which recognizes investors’ perception of risk, is captured by the risk aversion coefficients generated from regressions such as the famous capital asset pricing model (CAPM), the Fama and French Three-Factor model or the Carhart Four-Factor model (Bornholt, 2013; Gharghori, Chan, & Faff, 2007). Unfortunately, even though some findings agree risk aversion coefficients are positive, early financial researchers fail to reach a consensus due to most evidence being weak (Baillie & DeGennaro, 1990; French, Schwert, &

Stambaugh, 1987), whereas the existence of substantial negative relationships makes the story even more puzzling (Campbell, 1987; Glosten, Jagannathan, & Runkle, 1993). Therefore, given readily available risk aversion coefficients and corporate governance factors, it is a straightforward matter to explore what factors determine investors' attitudes towards volatility and how those factors change the investors' reactions.

According to López de Silanes, La Porta, Shleifer, and Vishny (1998), legal rules, which act as a mechanism through which investors protect themselves against expropriation by controlling shareholders and managers, surely have an impact on the size of financial markets, and ultimately, on economic development. The linkage between the legal system and investors' perception of risk is that poor protection of investors will distort the ability of external investors to receive their returns and increases the uncertainty of investments, thus depress investors' willingness to provide funds. As a result, economic growth might suffer. On the other hand, the more powerfully investors are able to execute their rights, the less risk averse they will be with respect to risky investments. In other words, the enforcement of laws and restrictions that limit insiders' controlling power and secures investors' property rights is a natural solution to corporate agency problems.

The fact is laws, resulting from different sources, address different degrees of investor protection. La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000) find common law systems generally have a higher level of protection of outside investors – both shareholders and creditors – compared with civil law countries. Alternatively, securities laws, focusing on regulating agency problems in new equity issuance, benefit stock markets by mandating disclosure and facilitating private enforcement rather than public enforcement through liability rules (La Porta, Lopez-de-Silanes, & Shleifer, 2006). Such regulations may further reduce investors' degree of risk aversion, thereby helping to attract more profitable opportunities and external financing due to the stronger protection for investors (Gompers, Ishii, & Metrick, 2003). Empirical evidence shows support for the previous notion that financial products issued by reputable authorities with less probability of default not only leads to higher stock returns but also to value enhancement (Bauer, Guenster, & Otten, 2004; Drobetz, Schillhofer, & Zimmermann, 2004). As a result, corporate governance factors, especially legal approaches, might be potential determinants in altering estimates of risk aversion, which represent the risk and return relationship.

2.5 Technical analysis

2.5.1 Trading stock indices

Researchers have examined the validity of technical analysis for more than a century since its origin in the late 1800s. Basically, technical analysis, a general heading for numerous technical trading rules, refers to studying the past price patterns of financial securities and related statistical summaries over time in order to better forecast future prices. Technical traders who believe price movements tend to repeat in the future will employ various types of technical trading rules. In fact, by simply following the technical analysis techniques with intuition, decisions made by investors indeed produce abnormal profits, whereas the efficient market hypothesis indicates there is no sign of compromise between market efficiency and technical abnormal returns. In hope of solving this on-going debate, researchers have undertaken extensive empirical studies, but conclusions on the usefulness of technical analysis remain elusive.

The term ‘efficient market hypothesis’ (EMH) implies that technical analysis should make investors no better off since past publicly available information should already be reflected in stock prices (Bodie, Kane, & Marcus, 2011). In other words, the existence of extra profits achieved from technical trading strategies is in sharp contrast to the widely accepted weak form of the EMH. Another reason technical analysis should be criticized is because past price tendencies are unlikely to re-occur. Therefore, simple technical trading rules aimed at identifying recurrent patterns should not yield abnormal returns. As a consequence of invertors choosing to adopt particular successful trading rules, the profitability of those rules would eventually be squeezed out and markets would be led to react to new information much faster (Reilly & Brown, 2012). Such a phenomenon illustrates an ongoing concern that the continuous outperformance of technical strategies is not guaranteed. Besides the efficient market hypothesis, other potential challenges that doubt the value of technical trading rules also exist.

Data snooping, which occurs when a set of data is analysed more than once, is also an important problem of technical trading and one from which academic researchers may suffer. Chartists who observe past price patterns hard enough and long enough will ultimately find rules that seem to generate extra profits. Theoretically, White (2000) formalizes the data snooping problem and states satisfactory investment performance based on selected models is possibly merely due to luck rather than any merit embedded in those models. Further, White's study also provides a reality check for data snooping in order to avoid mistaken results. The empirical study conducted by Ready (2002) also provides a reminder that the popularity of technical trading rules stems from a spurious result due to data snooping. Recently, as a more powerful approach to rule out the effect of data snooping, false discovery rate has been used to complement the existing White method and generally indicates little benefit is gained from technical analysis (Bajgrowicz & Scaillet, 2012).

In addition to data snooping, the impact of transaction cost is another issue that needs to be addressed. Alexander (1961) advocates that adjusting trading cost turns profitable technical trading strategies into inferior ones when compared to the naïve buy-and-hold strategy. This conclusion is supported by Fama and Blume (1966). Using genetic algorithms to derive trading rules leads to the conclusion that the market is efficient where earning excess returns after transaction cost is impossible more robust (Allen & Karjalainen, 1999). The false discovery rate approach mentioned earlier also provides evidence against the validity of simple technical trading rules in that the magnitude of the profitability is insufficient to make the after-transaction-cost returns attractive to investors.

In contrast, recent academic literature tends to provide reliable evidence in favour of technical analysis, which sheds light on examinations of the sources of profitability. In perhaps the cornerstone of most comprehensive technical trading strategies investigations yet conducted, Brock, Lakonishok, and LeBaron (1992) find 26 technical trading rules applied to the Dow Jones Index from 1897 to 1986 significantly outperform the benchmark of holding cash and that the four other popular models, random walk, AR(1), GARCH-M and Exponential GARCH, have weak explanatory power over the profits. Two of the simplest and most popular trading rules, moving average and trading range break strategy, which underpin the 26 variations, are tested through the bootstrap technique for data snooping. To illustrate, strategies like trading rang break are directly linked to local maximum and minimum stock prices, which are recognized to be especially useful when associated with high-low stock prices prediction. The corresponding price range forecasts derived from anticipated high-low prices are able to deliver superior investment performance with more certainty since investors are confident about future volatility (Caporin, Ranaldo, & de Magistris, 2013).

Brock, Lakonishok, and LeBaron’s (1992) findings are strongly supported by Sullivan, Timmermann, and White (1999) in particular, who test the positive results in more than 7000 variations in trading rules and formally quantify the data snooping bias using the White methodology. Unfortunately, they fail to find positive returns in the extended 10-year data set after 1986. The beneficial value of technical trading strategies to capture profit opportunities with bootstrap consideration is also valid in the New York Stock Exchange index (Kwon & Kish, 2002). On the premise that price movement is going to recur in the future, Gençay (1998) claims non-linear conditional estimates better characterize the predictability of stock returns dynamics in terms of simple technical trading analysis than do other estimates. Even in a costly trading environment, Alexander (1961) and Sweeney (1988) confirm the benefits derived from technical trading rules because they are able to beat the naïve buy-and-hold strategy.

On a demographic basis, technical analysis is shown to be successful not only in developed countries, but also in emerging markets, which are generally believed to be less efficient. In the absence of transaction cost, that the realization of positive returns building upon technical trading rules is replicable in the U.K. notes on a weak form efficiency of capital market (Hudson, Dempsey, & Keasey, 1996). Further, some supportive evidence from developed countries – the U.S., Hong Kong and Japan – is given by Cai, Cai, and Keasey (2005). On the other hand, emerging markets vary in size, age and level of market efficiency. Rapid economic growth in Asian countries has interested some researchers. In the case of the Chinese stock market, Tian, Wan, and Guo (2002) extend the arbitrary 26 trading rules as implemented by Brock, Lakonishok, and LeBaron (1992) and Bessembinder and Chan (1995) into 412 rules and promote the usefulness of technical trading strategies, even in the presence of transaction cost; their results are approved by Cai, Cai, and Keasey (2005). Bessembinder and Chan (1995) find simple technical trading strategies are applicable in some other Asian stock markets, such as those of Malaysia, Thailand and Taiwan. Rather than investigating data that is widely accessible, the employment of technical trading strategies also generates excess returns for investors even in four emerging countries in south Asia, for which data on the stock exchanges became available quite late; namely, indices for Bangladesh, India, Pakistan and Sri Lanka (Gunasekarage & Power, 2001). Potential profits of technical strategies are also reported in Latin American (Ratner & Leal, 1999).

In the context of foreign exchange markets, a variety of empirical studies support the notion that technical trading rules yield significantly positive returns. According to Levich and Thomas III (1993), abnormal profits produced by simple technical rules in exchange markets has survived in new robustness tests based on bootstrap methodology. LeBaron (1999) agrees the production of unusually large profits in excess of transaction cost can stem from technical analysis and further points out that the predictability of future exchange prices is strengthened by central bank intervention. In line with his previous study concerning stock price forecasting, Gençay (1999) shows nonlinearity plays an essential role in foreign exchange rate prediction from past buy-sell trading signals of simple technical trading strategies. The assessment of trading signals identified by penetration of support and resistance levels in terms of three exchange rate series highlights the profitability of trading the range break strategy in exchange markets, even after taking transaction cost into account (Curcio & Goodhart, 1992). The notion that price range forecasts capture the property of volatility ultimately underpins trading in derivatives.

2.5.2 Trading options

Derivatives, options especially, are heavily traded in modern financial markets and therefore receive considerable attention from researchers. Cheung, Cheung, He, and Wan (2010) propose an options trading strategy based on the co-integration concept once the Hong Kong callable bull/bear contract has been launched. Such a strategy produces market trading signals regarding entry and exit points when the forecasts of daily highs and lows are obtained that yields some decent returns on average, net of transaction and interest costs. Instead of investing in barrier options contracts, traders tend to choose straddles, which as one of the most popular options trading strategies constitutes a large amount of volatility trades except the naked call or put trades in the U.S. options market (Chaput & Ederington, 2005). Specifically, the straddle is preferable to other volatility trades in that it is proved to be more sensitive to the wave in volatility, to minimize transaction cost and to have high liquidity. Improvements on the conventional straddle strategies substantially enhance their ability to gain profits (Laubie, 2010). Supplementary to generating extra profits, straddle options are a powerful instrument to hedge and price market volatility (Brenner, Ou, & Zhang, 2006). Chen (2003) also confirms that it is profitable to engage in straddle trading based on different transaction cost assumptions in currency markets.

2.6 Hypotheses Development

On premises derived from previous studies, I formally state several hypotheses.

Hypothesis 1: *There is a positive relationship between risk and return across 48 specified countries.*

Rational investors, who are risk-averse, will require higher returns if they choose to bear greater risk. In other words, risky investments are undertaken only if investors are compensated by higher returns. The conclusion that there is a positive relationship between risk and return will be more reliable and robust based on empirical evidence from 48 countries all over the world.

Hypothesis 2: *The frequency of finding a positive risk-return relationship is higher when the volatility estimator is based on predicted high-low stock prices rather than on historical data.*

Examining historical data is similar to looking backwards. Researchers may fail to find positive risk and return trade-offs simply because the correlation does not occur due to reasons like a financial crash, market inefficiency, the different methods researchers choose or the different time periods they pick. On the contrary, only investors who expect higher future returns will be willing to bear more risk. Therefore, volatility estimators based on forecasts of high-low stock prices are more likely to present a strong positive correlation between risk and return than are historical data.

Hypothesis 3: *The relationship between risk and returns depends substantially on legal factors, especially laws and enforcement.*

Variance parameters generated from risk and return regressions are actually risk aversion coefficients. The linkage between risk aversion coefficients, which measure how investors dislike risk, and legal enforcement factors, a set of mechanisms through which investors prevent themselves from experiencing unfairness, could be explained by the rationale that stronger investor protection tends to persuade investors to provide funds, since they believe the investments are less risky. In other words, a reduction in the level of risk aversion by means of legal protection and law enforcement is central to understanding why firms raise more funds, which should be reflected in the numerical investigation.

Hypothesis 4: *The co-integration mechanism for generating trading signals should result in abnormal returns regardless of financial products.*

Using predicted high-low stock prices based on the Engle and Granger linear co-integration model to generate trading signals should confirm the superior performance of simple technical trading strategies applied in stock indices and options markets. Such successful trading strategies that rely on high-low prices' forecasts and by-product price ranges play key roles in trading financial products in that the high-low prices forecasts are able to better model trading bands while the range forecasts could be an accurate proxy for underlying return volatility.

Chapter 3 Data

The data series used in examining the risk and return relationship comprise 48 countries around the world, which cover a large share of international stock market capitalization and liquidity. The choice of those stock indices, which represent the market index for each country, is largely dictated by data availability. Therefore, the primary criterion driving the indices collection process is to ensure stock indices acquired provide data over the longest period available (see Appendix A for a complete country list and corresponding market stock indices). This principle is followed because the sample has the statistical property of representativeness because it contains bull as well as bear markets such as the recent global financial crisis. The whole data set is obtained from the website of Global Financial Data (GFD). Observations include data both on a daily and monthly basis and are cut and matched up when the first different monthly high and low indices prices appear. Although each country's stock index begins at a different time, the ending point is set to be November 2013 with three exceptions, which are Israel, Venezuela and Kenya due to the absence of trading volume in the last several months or years.

The most important reason 48 countries have been selected is that the country list is congruent with the list provided by La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000), who have assembled a large sample of countries to better understand the role of investor protection via legal approaches. Corporate governance characteristics that could be summarized such as the strength of legislation, the development of stock markets and the efficiency of corporate management might be able to explain why the risk and return relationship exhibits different patterns in different countries. That is to say, having different degrees of protection may explain why investors react to risk differently in one country than in another. Therefore, this paper focuses on the effective legal rules introduced by Rafael La Porta on explicating investors' perception of risk with corresponding data collected directly from the Data Library on his website. Initially, López de Silanes, La Porta, Shleifer, and Vishny (1998) build the country list with 49 countries. However, due to the absence of data from Zimbabwe on the GFD website, I remove that country from the list.

Specifically, U.S. data provides us with an ideal opportunity to estimate the validity of technical trading since the market is more efficient than other markets, which will minimize the probability of the presence of predictable risk in stock returns. In other words, it is least likely that abnormal returns will occur in the U.S. market since it is generally regarded as efficient. With respect to investigating simple trading rules on stock indices, both monthly and daily S&P 500 stock indices are applied. The monthly data set starts from the first trading day of 1918, while the daily data begins at the first trading day of 1930, but all end in November 2013. In total, it is a collection of observations on 96 and 84 years of monthly data and daily data, respectively. The yield of the three-month Treasury bill, with the same corresponding research time span as for the S&P 500 index, is a suitable proxy for the risk-free asset. GFD provides all the data mentioned above.

On the other hand, the exercise price and costs of related S&P 500 index call and put options are gathered from DataStream covering 14 years trading history from September 1999 until November 2013. The price level of the S&P 500 index on Friday of the third week in each month during the options trading period is recorded as the current price of underlying options in order to value the options' payoff. Whether the prices series used are in plain or logarithmic form will be mentioned before the discussion of each model.

Chapter 4 Methodology

4.1 Historical data

It is intuitively understood that the analysis of risk and return trade-off begins with the most straightforward single factor market model, the properties of which CAPM is often based on (Hillier, Grinblatt, & Titman, 2008). To understand the market model, the positive slope coefficient suggests that expected returns in equity markets vary positively with market variance. The expression for the model regression (Eq.1) is simply an equation between the historical market returns of each country with the corresponding market variance specified in month t:

$$R_{c,t} = \alpha_1 + \beta_1 * VAR_{c,t} \tag{1}$$

$$R_{c,t} = \mathrm{Log}(\mathrm{Pc}_{\mathrm{c,t}}/\mathrm{Pc}_{\mathrm{c,t-1}}) \tag{2}$$

where $R_{c,t}$ represents monthly market returns for country c and VAR is the symbol of variance, which is the standard deviation calculated from the daily returns in month t. The risk coefficient, β_1, measures the direction and sensitivity of market returns' co-movement with market variance; while the intercept α_1 should capture what else is left. Both risk and return data applied in Eq.1 rely on S&P 500 index closing prices without dividend adjustment. Eq.2 describes how to generate percentage returns when a logarithm form is used, in which $\mathrm{Pc}_{c,t}$ denotes either monthly or daily closing prices for country c corresponding to the respective data frequency.

As financial markets in the real world are not perfectly efficient, it is unavoidable that closing prices may fail to contain all available and necessary information. In practice, high and low prices could be monitored continuously while closing prices are merely snapshots in trading intervals. This makes concentrating only on intermittent closing prices not sufficient, and totally ignores other useful information embedded in other sources of prices. As a result, taking advantage of high and low prices rather than of closing prices alone might give us a better picture of how the risk and return relationship is affected, since the volatility estimator constructed on the basis of high and low prices is more efficient than the classic one. The difficulty is in the lack of a readily available transformation equation that incorporates both high and low equity prices to replace the variance factor in the first regression. Fortunately, Parkinson (1980) provides such a function, which is illustrated as follows,

$$VAR^{*}_{c,t} = \frac{(\mathrm{p}_{\mathrm{t}}^{\mathrm{H}} - \mathrm{p}_{\mathrm{t}}^{\mathrm{L}})^2}{4(\log_{\mathrm{e}}2)} \tag{3}$$

$$R_{c,t} = \alpha_2 + \beta_2 * VAR^{*}_{c,t} \tag{4}$$

The improved volatility representative is constituted of two parts (Eq.3). The numerator takes the square of the differences between the logarithms of high and low prices in the same month t, while the denominator is a constant. Basically, the second regression (Eq.4), including the historical high-low prices, has exactly the same format as the first one except the new monthly risk parameter, $VAR^{*}_{c,t}$. Again, a positive risk and return relationship will be proved by positive β_2, which detects if risk and return co-move in the same direction.

4.2 High-low prices' forecasting models

4.2.1 Engle and Granger ordinary least squares model

The notion of co-integration raises the chance for regressions involving integrated variables to be meaningful, but also produces risks of running spurious regressions in many cases. The applied co-integration methodology in this study is related to pursuing the dynamic properties of high and low prices, which might naturally lead to the answer to whether high and low prices are predictable, and thus better explore the relationship between risk and return. So far as is known by the literature, high and low equity prices follow a random walk individually, whereas the price difference is co-integrated and has integration of order zero. In other words, high and low price ranges might diverge temporarily, but in the long run, they converge. Therefore, the co-integrated variables provide a useful way to understand model predictability, which includes the plain high-low price prediction, the by-product, price range prediction and the new volatility estimator prediction. The main obstacle is how to model and forecast high and low prices by appropriately taking advantage of the co-integration property. Fortunately, with minor modifications, the simple and elegant two-step Engle and Granger ordinary least squares model focusing on the notion of co-integration illustrated in Enders (1995) is applied to enrich high-low price forecasting. All price series are de-trended by using logarithmic form before applying in the equations.

By definition, whether a co-integration relationship is applicable depends on whether the high-low prices are integrated of the same order. Hence, before formally implementing the Engle and Granger co-integration linear model, the frequently used Dicky-Fuller test (known as the DF test) is first carried out to pre-test this primary assumption. The DF test for high and low prices is summarized below.

$$\Delta p_t^H = \alpha_H + \theta_H p_{t-1}^H + \epsilon_t^H \qquad (5)$$

$$\Delta p_t^L = \alpha_L + \theta_L p_{t-1}^L + \epsilon_t^L \qquad (6)$$

The procedure of the DF test for high prices is illustrated in Eq.5, which is a regression between delta price high in time t (Δp_t^H) with itself, but one-period lagged. Following the same testing logic, Eq.6 is applicable for low equity prices. As stated by the unit root hypothesis, the null hypothesis is that the high and low equity prices should have θs (θ_H and θ_L) close to zero, and therefore variables are proved to infer the same number of unit root. The problem that the usual critical values for t statistics do not apply in unit root tests is solved by Dickey and Fuller, as they provide corresponding statistical values for DF or Augmented Dickey Fuller (ADF) tests at various significance levels. If the variables of interest, which are high and low prices in this case, exhibit a unit root process, or, say, integration of order one, the applicability of co-integration method is further tested by the Engle and Granger ordinary least squares procedure (EG-OLS).

$$\mathrm{p_t^H} = \beta_0 + \beta \mathrm{p_t^L} + \epsilon_\mathrm{t} \tag{7}$$

$$\hat{u}_t = \mathrm{p_t^H} - \hat{\beta}_0 - \hat{\beta}\mathrm{p_t^L} \tag{8}$$

$$\Delta\hat{u}_t = a_0 + a_1\hat{u}_{t-1} + \sum_{i=1}^{5} a_{i+1}\Delta\,\hat{u}_{t-i} + \epsilon_\mathrm{t} \tag{9}$$

Based on the intuition that the high and low prices are interlinked, in order to determine if they are actually co-integrated, the EG-OLS test is used to estimate their long-term relationship. In the form of Eq.7, price high $\mathrm{p_t^H}$ is regressed with the contemporaneous price low $\mathrm{p_t^L}$ directly, from which the correlation coefficient β captures the long-term equilibrium between high and low prices. After the value of β is estimated, residuals sequences, $\hat{u}_t$, given by Eq.8, are denoted as the series of estimated residuals of how high and low prices interacted dynamically. Studies suggest that only when beta is known in advance would the normal DF or ADF critical values be appropriate, since test statistics used to assess the significance magnitude of a_1 in Eq.9 should reflect the fact that the residual terms are generated from a beta-estimating regression (Enders, 1995; Wooldridge, 2009). To determine if these residual terms are stationary, an EG-OLS test is performed with the same format as ADF in that five residual lag terms are intended to correct any potential serial correlation problem, except the EG-OLS critical values that account for beta estimation is the correct tool to measure statistical inference. Again, the only difference between ADF and the EG-OLS test here is the corresponding critical values, which are compared in Appendix B.

Unless the estimated residual terms are integrated of order zero, the co-integration strategy is not suitable. In other words, if there exits any number β ($\beta \neq 0$) that guarantees the residuals do not contain a unit root, the conclusion that high and low prices are co-integrated can be drawn. Obviously, the EG-OLS test presented in Eq.9 has substituted the residual sequences with the high and low prices in the previous unit root tests (Eq.5 and Eq.6), along with five lag terms. If the null hypothesis, which is $a_1 = 0$, is rejectable, residuals based on the estimated beta are expressed zero order to integration, and thus high-low prices are co-integrated. While instead, failure to reject the null hypothesis implies residual sequences are governed by a unit root process, which sustains the non-stationary property. Given that, the criterion to decide whether the co-integration relationship between high and low prices is valid is clear. Loosely speaking, if a_1 is located between -2 and 0, residuals are concluded to be stationary and a co-integration relationship exits (Enders, 1995).

Basically, the formal implementation of the two-step EG-OLS strategy to forecast high-low prices is based on the rationale of first-step coefficient generation followed by price forecasting. In line with the EG-OLS co-integration test, the process of modelling high-low prices starts with the beta estimation, which captures how these two price series are correlated. In fact, even though Eq.10 and Eq.12 below show beta collection equations identical to Eq.7 and Eq.11 and Eq.13 also record residual terms following Eq.8 with differences in parameter presentation, they are listed again to make the procedure discussed easy to understand. To be more specific, beta coefficients and saved residuals generated from two separate sets of regressions, where Eq.10 and Eq.11 are for high prices while Eq.12 and Eq. 13 are for low prices, are the preparations for future high-low prices' forecasts. The underlying idea is that if high and low prices are co-integrated, the residual terms motivate the error correction mechanism, since it is an appropriate expression instrument (Enders, 1995).

$$\mathrm{p}_{\mathrm{t}}^{\mathrm{H}} = \beta_h + \beta_H \mathrm{p}_{\mathrm{t}}^{\mathrm{L}} + \epsilon_t^H \tag{10}$$

$$\hat{u}_t^H = \mathrm{p}_{\mathrm{t}}^{\mathrm{H}} - \hat{\beta}_h - \hat{\beta}_H \mathrm{p}_{\mathrm{t}}^{\mathrm{L}} \tag{11}$$

$$\mathrm{p}_{\mathrm{t}}^{\mathrm{L}} = \beta_l + \beta_L \mathrm{p}_{\mathrm{t}}^{H} + \epsilon_t^L \tag{12}$$

$$\hat{u}_t^L = \mathrm{p}_{\mathrm{t}}^{\mathrm{L}} - \hat{\beta}_l - \hat{\beta}_L \mathrm{p}_{\mathrm{t}}^{\mathrm{H}} \tag{13}$$

Building upon the beta estimates (Eq.10 and Eq.12), the saved residuals (Eq.11 and Eq.13) are able to appropriately express the error-correction terms and can be substituted in the following coefficient estimation equations (Eq.14 and Eq.15). Eq.16

and Eq.17 are the finalized equations.

$$\Delta P_t^H = a_0 + a_H\left(\mathrm{p}_{\mathrm{t-1}}^{\mathrm{H}} - \hat{\beta}_h - \hat{\beta}_H \mathrm{p}_{\mathrm{t-1}}^{\mathrm{L}}\right) + \sum_{i=1}^{5} a_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} a_{2i}\Delta P_{t-i}^L + \epsilon_t^H \quad (14)$$

$$\Delta P_t^L = b_0 + b_L\left(\mathrm{p}_{\mathrm{t-1}}^{\mathrm{L}} - \hat{\beta}_l - \hat{\beta}_L \mathrm{p}_{\mathrm{t-1}}^{\mathrm{H}}\right) + \sum_{i=1}^{5} b_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} b_{2i}\Delta P_{t-i}^L + \epsilon_t^L \quad (15)$$

$$\Delta P_t^H = a_0 + a_H \hat{u}_{t-1}^H + \sum_{i=1}^{5} a_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} a_{2i}\Delta P_{t-i}^L + \epsilon_t^H \quad (16)$$

$$\Delta P_t^L = b_0 + b_L \hat{u}_{t-1}^L + \sum_{i=1}^{5} b_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} b_{2i}\Delta P_{t-i}^L + \epsilon_t^L \quad (17)$$

Co-integration vectors are measured by parameters $\hat{\beta}_h$, $\hat{\beta}_H$, $\hat{\beta}_l$ and $\hat{\beta}_L$ while a_0, a_H, a_{1i}, a_{2i}, b_0, b_L, b_{1i}, b_{2i} are all coefficients of interest. Again, 5 lags are used for both high and low price changes in case serial correlation bias exists. As soon as all coefficients are estimated, predicting delta price high (low) at the next time period (ΔP_{t+1}^H & ΔP_{t+1}^L) is straightforward.

$$\Delta P_{t+1}^H = \widehat{a}_0 + \widehat{a}_H\left(\mathrm{p}_{\mathrm{t}}^{\mathrm{H}} - \widehat{\beta}_h - \widehat{\beta}_H \mathrm{p}_{\mathrm{t}}^{\mathrm{L}}\right) + \sum_{i=1}^{5} \widehat{a}_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} \widehat{a}_{2i}\Delta P_{t-i}^L + \in_{t+1}^H \quad (18)$$

$$\Delta P_{t+1}^L = \hat{b}_0 + \hat{b}_L\left(\mathrm{p}_{\mathrm{t}}^{\mathrm{L}} - \hat{\beta}_l - \hat{\beta}_L \mathrm{p}_{\mathrm{t}}^{\mathrm{H}}\right) + \sum_{i=1}^{5} \hat{b}_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} \hat{b}_{2i}\Delta P_{t-i}^L + \in_{t+1}^L \quad (19)$$

Obtaining forecasts of delta price high (low) one period after the estimation interval is relatively convenient according to Eq.18 and Eq.19, behind which the logic is the same as that for the coefficient estimation equations. As a consequence, the predicted high (low) price changes allow direct high-low price levels forecasts and indirect price range forecasts to be built. The one-step-ahead delta price high (low) prediction utilizes the information embodied in high and low prices just one period prior to the upcoming forecasting period, which represents the latest information available. Generally, the investigation is on a monthly basis. Two estimation periods are considered in the empirical employment of the linear co-integration approach. These are December, 2008 and October, 2011. The first estimation window is selected to obtain comparable results, for it concurs with the study conducted by Caporin, Ranaldo, and de Magistris (2013), in which the in-sample period covers the period from January, 2003 until December, 2008, while they leave an approximately two-year out-of-sample forecast interval. In the same manner, the second estimation period is determined to guarantee two years of out-of-sample data points corresponding to the data set in this study. Again, the Parkinson variance estimator is constructed by incorporating high-low prices forecasts to replace historical data, which creates a chance to better explain risk and return trade-off.

4.2.2 Engle and Granger non-linear least squares model

Previously, the high-low price prediction is based on a two-step Engle and Granger co-integration linear model, described as a parameter-generating followed by a forecasting process, which has its drawbacks. The major concern is that estimates obtained from ordinary linear-least squares, EG-OLS in this case, do not have standard asymptotic distributions, and thus result in difficulty in drawing meaningful statistical inferences. Furthermore, sample bias is unlikely to diminish but may persist in coefficient estimates under linear specification even though sample size gets larger, which may cause incorrect model assessment and decrease model efficiency. Instead, the main advantage of using the modified Engle and Granger non-linear least squares function (EG-NLS) is that estimates are asymptotically unbiased and normally distributed. In other words, the parameters are unbiased and are generated without losing model consistency. Supplementary to the two-step EG-OLS co-integration model, EG-NLS regression is also applied in order to improve forecasting accuracy and thus to better capture the exact relationship between risk and return.

$$\Delta P_t^H = c_0 + \mathrm{c}_1\left(\mathrm{p}_{\mathrm{t}-1}^{\mathrm{H}} - c_2\mathrm{p}_{\mathrm{t}-1}^{\mathrm{L}}\right) + \sum_{i=1}^{5} c_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} c_{2i}\Delta P_{t-i}^L + \epsilon_t^H \tag{20}$$

$$\Delta P_t^L = d_0 + d_1\left(\mathrm{p}_{\mathrm{t}-1}^{\mathrm{L}} - d_2\mathrm{p}_{\mathrm{t}-1}^{\mathrm{H}}\right) + \sum_{i=1}^{5} d_{1i}\Delta P_{t-i}^H + \sum_{i=1}^{5} d_{2i}\Delta P_{t-i}^L + \epsilon_t^L \tag{21}$$

The EG-OLS model is altered to suit the use of a non-linear high-low price prediction model on the premise that the variables of interest are clearly in a co-integrated relationship. The first step in relation to coefficient estimation is similar to that of the EG-OLS, except that there is no separation between error-correction generation and subsequent model simplification. The EG-NLS combines the two steps into one and removes the intercept from the error-correction term (Eq.20 and Eq.21). This means that two sets of parameters of interest, which account for the co-integration relationship and serial correlation, are generated directly at the same time. The prediction step under EG-NLS is exactly the same as that under EG-OLS, despite the non-linear specification remaining. With the help of the R package “minpack.lm”, a function is provided to solve non-linear model implementation. Likewise, high and low price levels and price ranges could be generated based on results from predicted delta price highs and lows, providing two estimation periods of monthly frequency. The Parkinson new variance estimator is constructed once again.

4.2.3 MIDAS

A situation is often encountered in practice where available high-frequency data cannot be used directly if some of the other variables under examination are presented only in low frequency. Choosing to process data beforehand and thus render variables at the same frequency will result in giving up potentially useful information. As an alternative, Ghysels, Santa-Clara, and Valkanov (2005) recently propose a new regression framework to help analysts utilize time series data in different frequencies. This framework is so-called mixed data sampling (MIDAS). Together with the use of high- and low-frequency data simultaneously, the flexibility of the MIDAS technique may provide superior performance in constructing a new variance estimator and forecasting high and low prices. In other words, the MIDAS approach provides us with an opportunity to investigate the risk-return relationship from a new angle by mixing daily data with monthly data in order to better assess the conditional market variance.

Technically speaking, the MIDAS model involves regressing available low-frequency variables with explanatory vectors in various frequencies. Concerning the simple risk-return regressions in this study, returns on the left-hand side are in monthly intervals, while the representative agent of conditional variance on the right-hand side is the weighted average of lagged daily squared returns derived from a weighting scheme produced by a flexible function under the MIDAS approach. Monthly returns rather than daily returns are applied because higher-frequency data might be too noisy to be nicely exploited as conditional means, even though both data sets are available. On the other hand, the monthly variance, which is converted from daily squared returns, is described by the following formula:

$$V_t^{MIDAS} = 22 \sum_{d=0}^{\infty} w_d r_{n-d}^2 \tag{22}$$

V_t^{MIDAS} stands for the conditional variance calculated from the MIDAS approach in month t, which is comprised of the summation of the weighted average of lagged daily return squares. w_d is the optimal weight assigned to squared daily returns d days prior to the date n in month t, which is stated as r_{n-d}^2. The number 22 guarantees the variance is converted into a monthly frequency, as 22 is approximately the average number of trading days per month. In order to distinguish daily returns from monthly returns, lower case r is denoted as daily returns while upper case R signifies monthly returns throughout this paper. Conventionally, all weights have to sum to one. The scheme of the weights appointed to the squared daily returns is illustrated below in detail:

$$w_d(k_1, k_2) = \frac{\exp(k_1 d + k_2 d^2)}{\sum_{i=0}^{\infty} \exp(k_1 i + k_2 i^2)} \tag{23}$$

Eq.23 shows the weighting scheme works well with only two parameters k_1 and k_2 needing to be estimated, which has several advantages. First, the equation ensures the weights are all positive and in turn the conditional variance in Eq.22 is also positive. Furthermore, the weights capture how quickly the distant daily squared returns decay. If the weights weigh more on distant past returns, in other words, if the weights decay slowly, a large number of daily returns would enter into the measurement of conditional variance. In contrast, fast decay equates to less data at the cost of estimation accuracy. A practical issue is the infinity signs that are present in both Eq.22 and Eq.23, which make the empirical application of the MIDAS technique slight ambiguous. Because volatility varies with time and market conditions, recent observations should be able to more precisely measure and predict the level of variance in the next month. Therefore, 22 days is selected to replace the first infinite sum for d on account of data limitation, though Ghysels, Santa-Clara, and Valkanov (2005) use 252 days as the maximum lag length in the case of the U.S. market. In fact, 252 days, which is close to the average number of trading days in one year, seems to be too long to apply for some countries that have only short trading histories, while data availability is not an issue for studies based on the U.S. market. On the other hand, i in Eq.23 is also set to be 22 to simplify the calculation of weights. To estimate coefficients for future high-low price prediction, risk-return regressions have been applied separately for high prices and low prices with the new MIDAS variance:

$$R_{t+1}^{H} = \mu_H + \gamma_H * \mathrm{V}_{\mathrm{t}}^{\mathrm{Midas}} \tag{24}$$

$$R_{t+1}^{L} = \mu_L + \gamma_L * \mathrm{V}_{\mathrm{t}}^{\mathrm{Midas}} \tag{25}$$

Eq.24 and Eq.25 examine the relationships between high-low prices and conditional MIDAS variances, respectively. Subscripts denoting different time periods indicate that monthly risk in a specified month depends on daily return squares up to the last trading day in the previous month. That is to say, the risk and return regression for September relies on the monthly variance derived from daily returns until the last trading day of August. As soon as $\mathrm{k}_1, \mathrm{k}_2$ and risk coefficients are known jointly, out-of-sample forecasts for high and low prices could be calculated sequentially. Nevertheless, distinguished from the previous two co-integration prediction models, the MIDAS approach gives direct forecasts of high and low prices. Therefore, in constructing a new Parkinson volatility estimator, taking logarithms of forecast prices is necessary. The MIDAS technique seems to be complicated to apply. Fortunately, the R package specified as “Midasr” introduces handy tools that deal with the parameters’ generation and forecasting with mixed-frequency data.

4.3 Risk aversion method

For brevity, the risk aversion (RA) method is a combination of MIDAS and NLS technique. Such a method is independent of the high-low prices on which the previous three prediction models are based, assuming instead that only close-to-close variance from historical daily and monthly closing prices data is relevant. The underlying rationale of RA is similar to the market model, which is reflected by the same risk and return regression format demonstrated below. What differs is that the RA method uses a non-linear specification.

$$R_{\mathrm{t+1}} = \mu + \gamma * \mathrm{V_t^{Midas}} \tag{26}$$

$$\mathrm{V_t^{MIDAS}} = 22 \sum_{\mathrm{d=0}}^{22} \mathrm{r_{n-d}^2} * \frac{\exp(\mathrm{k_1 d + k_2 d^2})}{\sum_{\mathrm{i=0}}^{22} \exp(\mathrm{k_1 i + k_2 i^2})} \tag{27}$$

$R_{\mathrm{t+1}}$ on the left side of Eq.26 represents normal monthly returns, while the conditional variance on the right-hand side of the regression is based on MIDAS technique, which is shown in Eq.27. Obviously, the monthly variance is transferred from the weighted average of lagged daily squared returns, which is an expanded function of how variance is calculated under the MIDAS approach. The variable of most interest, coefficient γ, measures the magnitude of risk aversion and further determines whether a significant positive risk-return relationship exists. The Parkinson volatility estimator does not apply to the RA method since no high and low prices are included.

To sum up, there are nine series of risk aversion coefficients, three of them obtained from models using historical data only, that is, (1) historical closing prices, (2) historical high-low prices, and (3) the RA method. The other six are obtained from high-low price-prediction models, including (1) EG-OLS, (2) EG-NLS, and (3) MIDAS, with two estimation periods investigated for each of these. Whether the corporate governance factors addressed by La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000) could explain the puzzle of risk and return trade-off depends on the results of the analysis of nine series of risk aversion coefficients generated from previous regressions and two sets of corporate governance variables related to legal rules.

4.4 Technical analysis

4.4.1 Trading stock indices

Since high and low equity prices are key components in technical trading strategies, especially related to the strategy of trading range break (support and resistance), similar trading rules using high-low forecasting outcomes based on the EG-OLS model mentioned earlier are implemented, which contributes to the current literature to some extent. The development of the simple trading strategies in this paper aims to evaluate whether specific moving patterns that have appeared in historical high-low prices will re-occur in predicted price series. In other words, whether forecast high-low prices indeed carry relevant information in favour of profitable trading rules accompanying unexplained abnormal returns not due to common risk factors or luck. Although the success of simple technical trading strategies has already been proved by Brock, Lakonishok, and LeBaron (1992), their study concentrates on the ability to predict equity returns from past returns. Alternatively, Caporin, Ranaldo, and de Magistris (2013) conclude that anticipated high-low price ranges provide more accurate timing for investments, which improves trading performance. However, model outcomes obtained from EG-OLS in terms of high-low price forecasts have rarely been examined to draw conclusions about the usefulness of technical analysis.

Two simple technical trading rules are investigated. The first, range-based trading strategy, introduced by Caporin, Ranaldo, and de Magistris (2013), is quite similar to the frequently applied trading range break (resistance and support) strategy. Once the forecast high and low prices are generated from the EG-OLS model, the range forecasts come out automatically, denoted as $\hat{R}_{t+1}$. Two bands, the forecast upper and lower bands, centred on the opening price available today, P_t^o, are equal to $\hat{P}\,^U_{t+1} = P_t^o + \hat{R}_{t+1}$, and $\hat{P}\,^L_{t+1} = P_t^o - \hat{R}_{t+1}$, respectively, the width of which is two times the price range. From the high-low bands, a sell signal is defined when today's closing price penetrates the forecast upper band; if today's closing price crosses the lower band, a buy signal is obtained. The range-based trading strategy is characterised as the upper band being used as a resistance level to stop an uptrend while the lower band is treated as a support level to revive a downtrend, which is opposite to how trading signals are initiated under the range break strategy, but fits well with the features of contrarian strategy.

Another trading method is the midpoint strategy. The name itself notifies the relevant idea, which is the average of the forecast high and low prices and is stated as $\hat{P}_{t+1}^M = (\hat{P}_{t+1}^H + \hat{P}_{t+1}^L)/2$. To implement the strategy, investors should step into the market and initiate a buy position in a financial asset when the closing price today is below the predicted midpoint, and should exit the market and sell the assets once the closing price available today exceeds the midpoint forecast. The logic of the midpoint strategy is in accordance with the first range-based strategy discussed above, but is in a more flexible form and thus should result in more trading signals. Generally, for both strategies, restrictions on short selling are consistent with holding risk-free assets, but will be soon released. Concurring with Holmberg, Lönnbark, and Lundström (2013), no money management techniques such as stop-loss and take-profits are added. Depending on when the new highs and lows are hit, performance evaluation for both the range-based trading strategy and midpoint strategy on trading monthly and daily indices is measured on a percentage return basis.

4.4.2 Trading options:

Intuitively, predicted price ranges based on forecast high and low securities' prices signal directions towards which future volatility might move. Therefore, forecasting high and low prices not only helps develop profitable trading strategies, but also makes future risk feasible, which plays a key role in pricing options. In addition to the trading of stock indices, this study also focuses on analysing whether trading signals based on forecast high-low prices facilitate positive returns in trading options with the help of particular trading strategy designs. Such analysis of whether trading rules stand up to inspection for different financial products further helps evaluate the usefulness of technical trading rules.

Except the plain call and put options, financial literature shows that, in practice, the straddle is the most heavily traded volatility technique among other options strategies because it is more cost-efficient and sensitive to volatility. These merits also explain why the straddle is the choice for both many traders and this study. We collect from DataStream 14 years trading data of S&P 500 index options including call and put options prices, the exercise prices and index price levels once the data becomes available, from September 1999 until November 2013. The closing price for the index on Friday of the third week in each month is treated as the current price for the time when options mature. For each month, both dollar and percentage profits, irrespective whether they are positive or negative, are presented for the always buy and sell straddles strategies individually. To be more specific, the always buy straddle strategy corresponds to buying a call and a put options at the same exercise prices while the always sell straddle strategy means selling a call and put options at the same exercise prices.

Money Profit for buying a straddle = $\big(Max(S_t - Ex, 0) + Max(Ex - S_t, 0)\big) - (C_t + P_t)$

Money Profit for selling a straddle = $(C_t + P_t) - \big(Max(Ex - S_t, 0) + Max(S_t - Ex, 0)\big)$

Percentage Profit for buying a straddle = $\frac{\big(Max(S_t - Ex, 0) + Max(Ex - S_t, 0)\big)}{C_t + P_t} - 1$

Percentage Profit for selling a straddle = $\frac{(C_t + P_t)}{\big(Max(Ex - S_t, 0) + Max(S_t - Ex, 0)\big)} - 1$

In the four profit-calculating equations, S_t stands for the index value when options expire and Ex is the symbol for the exercise price. Call options generate positive payoff when the current price is higher than the exercise price, while put options buyers expect current price to drop below the exercise price. The payoffs of call and put options are represented by $Max(Ex - S_t, 0)$ and $Max(Ex - S_t, 0)$, respectively. Money profits is the options payoffs in excess of transaction cost illustrated by the summation of call options prices (C_t) and put options prices (P_t). The last two equations provide to the means of calculating percentage returns. Again, trading signals derived from the two trading strategies discussed above determine the timing of entry to and exit from the options market. Here, the buy signals give investors a recommendation to buy straddles and the sell signals mean it is better to sell the position in straddles. The usefulness of technical analysis depends on whether trading signals based on co-integration mechanisms yield abnormal returns for different types of financial assets. The following section discusses empirical results.

Chapter 5 Empirical Results

5.1 Risk and return relationship

5.1.1 Historical data

Appendix A contains the summary country list for the entire data series applied in the investigation of the risk and return relationship. Data with different frequencies has been processed in accordance with model assumptions, which will be mentioned before discussion. Beginning with the basic market factor model, which is a simple regression between risk and return, the model varies in volatility inputs depending on different price series and thus makes the outcomes comparable.

Table 5.1

Summary Risk Aversion Coefficients Using Historical Data

	Historical closing prices	**Historical High-low prices**
Positive	10	17
Negative	38	31
Significant 10%	P8&N31	P11&N27
Significant 5%	P8&N29	P11&N27

Notes: This table summarizes how frequently positive and negative risk and return trade-offs appear when different historical price series are examined. The market factor model is a simple regression between risk and return, with variations in volatility estimates. Historical monthly closing prices constitute the standard close-to-close variance, while the new volatility estimator incorporating historical monthly high and low prices needs the Parkinson transformation equation. In the table, Positive means the frequency of positive risk and return trade-off detected and the same logic applies to Negative. Numbers beside the capitalized characters P and N record the number of significant positive or negative coefficients. The corresponding statistical inference is provided at both 10% and 5% significance levels.

Table 5.1 summarizes how frequently positive or negative risk-return correlation coefficients occur among 48 countries, with accompanying t-statistics at both 5% and 10% significance levels. The capitalized characters P and N record the numbers of significant positive or negative risk aversion coefficients, respectively. Simply put, model outcomes only differ in variance inputs for the left-hand side outcomes is based on standard close-to-close variance while the new volatility estimator, which necessities the Parkinson transformation equation to incorporate high-low prices, is substituted in the market model and produces the right-hand side results. In other words, everything in common for monthly data in 48 countries has been processed in the same regression model except different data series are applied to construct volatility estimators, which makes the results comparable.

According to the market factor model, the volatility coefficient measures the relative magnitude of risk aversion. Unfortunately, neither the analysis based on closing prices, nor the analysis based on high-low prices yield expected significant positive risk and return trade-off. To be more specific, risk aversion parameters of only 10 out of 48 countries, which is merely 20.8%, are positive when standard variance is examined, while 35.4% (17 out of 48), which is slightly higher but is still less than 50% of risk aversion coefficients, is positive in the case of historical high-low prices, even without reviewing statistical inference. Apparently, the presence of a positive risk and return relationship is more frequent when the volatility estimator is based on high and low prices compared to merely using closing prices, which verifies the notion that high-low prices indeed convey more information. However, the fact that the majority of risk aversion coefficients are significantly negative at both the 5% and 10% levels clearly rejects hypothesis 1 regardless of which series of historical data is used. In particular, more than 76% (29 out of 38) negative volatility coefficients are significant at the 5% level and the percentage is even higher at a lower significance level for the outcomes of historical closing prices. The circumstances mentioned above are generally consistent with what Glosten, Jagannathan, and Runkle (1993) find in the case of the U.S. stock market. The second series of outcomes based on historical high and low prices underperform the first series results: as much as 87% (27 out of 31) risk coefficients are significantly negative at both two significance levels.

In addition to the simple risk and return market factor model, the alternative RA technique, which is a combination of non-linear specification and MIDAS volatility, provides opportunities to investigate the risk and return trade-off from a new perspective. The RA method particularly attempts to characterize the nature of closing prices, since it assesses both high and low frequencies data contemporaneously in one equation; in other words, both daily and monthly closing prices are modified to facilitate risk estimation in a non-linear sense. Results from the RA method are also comparable with the previous outcomes generated from historical closing prices because closing prices are the only data input in both approaches.

Table 5.2

Summary Risk Aversion Coefficients Using Historical Closing Prices

	Historical closing prices	**RA**
Positive	10	14
Negative	38	34
Significant 10%	P8&N31	P12&N34
Significant 5%	P8&N29	P10&N33

Notes: This table outlines to the frequency of positive and negative risk and return trade-off, based on two different models but with similar data inputs. The simple market factor model gives the results using historical closing prices while both monthly and daily closing prices have been applied in the RA method, which is a more complex model combining a non-linear specification and mixed data sampling. Positive and Negative represent the signs of risk aversion coefficients while the capitalized characters P and N account for the statistical significance at 5% and 10% levels in the same way as in Table 5.1.

Table 5.2 provides the answer to which model, the simple risk and return market factor model or the more complicated RA method using mixed data sampling, enjoys superiority. That is to say, the discussion of the RA method focuses on whether model complexity and different data frequencies actually contribute to impressive performance in understanding the risk and return relationship. In fact, in 48 countries, nearly 30% of risk aversion coefficients under the RA method are positive, with the magnitude of statistical significance increasing proportionally, which is roughly 10% higher than the results documented by the simple market regression. However, the power of the MIDAS approach to generate positive risk and return relationships has weakened in countries other than in the United States, since Ghysels, Santa-Clara, and Valkanov (2005) have disclosed a very significant positive risk and return trade-off in the U.S. stock market after ruling out the effect of subsamples and business cycles. Further, highlighted by almost 100% significant negative risk aversion parameters, the negative risk and return correlation is more robust under the RA method at both the 5% and 10% significance levels, which is at odds with hypothesis 1. A comparison of the two models illustrates that the evidence does not match the perception that the more comprehensive model seems to obviously outperform the simple one: thus, the non-satisfactory empirical results leave the problem of the risk and return relationship unresolved.

5.1.2 Forecast high-low prices

Thus far we have examined the risk aversion coefficients in regressions of returns on different variance approximation techniques using historical data. However, these are not the only possible choices: variations in methodology remain unexhausted. In fact, the main difficulty in uncovering the true risk and return relationship is the lack of an unbiased volatility representative, since market conditional variance is not observable. Therefore, in addition to using historical data, the features of anticipated high-low prices might also offer some needed explanatory power. To explain, conflicting findings of positive or negative risk and return trade-offs may vary in particular time periods or in particular approaches researchers choose that are based on historical data, while investors might be willing to bear more risk only if they expect higher future returns. Therefore, hypothesis 2 states that volatility estimators based on anticipated high and low prices are more likely to disclose a positive risk and return relationship than is historical data. The investigation of whether that phenomenon is valid will be discussed in the following paragraphs.

Table 5.3 displays the results in much the same way as in the previous two tables. Nevertheless, several differences should be noted. One of the differences is the data is input in the Parkinson transformation equation, which is forecast instead of historical high and low prices; another difference is the selection of two forecast periods. In the former analysis, it is not necessary to recognize forecast periods in that the entire historical data sample has been proceeding; that is not the case in forecasting models. The quality of prediction is directly determined by whether the selection of the estimation window is reasonable. The sample data utilized until the last trading day of 2008 and October 2011, corresponding to two forecast windows, separates the table 5.3 into two parts. As explained in the earlier discussion of methodology, the first estimation period has been chosen in order to be congruent with Caporin, Ranaldo, and de Magistris (2013). In their study, the estimation period ends on the last trading day of 2008. The second window is selected with the direct purpose of providing two years' out-of-sample forecasts, corresponding to around 500 sample data points, similar to Caporin, Ranaldo, and de Magistris (2013). In fact, the two forecast periods have gone beyond some countries' data availability, so that these forecasting blanks are left with NAs. As a result, in total, there are 47 countries represented in the first forecast period due to data from one country being missing, while analysis of the shorter forecast period is performed on 46 countries.

Table 5.3
Summary Risk Aversion Coefficients Using Forecast High-low Prices

2009.1-2013.11	**EG-OLS**	**EG-NLS**	**MIDAS**
Positive	37	45	36
Negative	10	2	11
NA	1	1	1
Significant 10%	P11&N8	P24&N0	P17&N2
Significant 5%	P7&N0	P20&N0	P12&N0
2011.11-2013.11	**EG-OLS**	**EG-NLS**	**MIDAS**
Positive	34	42	28
Negative	12	4	18
NA	2	2	2
Significant 10%	P9&N0	P14&N0	P10&N0
Significant 5%	P5&N0	P11&N0	P4&N0

Notes: This table presents the results for risk aversion coefficients with statistical inference at both the 5% and 10% significance levels. Three models, namely, (1) EG-OLS, (2) EG-NLS, and (3) MIDAS construct three distinct volatility estimators, which are applied in the risk and return regressions, continuously. Positive and Negative summarize the numbers of positive and negative risk aversion coefficients. Additionally, numbers besides the capitalized P and N represent the number of positive and negative risk aversion coefficients that are significant. The separation of the table into two parts is contingent on two forecast periods, in which the first interval forecasts data starting from the first trading day of 2009 while the other refers to data predicting after November 2011. NAs accounts for country indices' missing data.

Regarding the first forecast period, most of the estimated risk aversion coefficients that are based on three series of anticipated high and low prices in terms of new volatility measurements exhibit positive risk and return relationships, which could be interpreted from the high percentages of positive coefficients among the 47 countries in total, namely 78.7% (37 out of 47), 95.7% (45 out of 47) and 78.7% (36 out of 47). As usual, the characters P and N represent the numbers of significant positive and negative risk aversion coefficients. On average, the EG-NLS generates the greatest number of significant positive coefficients, even more than 50% (24 out of 45) at the 10% significance level in particular, than do the two other models, whereas none of the negative risk coefficients is robust. It is obvious that the non-linear specification, which corrects the potential problems in EG-OLS estimators, performs better in capturing a positive correlation between risk and return, which is explicated by the fact that EG-OLS obtains only 29.7% (11 out of 37) and 18.9% (7 out of 37) significant positive risk and return parameters at the 10% and 5% significance levels, respectively. On the other hand, the MIDAS technique outperforms the EG-OLS as well in displaying 47.2% (17 out of 36) and 33.3% (12 out of 36) significant positive risk-return parameters relative to two t-statistical tests, roughly 17.5% and 14.4% higher than in the EG-OLS framework. Alongside 2 robust negative coefficients, 6 less than the EG-OLS model at 10% level, MIDAS also performs better in terms of the downside of the model.

In the second forecast period, the relationship among the three prediction models in explaining the risk and return relationship is slightly changed, along with the decreasing proportions in all aspects. Although the EG-NLS continues to enjoy the highest ratio in attaining positive risk aversion coefficients without considering statistical tests, at 91.3% (42 out of 46), it fails to provide the highest percentage with respect to significant positive variance coefficients at the 10% significance level (33.3%), although it remains the highest at the 5% level (26.2%). The MIDAS technique provides the highest ratio at the 10% level but lowest at 5% level, which are 35.7% (10 out of 28) and 14.3% (4 out of 28), respectively. Again, the EG-OLS framework generates the fewest positive coefficients of risk aversion concerning 10% statistical hypothesis testing while it occupies the middle position at the 5% significance level. In general, the longer forecasting period, starting from January 2009 till November 2013, reports a higher magnitude and significance of positive risk aversion coefficients than does the shorter period, which corresponds to the last two years of the sample. The changes in the ratios might reveal the impact of adding 34 more months (2 years and 10 more months) to the estimation period, which automatically decreases the forecasting interval to two years. Exemplified by the smallest differences, altering the estimation window has the weakest effects on EG-OLS, while results from the non-linear model depend substantially on the selection of estimation periods. Due to the minor effect, EG-OLS is considered to be the model least affected by time intervals.

More importantly, the fact that a positive risk-return relationship is present more frequently when the volatility estimators are based on anticipated high and low prices rather than historical data, regardless of forecast periods, accompanying stronger statistical evidence, supports hypothesis 2. To illustrate, the minimum number of positive risk aversion coefficients based on forecast data is 28 under the MIDAS technique in the shorter forecast period, beginning in November 2011, which still exceeds by a large margin the maximum of 17 positive coefficients found by using historical high and low data for the entire period. Such findings confirm the statement that a positive and significant relationship between risk and return appears to be more frequent if high and low prices forecasts are examined in comparison to historical data.

Among the nine series of risk aversion coefficients constructed on the basis of nine variations in volatility measures, some countries express strong persistence in generating a consistent positive or negative risk and return relationship. Historical data contributes to three sequences of risk parameters, while the other six are derived from forecast models, including (1) EG-OLS, (2) EG-NLS and (3) MIDAS, in two estimation periods. Table 5.4 outlines that both Indonesia and Kenya continuously observe positive risk aversion coefficients across all nine variations in models, of which 66.7% (6 out of 9) coefficients are significant in the Indonesian market while the result is more robust in

Kenya, at 100%. The capability to extract positive risk and return trade-offs is slightly weaker in Brazil, Chile, Ecuador, Egypt, Korea and Turkey, where only one model fails to yield the expected correlation. In particular, 5 out of 9 risk aversion coefficients in the United States are positive with 2 significant at both the 5% and 10% levels. Such an outcome is mentioned because the United States is the most extensively examined country.

Table 5.4

Summary Risk Aversion Coefficients For Countries With Strong Persistence

Country	**Positive**	**Negative**
Indonesia	9	0
	(6/6)	(0/0)
Kenya	9	0
	(9/9)	(0/0)
Brazil	8	1
	(5/5)	(0/0)
Chile	8	1
	(5/5)	(0/0)
Ecuador	8	1
	(7/7)	(0/0)
Egypt	8	1
	(4/3)	(1/1)
Korea	8	1
	(3/3)	(1/1)
Turkey	8	1
	(4/3)	(0/0)
Nigeria	0	9
	(0/0)	(3/2)
Jordan	1	8
	(0/0)	(3/2)

Notes: This table reports the countries that show strong persistence in generating consistent positive or negative risk aversion coefficients across nine variations in investigation methods. Specifically, the nine models are related to regressions using (1) historical closing prices, (2) historical high-low prices, (3) the RA method, (4) EG-OLS, (5) EG-NLS and (6) MIDAS technique. Investigations using the last three models are conducted with two estimation windows. Numbers in parentheses beneath summarize the occurrence of significant coefficients at both the 10% and 5% significance levels, where the 10% level is given first followed by the 5%.

Nevertheless, Nigeria consistently reports 100% negative risk aversion coefficients throughout the nine methods and a consistent negative performance also appears in Jordan, but the statistical evidence is insufficient due to the small proportions of robust coefficients. Obviously, eight nations address a positive risk and return relationship in at least eight out of nine models, which outweighs the two countries with respect to consistent negative correlation by a wide margin. A statistical comparison between the 5% and 10% significance levels does not discover a large magnitude of change. Almost all the countries displaying persistent outcomes, no matter positive or negative, are developing countries, with only one exception, Korea. Reasons such as market instability, political issues or corporate governance problems may help to explain the extreme good or bad performance to some extent. Therefore, different risk and return relationship patterns taking place in the 48 countries motivates the necessity to explain.

5.2 Corporate governance

The volatility parameters generated in the previous section, which capture the exact relationship between risk and return, actually measure the magnitude of investors' risk aversion. Specifically, risk-averse investors will be willing to accept additional risk only if they are compensated by higher future returns, which exemplifies an obvious positive risk and return trade-off. Research on corporate governance has established a number of empirical factors to explain what affects risk aversion coefficients. Intuitively, whether shareholders and creditors are well protected should directly link to their perceptions of risk, which in turn relate to differences in the elements of financial systems, such as market liquidity, firms' ownership structures and the ability to attract external finance. Naturally, rational investors are supposed to be reluctant to invest in financial products which are dominated by controlling shareholders, since those controlling shareholders might benefit themselves at the expense of external investors in a variety of ways, such as simply stealing profits, diverting assets or overpaying executives (La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 2000). Extensive expropriation in a financial system may trigger investors' overreaction to risk and depress their willingness to provide funds. On the other hand, preventing investors from potential mistreatment through the law and its enforcement is likely to reduce investment uncertainty by diminishing insiders' controlling power.

In recent years, researchers have begun to examine, both conceptually and empirically, the cost and benefits of legal protections that might help explain why investors react so differently towards risky investments in different countries. La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000) provide two sets of key legal factors for 48 countries around the world on the measurement of investor protection in the forms of individual factors and classified groups, as well as the degree of law enforcement. Simple regressions between risk aversion coefficients and legal variables provide a novel way to consider the benefits of legal approaches to the reduction of risk aversion. Laws, protecting shareholders' and creditors' exercise of their intrinsic rights, are inherently characterized by different jurisdictions where securities are issued. The fact that investors are not granted the same level of power in all countries naturally determines investors' sensitivity to risk. Commercial law can be divided into two types, common law and civil law, which can be further sub-divided into families based on U.K. common law and those, based on French, German and Scandinavian civil law traditions.

Table 5.5

Results Summary for Four Legal Origins

	United Kingdom	**France/Spain**	**Scandinavia**	**Germany**
Positive	4	6	7	3
	(0/0)	(3/2)	(0/0)	(0/0)
Negative	5	3	2	6
	(3/3)	(0/0)	(0/0)	(0/0)

Notes: This table describes the relationship between risk aversion coefficients and four legal origins, namely U.K., France/Spain, Scandinavia and Germany. Investors will be more risk averse if the parameter generated with the legal family is positive, and vice versa. Similar to the previous section, there are nine variations in risk aversion coefficients under examination, where Positive indicates a positive relationship and Negative is a negative correlation. Statistical significance is reported beneath. The number first shown indicates how many t-values are significant at the 10% level, and the second number indicates how many t-values are significant at the at the 5% level.

In brief, table 5.5 shows that results vary across the four legal systems examined. Noticeably, there is a negative relationship between risk aversion coefficients and U.K. legal origin, summarized as 5 negative parameters out of the 9 variations in volatility estimators, 3 of which are significant at the 10% level. Concentrating on statistical significance helps us recognize that the France/Spain civil law family has the weakest investor protection, since half of the positive parameters are significant at the 10% level. That is to say, investors feel they have stronger protection in U.K. common law countries since negative parameters indicate a U.K. legal origin reduces risk aversion coefficients, and thus investors are less risk averse, whereas they feel especially unsafe in jurisdictions aligned to the French/Spanish legal family as reflected in significant positive parameters. The general patterns of the results are exactly the same as the findings in López de Silanes, La Porta, Shleifer, and Vishny (1998) and La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000). Countries aligned to the Scandinavian and German civil codes fall in the middle, but the order is inconclusive due to the absence of statistical significance.

According to La Porta, Lopez-de-Silanes, Shleifer, and Vishny (2000), investor protection against expropriation could be classified into three broad categories: shareholder rights' protection, creditor rights' protection and legal enforcement. The corresponding three indices could be further sub-divided into 28 variables. Shareholder protection focuses on elements such as voting rights, the ease of participation in making decisions, legal prevention of management expropriation. Rules to protect creditors include such matters as restrictions on reorganization, security of a loan, and the inability of management to receive undue profits. The quality of law enforcement addresses the risk of corruption, accounting standards and the efficiency of the judicial system, which are related to effectively preventing investors being expropriated. In fact, regressing volatility coefficients with a wide range of investor protection factors separately might dilute the explanatory power of such variables and cause insignificance, while the use of aggregating indices might help to enhance the effect. Therefore, a summary based on regressions between risk aversion coefficients and three classified grouping indices is shown in the following table.

Table 5.6

Results Summary for Investor Protection and Law Enforcement

	Shareholders	**Creditors**	**Enforcement**
Positive	4	4	4
	(0/0)	(0/0)	(0/0)
Negative	5	5	5
	(0/0)	(0/0)	(2/2)

Notes: This table tests how investors' perception of risk varies with the level of shareholders and creditors' protection and law enforcement. Intuitively, Positive indicates a simple positive relationship between risk aversion coefficients and legal factors while Negative indicates a negative correlation. Summations of significant t-values are provided in parentheses at both the 5% and 10% significance levels, where the 10% level is showed first followed by the 5% level. Again, nine variations in volatility estimators are applied.

In table 5.6, the relationship between risk aversion coefficients and shareholders and creditors' protection indices are vague in the absence of significantly uniform correlation parameters, which demonstrates that strengthening protection rules for investors is not valuable enough to change investors' perception of risk. On the other hand, law enforcement, as a substitute for weak performance in shareholders and creditors' protection rules, performs slightly better in favouring outsider investors. Compared to investors' protection, 40% of negative parameters are significant at both the 5% and 10% levels, indicating a strong system of legal enforcement keeps investors from improper expropriation and in turn reduces investors' resistance towards risky investments to some extent. Nevertheless, the evidence is too weak to support hypothesis 3.

Alternatively, La Porta, Lopez-de-Silanes, and Shleifer (2006) criticize the optimal legal arrangements hypothesis, suggesting government policy is meaningless, but promote securities laws to facilitate stock market development by means of regulating agency problems between insiders and outside investors. Based on their findings, the effect of securities laws on stock market development, focusing especially on mandatory disclosure, liability standards and public enforcement, might partially reduce investors' degree of risk aversion and thus offer some explanatory power over the variations in volatility estimators. The data provided by La Porta, Lopez-de-Silanes, and Shleifer (2006) is implemented in terms of indices, again in a combination of individual variables, rather than 88 provisions, to avoid a reduction of the statistical influence of characteristics. Table 5.7 shows there are eight dimensions of securities laws' attributes, where the last six could be summarized as the public enforcement variable. Specifically, public enforcement here differs from the enforcement factor mentioned previously in that the former concentrates on the role of a public enforcer in securities markets while the latter is more concerned with the avoidance of investor expropriation.

Table 5.7

Results Summary for Securities Law Factors

	Disclose	**Liability**	**Supervisor**	**Rules**	**Investigative**	**Orders**	**Criminal**
Positive	0	5	2	5	7	9	8
	(0/0)	(0/0)	(0/0)	(0/0)	(0/0)	(0/0)	(3/2)
Negative	9	4	7	4	2	0	1
	(3/3)	(0/0)	(4/4)	(0/0)	(0/0)	(0/0)	(0/0)

Notes: This table summarizes the relationship between risk aversion coefficients and securities law factors, which are disclosure requirements (Disclose), liability standards (Liability), characteristics of supervisor of securities markets (Supervisor), power of the supervisor to issue rules (Rules), investigative power of supervisor of securities markets (Investigative), stop and orders (Orders) and criminal sanctions (Criminal). Positive indicates a simple positive relationship between risk aversion coefficients and law variables and Negative is a negative relationship. Summations of significant t-values are provided in parentheses at both the 5% and 10% significance levels, where the 10% level is given first followed by the 5% level. Again, nine variations in volatility estimators are applied.

The benefit of disclosure requirements, uncovered by 9 unified negative parameters with 3 significant at the 5% and 10% level, indicates that the more restrictive the disclosure requirements are, the less risk averse investors tend to be, which is congruent with La Porta, Lopez-de-Silanes, and Shleifer's (2006) findings that disclosure is valuable to stock markets. In sharp contrast to their study, liability standards fail to exhibit an expected negative relationship through better facilitation of investors' recovery of losses from issuers, directors, distributors and accountants.

There is little evidence to confirm the ability of public enforcers to relieve investors' stress towards risk, except the Supervisor factor. The exception, which represents the characteristics of the supervisor of securities markets, is different to the findings in La Porta, Lopez-de-Silanes, and Shleifer (2006), who clarify public enforcement does not benefit the stock market at all. To explain, the attributes of the Supervisor including isolation from executives, demission after proper process instead of due to the will of the appointing authority and focusing only on securities markets, help to reduce investment uncertainty since less power has been delegated to the controlling party. However, factors with similar attributes regulating agency problems, that is, the power of the supervisor to issue rules (Rules) and the investigative power of the supervisor of securities markets (Investigative), do not reduce risk aversion coefficients.

In the case of stop and orders (Orders), which define certain types of actions that corresponding participants should conduct or be limited from, yield only positive parameters across the nine series of volatility estimators, but without statistical significance. Also, it is unreasonable that there is a positive relationship between risk aversion coefficients and criminal sanctions for the violation of securities laws (Criminal), let alone that the correlation is fostered by a few significant t-values. The unexpected effect of both criminal and non-criminal sanctions, accompanying the unidentified influence of the supervisor's power in relation to Rules and Investigative, except the Supervisor factor, fail to provide a consensus on whether public enforcement could reduce investors' perception of risk. As a result, the effect of the provisions of securities laws on altering risk aversion coefficients could not be established with certainty, and hypothesis 3 is rejected again. In general, although some of the legal variables and the quality of their enforcement factors indeed explain some differences in risk aversion coefficients across 48 countries, it is difficult to conclude that the risk and return relationship depends substantially on corporate governance, and especially on legal approaches, in the absence of convincing evidence.

5.3 Technical analysis

5.3.1 Trading stock indices

Technical analysis refers to studying past price patterns and summary statistics long enough and hard enough to better model and anticipate future prices without losing any persistence embodied in price dynamics, and thus generate abnormal returns. Based on high and low prices, several simple trading strategies are indeed supportive of the usefulness of technical analysis. There are two simple trading strategies specified in this study. The underlying trading mechanism of the first one, range-based strategy, is when the closing price available today penetrates the forecast upper band, a sell signal is generated; while a buy signal is initiated if the closing price available today crosses the forecast lower band.

The second trading mechanism, the midpoint strategy, defines buy and sell signals by comparing the closing price available today with the predicted midpoint, which is a simple arithmetic mean of predicted high and low prices. During the trading interval, investors should step into the market if the closing price available today is below the forecast midpoint, while investors should sell the underlying asset if the closing price known today is above the forecast midpoint. The midpoint technical trading rule is generally more flexible than the range-based strategy since it has only one band in comparison to the upper-lower two bands. Therefore more trading signals are expected. Both trading rules could be regarded as a type of contrarian strategy in that an ascending trend is resisted when price moves to the upper area of the price range and a descending trend is supported in the lower area of the range, which is consistent with the finding of Cheung, Cheung, and Wan (2009) that price range is regressive. The analysis of the performance of these two trading rules has been carried out on both a daily and monthly basis for the purpose of comparison. The created positions classify all trading days or months into either buys or sells without additional bands accounting for money management technique.

Table 5.8 reports the statistical summary for both monthly and daily returns based on the S&P 500 index. Returns are measured in log function and expressed in percentage terms. Full sample shows the length of time for which data was assessed. For both series of returns, all of the medians are higher than the averages, and the accompanying negative skewness values indicate the two sample series are skewed to the left. In addition, daily returns are more leptokurtic than are monthly returns, due to the reduction in Kurtosis values; nevertheless, the peaked distributions lead to small standard deviations. Table 5.8 has a relatively similar sample pattern to the data covered in Brock, Lakonishok, and LeBaron (1992), which is from the Dow Jones Industrial Average from 1897 to 1986, a collection of 90 years of daily data.

Table 5.8
Summary Statistics for Monthly and Daily Returns

	Full sample	**Mean**	**Median**	**Standard Deviation**	**Skew**	**Kurtosis**
Monthly return	1918.1-2013.11	0.6247%	0.9297%	0.0537	-0.5359	7.8559
Daily return	1930.1-2013.11	0.0201%	0.0439%	0.0114	-0.0275	16.5757

Notes: This table presents the statistical summary for both monthly and daily returns, which are measured as the log differences of S&P 500 index price levels and expressed in percentage terms. Data availability is denoted in the full sample while mean, median and standard deviations are calculated from time series data. Skew, which represents skewness, and Kurtosis are used to characterize the distribution of the data set.

For high-low price prediction purposes, table 5.9 describes selected results of co-integration relationship pre-tests based on two estimation periods, which are congruent with the periods examined in the risk and return section, with a minor modification. In the risk and return part, one of the estimation windows stops at October 2011 in order to leave two years out-of-sample forecast points, while instead, in the technical analysis section, a similar estimation window is investigated by utilizing the data until the last trading day of 2011. This is because the initial estimation period covers the first five years once the data is available on the first trading day in January, and expands one year each time, and thus it is more coherent if we do not use October, but use December, in the year 2011.

Table 5.9

Results for Co-integration Relationship Pre-test

	Estimation Period	URT (High)	URT (Low)	Coin
Monthly	1918.1-2008.12	-0.0003	-0.0004	-0.1452
		(-1.1282)	(-1.1866)	(-5.1353)***
Monthly	1918.1-2011.12	-0.0003	-0.0004	-0.1581
		(-1.0959)	(-1.1378)	(-5.7374)***
Daily	1930.1-2008.12	0.0000	0.0000	-0.0765
		(-0.3689)	(-0.4826)	(-16.9336)***
Daily	1930.1-2011.12	0.0000	0.0000	-0.0781
		(-0.3214)	(-0.4332)	(-17.3780)***

Notes: This table shows the results of co-integration relationship pre-tests for both daily and monthly S&P 500 indices from two estimation periods, which are before 2009 and before 2012, respectively. URT (High) and URT (Low) refer to unit root tests for high and low prices separately, while Coin examines the existence of a co-integration relationship for price ranges. T-values reported beneath for unit root test are compared with the critical values provided by the Dickey-Fuller test, while the EG-OLS hypothesis testing technique is applied to the later co-integration test. Asterisks indicate significance at * 10% level, ** 5% level and *** 1% level.

The Dickey-Fuller test, which is designed to test for the null hypothesis of unit root against the integration of order zero alternative, yields the expected results. By comparing the critical values presented in Appendix B, the postulation that the high and low prices of the S&P 500 index individually follow a random walk process is not rejectable at all three significance levels, since the coefficients of interest are not statistically different from zero. To illustrate, all of the coefficients in columns three and four in table 5.9 are very close to zero, daily data especially, without statistical significance. The EG-OLS test confirms the existence of a co-integration relationship embodied in price ranges for all of the co-integration parameters in column five are significantly different from zero even at the 1% significance level. Further, the co-integration relationship is found to be more robust when daily data is analysed, which is exemplified by statistical values that are far less than -3.73. In accordance with the EG-OLS test, the corresponding EG-OLS prediction model is subsequently performed to anticipate high-low prices and trading signals.

In order to be coherent with the two estimation periods previously examined, part of the results concerning the two trading rules are summarized and compared in Table 5.10 based on the out-of sample forecasts for the year 2009.1-2013.11 and 2012.1-2013.11. Short selling is first restricted, but the constraint is soon released; these are stated as sc and ss, respectively. In Panel A, Buy and Sell denote the numbers of buy and sell signals collected in the forecasting periods. In the case of the shorter estimation period, when monthly data is applied, two times as many sell signals are generated as buy signals, and four times as many in the longer estimation period. Although a greater number of sell signals is also apparent in the daily data, it has been remedied since the number of sell signals is kept to a level of slightly more than 1.5 times larger than the number of buy signals. In sharp contrast to the situation when Brock, Lakonishok, and LeBaron's (1992) study was conducted, high selling pressure is consistent with a downward trending market, probably due to the global financial crisis. Therefore the ratio between the buy and sell signals in the second estimation period before 2012 should be affected more substantially in that it contains longer period of the crisis. As expected, the differences between the buy and sell signals are found to be lager in the shorter forecast period regardless of the data frequencies.

Following Brock, Lakonishok, and LeBaron (1992), Reti (Buy) and Reti (Sell) represent the differences between average returns from buy and sell trading signals and the unconditional mean, reported and tested in columns five and six. The calculation of t-statistics for the Reti (Buy) and Reti (Sell) is,

$$\frac{M_i - M}{(Var/N + Var/N_i)^{0.5}} \tag{28}$$

$$\frac{M_b - M_s}{(Var/N_b + Var/N_s)^{0.5}} \tag{29}$$

where in Eq.28 M_i and N_i are the mean returns and numbers of trading signals related to buys or sells, while M and Var represent the unconditional mean and variance for the entire sample. N accounts for the number of total observations. In addition, Eq.29 shows how to measure the t-value for Buy-Sell. M_b and M_s are denoted as the mean returns for buy and sell signals while N_b and N_s are the numbers of trading signals. Var is identical to the Var in Eq.28, which is the unconditional mean.

In general, buy signals consistently yield higher returns than do sell signals, explicated by always positive Reti (Buy) compared to always negative Reti (Sell), which is exactly the same as Brock, Lakonishok, and LeBaron (1992) find. The buy returns generated from the range-based strategy on a monthly basis are all positive in excess of the monthly mean of 0.6247% provided in Table 5.8. The fact that even the lowest positive mean return for buy signals, which is 0.6314%, is still higher than the unconditional mean, highlights that the quality of buy signal derivation is quite satisfactory. Despite the mean buy not yielding positive returns when processing daily data prior to 2012, two significant positive returns relying on the estimation period before 2009 reject the hypothesis that mean buy returns are equal to the mean daily returns at the 10% significance level. For the sells, almost all of the mean returns are negative, with only one exception, when monthly data before 2012 are estimated, though modified t-tests for equality with the unconditional mean return do not show statistical significance. Overall, mean return performance for both buy and sell signals appears to be more robust in Brock, Lakonishok, and LeBaron's (1992) study.

The last column lists the differences between mean returns from buy and sell signals, which demonstrates the payoff of the strategy for the reason that technical strategies should be unable to provide profitable trading signals, and thus mean returns should be equal for both buys and sells. Thus, positive none-zero Buy-Sells is the fundamental of abnormal returns. Apparently, all of the trading returns are positive and some of them are highly significant at the 5% significance level. In other words, all of the return differences depart from equality with some extent of statistical robustness, which indicates the range-based strategy is profitable and, in turn, provides evidence to support hypothesis 4. In general, the short selling constraint does not alter the results to a large extent.

Table 5.10
Results for Simple Technical Trading Strategies from Two Estimation Periods

Panel A: Range-based Strategy

	Estimation Period	**Buy**	**Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**
Monthly (ss)	1918.1-2008.12	13	27	0.6314%	-0.1542%	0.7856%
				(0.4456)	(-0.1437)	(0.5024)
Monthly (ss)	1918.1-2011.12	3	13	2.7772%	0.5657%	2.2115%
				(1.6045)	(0.5812)	(1.2215)
Monthly (sc)	1918.1-2008.12	13	27	0.6314%	-1.2346%	1.8660%
				(0.4456)	(-1.1503)	(1.1934)
Monthly (sc)	1918.1-2011.12	3	13	2.7772%	-1.0496%	3.8268%
				(1.6045)	(-1.0783)	(2.1137)**
Daily (ss)	1930.1-2008.12	150	234	0.1710%	-0.1135%	0.2845%
				(1.6970)*	(-1.3659)	(2.3335)**
Daily (ss)	1930.1-2011.12	56	96	-0.0482%	-0.0774%	0.0293%
				(-0.4636)	(-0.9418)	(0.2368)
Daily (sc)	1930.1-2008.12	150	234	0.1710%	-0.0665%	0.2374%
				(1.6970)*	(-0.8000)	(1.9478)**
Daily (sc)	1930.1-2011.12	56	96	-0.0482%	-0.0741%	0.0260%
				(-0.4636)	(-0.9016)	(0.2101)

Panel B: Midpoint Strategy

	Estimation Period	**Buy**	**Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**
Monthly (ss)	1918.1-2008.12	20	39	0.9677%	-0.4963%	1.4640%
				(0.8092)	(-0.5209)	(1.1493)
Monthly (ss)	1918.1-2011.12	6	17	1.0317%	0.3473%	0.6845%
				(0.7997)	(0.3876)	(0.5100)
Monthly (sc)	1918.1-2008.12	20	39	0.9677%	-1.2344%	2.2021%
				(0.8092)	(-1.2957)	(1.7287)*
Monthly (sc)	1918.1-2011.12	6	17	1.0317%	-1.0494%	2.0812%
				(0.7997)	(-1.1712)	(1.5506)
Daily (ss)	1930.1-2008.12	545	692	0.0886%	-0.0698%	0.1585%
				(1.4796)	(-1.2621)	(2.3741)**
Daily (ss)	1930.1-2011.12	208	273	0.0043%	-0.0033%	0.0076%
				(0.0709)	(-0.0592)	(0.1127)
Daily (sc)	1930.1-2008.12	545	692	0.0886%	-0.0664%	0.1551%
				(1.4796)	(-1.2009)	(2.3234)**
Daily (sc)	1930.1-2011.12	208	273	0.0043%	-0.0741%	0.0785%
				(0.0709)	(-1.3303)	(1.1588)

Notes: This table summarizes the performance of two simple technical trading strategies based on daily and monthly data from two estimation periods, where Panel A presents the results for the range-based strategy and Panel B reports the midpoint strategy. Buy and Sell are the number of buy and sell signals generated in the forecasting periods. Reti

(Buy) and Reti (Sell) denote the differences between mean returns obtained from buy and sell signals from the unconditional mean, while Buy-Sell is the variable of the most interest, which measures the success of the trading strategies. A modified t-test is applied to investigate whether Reti (Buy) and Reti (Sell) are statistically different from the unconditional mean, and Buy-Sell from zero, with t-values presented in parentheses. Short selling is first constrained, denoted as (sc), but the restriction is soon released and denoted as (ss). Asterisks indicate significance at * 10% level, ** 5% level and *** 1% level.

In particular, it is worth discussing why the mean returns for sell signals exceeding the unconditional mean are negative. Interestingly, the negative returns could not be explained by financial anomalies since they are based on a large number of trading months or days, but instead, shed light on the rationale of return predictability. Brock, Lakonishok, and LeBaron (1992) and early studies posit that returns' predictability may be caused by either market inefficiency or changes in models. It is possible that lack of significant t-values in negative returns in this study indicate the market is becoming more efficient, which diminishes forecasting power.

In Panel B, the midpoint strategy yields similar results. The number of sell signals exceeds the number of buy signals in all cases, especially when data in the longer estimation period is investigated with the direct purpose of modelling and anticipating future high and low prices. Likewise, the daily data reduces the proportional differences between the two signals compared with the monthly data. Again, all of the mean buy returns in column three are positive, while all of the mean sell returns in column four are negative, the only exception being positioned in exactly the same place as in Panel A. It is disappointing that none of the mean returns for buys and sells show statistical significance and the smallest mean return for buy signals (0.0043%) fails to surpass the daily unconditional mean. However, the midpoint strategy successfully derives positive trading returns in the Buy-Sell column, which provides further evidence to support hypothesis 4, or the profitability of technical trading strategies in trading stock indices.

For daily data, both strategies based on the shorter estimation periods outperform the same strategies based on the longer periods in terms of profits and statistical significance. To be more specific, the daily returns from the range-based strategy and midpoint strategy without short-selling constraint based on price series data before 2009 are 0.2845% and 0.1585%, respectively, which are not only higher but also more robust than yields in the second estimation period, which are 0.0293% and 0.0076%, respectively. A similar pattern of results applies when short selling is restricted. On the other hand, there is no clear relationship in the results from monthly data, which are mixed. In general, the range-based strategy outperforms the midpoint strategy in that the majority of positive trading returns addressed by the former trading rule are higher than the returns from using the latter rule.

Earlier, Sullivan, Timmermann, and White (1999) expand and enrich Brock, Lakonishok, and LeBaron’s (1992) research by applying more than 7000 variations of technical trading rules; their investigation covers a period of nearly 100-years, starting from 1897 to 1996. Nowadays, access to another 13 years of data from the S&P 500 index provides an opportunity to witness whether the historical success of technical trading strategies remains favourable or not. Tables 5.11 and 5.12 list the results of two trading rules separately. For each rule, 16 estimation periods are investigated, starting with the first year of extra data, which means index prices until 1997 are employed to model high and low prices and then another year is included in each iteration. As usual, both monthly and daily price dynamics with variations in the presence or absence of a short-selling constraint constitute four data series, while Buy-Sells for each data series are the basis to measure the profitability of the strategies adopted.

Table 5.11

Summary Results for Range-based Strategy

	Monthly (ss)			Monthly (sc)			Daily (ss)			Daily (sc)		
Periods	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**
1930.1-1997.12	-0.0652%	0.3414%	-0.4065%	-0.0652%	-0.1963%	0.1312%	0.1134%	-0.0649%	0.1782%	0.1134%	-0.0160%	0.1293%
	(-0.0915)	(0.5684)	(-0.5048)	(-0.0915)	(-0.3269)	(0.1629)	(2.0416)**	(-1.2846)	(2.5528)***	(2.0416)**	(-0.3163)	(1.8525)*
1930.1-1998.12	0.1476%	0.1564%	-0.0088%	0.1476%	-0.0947%	0.2424%	0.1076%	-0.0743%	0.1819%	0.1076%	-0.0128%	0.1204%
	(0.2064)	(0.2555)	(-0.0108)	(0.2064)	(-0.1548)	(0.2974)	(1.8782)*	(-1.4152)	(2.5158)***	(1.8782)*	(-0.2443)	(1.6655)*
1930.1-1999.12	-0.0484%	0.1987%	-0.2471%	-0.0484%	-0.0260%	-0.0224%	0.1136%	-0.0758%	0.1894%	0.1136%	-0.0115%	0.1250%
	(-0.0645)	(0.3077)	(-0.2875)	(-0.0645)	(-0.0403)	(-0.0261)	(1.8961)*	(-1.3816)	(2.5051)***	(1.8961)*	(-0.2089)	(1.6537)*
1930.1-2000.12	-0.2149%	0.3732%	-0.5881%	-0.2149%	-0.1291%	-0.0858%	0.1118%	-0.0867%	0.1985%	0.1118%	-0.0178%)	0.1295%
	(-0.2728)	(0.5632)	(-0.6570)	(-0.2728)	(-0.1948)	(-0.0959)	(1.8046)*	(-1.5377)	(2.5476)***	(1.8046)*	(-0.3149)	(1.6626)*
1930.1-2001.12	-0.1893%	0.4169%	-0.6061%	-0.1893%	-0.2402%	0.0509%	0.1392%	-0.0953%	0.2346%	0.1392%	-0.0204%)	0.1596%
	(-0.2345)	(0.6269)	(-0.6665)	(-0.2345)	(-0.3612)	(0.0560)	(2.1600)**	(-1.6385)	(2.9063)***	(2.1600)**	(-0.3501)	(1.9774)**
1930.1-2002.12	-0.4023%	0.2210%	-0.6233%	-0.4023%	-0.4605%	0.0583%	0.1591%	-0.1104%	0.2694%	0.1591%	-0.0302%	0.1893%
	(-0.4949)	(0.3399)	(-0.6886)	(-0.4949)	(-0.7083)	(0.0644)	(2.4063)**	(-1.8818)*	(3.2823)***	(2.4063)**	(-0.5158)	(2.3063)**

1930.1-2003.12	-0.4308%	0.2604%	-0.6912%	-0.4308%	-0.3228%	-0.1080%	0.1575%	-0.1086%	0.2660%	0.1575%	-0.0248%	0.1823%
	(-0.5106)	(0.3794)	(-0.7355)	(-0.5106)	(-0.4704)	(-0.1149)	(2.2673)**	(-1.7501)*	(3.0803)***	(2.2673)**	(-0.3998)	(2.1104)**
1930.1-2004.12	-0.3882%	0.2648%	-0.6530%	-0.3882%	-0.2891%	-0.0991%	0.1846%	-0.1077%	0.2923%	0.1846%	-0.0240%	0.2087%
	(-0.4197)	(0.3476)	(-0.6302)	(-0.4197)	(-0.3795)	(-0.0957)	(2.4106)**	(-1.5887)	(3.0796)***	(2.4106)**	(-0.3545)	(2.1982)**
1930.1-2005.12	-0.6935%	0.5149%	-1.2084%	-0.6935%	-0.3274%	-0.3661%	0.2100%	-0.1175%	0.3274%	0.2100%	-0.0269%	0.2368%
	(-0.6561)	(0.6059)	(-1.0240)	(-0.6561)	(-0.3852)	(-0.3102)	(2.4049)**	(-1.5542)	(3.0472)***	(2.4049)**	(-0.3556)	(2.2041)**
1930.1-2006.12	-0.6852%	0.6172%	-1.3024%	-0.6852%	-0.2990%	-0.3862%	0.2396%	-0.1255%	0.3651%	0.2396%	-0.0258%	0.2654%
	(-0.5818)	(0.6301)	(-0.9787)	(-0.5818)	(-0.3052)	(-0.2902)	(2.4532)**	(-1.4637)	(3.0201)***	(2.4532)**	(-0.3005)	(2.1950)**
1930.1-2007.12	-0.6606%	0.6867%	-1.3473%	-0.6606%	-0.3867%	-0.2739%	0.2673%	-0.1261%	0.3935%	0.2673%	-0.0303%	0.2976%
	(-0.4814)	(0.5920)	(-0.8563)	(-0.4814)	(-0.3334)	(-0.1741)	(2.3905)**	(-1.2923)	(2.8441)***	(2.3905)**	(-0.3101)	(2.1513)**
1930.1-2008.12	0.6314%	-0.1542%	0.7856%	0.6314%	-1.2346%	1.8660%	0.1710%	-0.1135%	0.2845%	0.1710%	-0.0665%	0.2374%
	(0.4456)	(-0.1437)	(0.5024)	(0.4456)	(-1.1503)	(1.1934)	(1.6970)*	(-1.3659)	(2.3335)**	(1.6970)*	(-0.8000)	(1.9478)*
1930.1-2009.12	0.5121%	-0.1139%	0.6260%	0.5121%	-1.0320%	1.5441%	0.1365%	-0.1063%	0.2428%	0.1365%	-0.0532%	0.1897%
	(0.3883)	(-0.1099)	(0.4302)	(0.3883)	(-0.9960)	(1.0613)	(1.3695)	(-1.3058)	(2.0218)**	(1.3695)	(-0.6534)	(1.5797)
1930.1-2010.12	-0.3775%	0.2943%	-0.6719%	-0.3775%	-1.0491%	0.6715%	0.0925%	-0.1019%	0.1944%	0.0925%	-0.0526%	0.1451%
	(-0.2727)	(0.2879)	(-0.4464)	(-0.2727)	(-1.0261)	(0.4462)	(0.8186)	(-1.0891)	(1.4235)	(0.8186)	(-0.5623)	(1.0626)

1930.1-2011.12	2.7772%	0.5657%	2.2115%	2.7772%	-1.0496%	3.8268%	-0.0482%	-0.0774%	0.0293%	-0.0482%	-0.0741%	0.0260%
	(1.6045)	(0.5812)	(1.2215)	(1.6045)	(-1.0783)	(2.1137)**	(-0.4636)	(-0.9418)	(0.2368)	(-0.4636)	(-0.9016)	(0.2101)
1930.1-2012.12	2.6975%	0.4724%	2.2251%	2.6975%	-1.0510%	3.7484%	0.0033%	-0.0735%	0.0768%	0.0033%	-0.0967%	0.1000%
	(1.3549)	(0.3970)	(1.0798)	(1.3549)	(-0.8833)	(1.8190)*	(0.0240)	(-0.7245)	(0.4872)	(0.0240)	(-0.9533)	(0.6344)

Notes：This table lists the result summary for the range-based strategy based on extra data that Brock, Lakonishok, and LeBaron (1992) and Sullivan, Timmermann, and White (1999) do not have access to. Altogether, there are 16 estimation periods examined, with one year added in each row. Both monthly and daily prices are used, varied by the presence or absence of a short-selling constraint, thus constituting four series of data. Reti (Buy) and Reti (Sell) are the returns from buy and sell trading signals in excess of the unconditional mean while Buy-Sell is the measurement of a trading strategy's ability to generate abnormal returns. T-values provided beneath test whether the returns are substantially different from unconditional mean or zero. Asterisks indicate significance at * 10% level, ** 5% level and *** 1% level.

Table 5.12

Summary Results for Midpoint Strategy

	Monthly (ss)			Monthly (sc)			Daily (ss)			Daily (sc)		
Periods	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**	**Reti (Buy)**	**Reti (Sell)**	**Buy-Sell**
1930.1-1997.12	-0.1679%	0.0928%	-0.2608%	-0.1679%	-0.2177%	0.0498%	0.0656%	-0.0599%	0.1255%	0.0656%	-0.0162%	0.0818%
	(-0.2592)	(0.1751)	(-0.3759)	(-0.2592)	(-0.4106)	(0.0718)	(1.9142)*	(-1.8028)*	(3.2189)***	(1.9142)*	(-0.4868)	(2.0968)**
1930.1-1998.12	-0.0077%	0.0044%	-0.0121%	-0.0077%	-0.1137%	0.1060%	0.0688%	-0.0629%	0.1316%	0.0688%	-0.0129%	0.0817%
	(-0.0119)	(0.0082)	(-0.0174)	(-0.0119)	(-0.2122)	(0.1524)	(1.9416)*	(-1.8290)*	(3.2653)***	(1.9416)*	(-0.3765)	(2.0268)**
1930.1-1999.12	-0.1322%	0.0741%	-0.2063%	-0.1322%	-0.0386%	-0.0935%	0.0734%	-0.0673%	0.1407%	0.0734%	-0.0116%	0.0850%
	(-0.1947)	(0.1327)	(-0.2833)	(-0.1947)	(-0.0692)	(-0.1285)	(1.9849)**	(-1.8732)*	(3.3411)***	(1.9849)**	(-0.3222)	(2.0179)**
1930.1-2000.12	-0.4529%	0.2491%	-0.7019%	-0.4529%	-0.1447%	-0.3082%	0.0793%	-0.0717%	0.1511%	0.0793%	-0.0180%	0.0974%
	(-0.6434)	(0.4332)	(-0.9316)	(-0.6434)	(-0.2516)	(-0.4090)	(2.0694)**	(-1.9346)*	(3.4674)***	(2.0694)**	(-0.4864)	(2.2351)**
1930.1-2001.12	-0.3781%	0.2096%	-0.5877%	-0.3781%	-0.2626%	-0.1155%	0.0911%	-0.0822%	0.1734%	0.0911%	-0.0208%	0.1119%
	(-0.5300)	(0.3587)	(-0.7690)	(-0.5300)	(-0.4494)	(-0.1511)	(2.2821)**	(-2.1311)**	(3.8217)***	(2.2821)**	(-0.5388)	(2.4673)**
1930.1-2002.12	-0.2367%	0.1281%	-0.3648%	-0.2367%	-0.4842%	0.2475%	0.1007%	-0.0892%	0.1899%	0.1007%	-0.0307%	0.1314%
	(-0.3310)	(0.2206)	(-0.4772)	(-0.3310)	(-0.8337)	(0.3238)	(2.4594)**	(-2.2690)**	(4.0947)***	(2.4594)**	(-0.7809)	(2.8330)***

1930.1-2003.12	-0.2000%	0.1131%	-0.3131%	-0.2000%	-0.3465%	0.1466%	0.0940%	-0.0827%	0.1767%	0.0940%	-0.0253%	0.1193%
	(-0.2653)	(0.1820)	(-0.3869)	(-0.2653)	(-0.5574)	(0.1811)	(2.1547)**	(-1.9780)**	(3.5787)***	(2.1547)**	(-0.6046)	(2.4160)**
1930.1-2004.12	-0.1523%	0.0873%	-0.2396%	-0.1523%	-0.3160%	0.1638%	0.0923%	-0.0798%	0.1721%	0.0923%	-0.0246%	0.1168%
	(-0.1843)	(0.1276)	(-0.2698)	(-0.1843)	(-0.4616)	(0.1843)	(1.9274)*	(-1.7503)*	(3.1848)***	(1.9274)*	(-0.5383)	(2.1617)**
1930.1-2005.12	-0.1393%	0.0777%	-0.2170%	-0.1393%	-0.3541%	0.2148%	0.1007%	-0.0838%	0.1846%	0.1007%	-0.0273%	0.1280%
	(-0.1507)	(0.1024)	(-0.2189)	(-0.1507)	(-0.4669)	(0.2167)	(1.8816)*	(-1.6653)*	(3.0714)***	(1.8816)**	(-0.5421)	(2.1303)**
1930.1-2006.12	-0.2198%	0.1244%	-0.3443%	-0.2198%	-0.3190%	0.0992%	0.1132%	-0.0936%	0.2068%	0.1132%	-0.0260%	0.1392%
	(-0.2102)	(0.1442)	(-0.3064)	(-0.2102)	(-0.3698)	(0.0883)	(1.8727)*	(-1.6499)*	(3.0503)***	(1.8727)**	(-0.4584)	(2.0533)**
1930.1-2007.12	-0.2535%	0.1464%	-0.3999%	-0.2535%	-0.3805%	0.1270%	0.1114%	-0.0910%	0.2024%	0.1114%	-0.0301%	0.1414%
	(-0.2127)	(0.1480)	(-0.3117)	(-0.2127)	(-0.3845)	(0.0990)	(1.6306)	(-1.4253)	(2.6462)**	(1.6306)	(-0.4707)	(1.8493)*
1930.1-2008.12	0.9677%	-0.4963%	1.4640%	0.9677%	-1.2344%	2.2021%	0.0886%	-0.0698%	0.1585%	0.0886%	-0.0664%	0.1551%
	(0.8092)	(-0.5209)	(1.1493)	(0.8092)	(-1.2957)	(1.7287)*	(1.4796)	(-1.2621)	(2.3741)**	(1.4796)	(-1.2009)	(2.3234)**
1930.1-2009.12	1.2172%	-0.6282%	1.8454%	1.2172%	-1.0327%	2.2499%	0.0632%	-0.0494%	0.1125%	0.0632%	-0.0532%	0.1163%
	(1.0320)	(-0.6673)	(1.4673)	(1.0320)	(-1.0970)	(1.7889)*	(1.0658)	(-0.9043)	(1.7059)*	(1.0658)	(-0.9741)	(1.7637)*
1930.1-2010.12	0.8189%	-0.3276%	1.1464%	0.8189%	-1.0497%	1.8686%	0.0268%	-0.0208%	0.0476%	0.0268%	-0.0526%	0.0794%
	(0.6468)	(-0.3553)	(0.8651)	(0.6468)	(-1.1384)	(1.4101)	(0.3897)	(-0.3288)	(0.6221)	(0.3897)	(-0.8331)	(1.0387)

1930.1-2011.12	1.0317%	0.3473%	0.6845%	1.0317%	-1.0494%	2.0812%	0.0043%	-0.0033%	0.0076%	0.0043%	-0.0741%	0.0785%
	(0.7997)	(0.3876)	(0.5100)	(0.7997)	(-1.1712)	(1.5506)	(0.0709)	(-0.0592)	(0.1127)	(0.0709)	(-1.3303)	(1.1588)
1930.1-2012.12	1.0353%	1.0764%	-0.0411%	1.0353%	-1.0507%	2.0860%	0.0285%	-0.0214%	0.0499%	0.0285%	-0.0967%	0.1253%
	(0.6153)	(0.9047)	(-0.0233)	(0.6153)	(-0.8831)	(1.1820)	(0.3567)	(-0.2946)	(0.5636)	(0.3567)	(-1.3312)	(1.4136)

Notes: This table lists the result summary for the midpoint strategy based on extra data that Brock, Lakonishok, and LeBaron (1992) and Sullivan, Timmermann, and White (1999) do not have access to. Altogether, there are 16 estimation periods examined, with one year added in each row. Both monthly and daily prices are used, varied by the presence or absence of a short-selling constraint, thus constituting four series of data. Reti (Buy) and Reti (Sell) are the returns from buy and sell trading signals in excess of the unconditional mean, while Buy-Sell is the measurement of the trading strategy's ability to generate abnormal returns. T-values provided beneath test whether the trading returns are substantially different from unconditional mean or zero. Asterisks indicate significance at the * 10% level ** 5% level and *** 1% level.

In both tables, for monthly data without a short-selling restriction evidence to support hypothesis 4 is scant: the majority of the mean returns from buy signals are less than the unconditional average. However, the absence of statistical significance demonstrates the mean returns are actually indifferent from the unconditional mean, which argues against the existence of abnormal returns. Similarly, the equality between mean returns from sell signals and the monthly average is due to insignificant t-values, which disproves a positive return. According to Buy-Sell, a poor trading performance is displayed in the negative trading profits obtained in estimation periods before 2008. Although trading profits become positive consequently, the lack of statistical robustness suggests the trading strategies fail to generate abnormal profits. The short-selling constraint on monthly data, which is operated as investors hold risk-free assets when they do not have positions in an index, improves the performance of both trading strategies in several respects. Despite the mean returns from buys in both strategies not exceeding the unconditional mean, nor showing statistical significance, the mean returns from sell signals present the expected signs. More importantly, most of the estimation periods yield positive trading returns, illustrated by positive Buy-Sell values accompanying a few significant t-values.

The encouraging performance of trading strategies is remarkably enhanced when daily data is applied. To illustrate, all of the mean returns in excess of unconditional mean from buy and sell trading signals obtain the anticipated signs and furthermore most positive buy mean returns are significant at the 5% or 10% level in both tables. Moreover, the Buy-Sell differences are significantly positive for almost all estimation periods, independent of whether the restriction of short selling is imposed. Few exceptions occur when the estimation periods finish after 2010, which might reveal the post-effect of the global financial crisis. In fact, the satisfactory performance is much stronger when the short-selling constraint is removed, which is exemplified by the considerable amount of t-values significant at the 1% level. The fact that daily data yields more satisfactory results should not be surprising, since the positive returns found by most technical analysis studies such as Brock, Lakonishok, and LeBaron (1992) and Sullivan, Timmermann, and White (1999) are also on a daily basis. Overall, the two trading rules under consideration in this paper are capable of producing valuable signals and in turn, provide superior investing performance when daily data is investigated, which generally promotes hypothesis 4. In addition to trading stock indices, it is necessary to consider derivatives, since they play an important role in modern financial markets. The performance of such financial assets is discussed in the next section.

5.3.2 Trading options

Options are supposed to be indirectly related to high and low prices. This supposition is based on the rationale that high-low price ranges effectively predict volatility, and volatility is, in turn, extremely important in pricing options. As a result, options are selected to evaluate the profitability of technical trading strategies among various types of derivatives. In particular, except the plain call and put options, straddle is the most heavily traded volatility technique and thus is examined in this study.

Decisions on buying or selling straddles depend solely on the trading signals generated from the previous two trading strategies on a monthly basis, with the results shown in Table 5.13. The judgment of whether trading signals are valuable enough to produce abnormal returns depends on both dollar and percentage return measurements. In the case of trading options, the estimation period is different from the previous windows for the reason that the S&P 500 index call and put options become available in DataStream only from September 1999. In other words, the forecasting period covers the entire available data of the S&P 500 index call and put options.

Table 5.13
Results Summary for Trading Options

1999.9	Range-based Strategy	Midpoint Strategy
Dollar Return	3.2527	2.6684
	(37.4552)***	(30.7266)***
Percentage Return	7.8135%	6.7130%
	(70.4634)***	(60.5389)***

Notes: This table summarizes the results from trading options based on trading signals derived from either a range-based strategy or midpoint strategy. Performance measurement is conducted in both dollar and percentage return frameworks. A standard t-test is applied. Asterisks indicate significance at the * 10% level ** 5% level and *** 1% level.

Chiefly, the results of trading straddles are satisfactory, since both dollar returns and percentage returns are all positive. Noticeably, the percentage returns are remarkably significant. On the other hand, the midpoint strategy is dominated by the range-based strategy in terms of both magnitude of profitability and statistical significance. With reference to dollar returns, $2.6684 under the midpoint strategy is smaller than the $3.2527 under the range-based strategy and the same pattern applies to percentage returns and t-values.

So far, the predictability of high and low prices is helpful in generating valuable trading signals, based on which two simple technical trading strategies are able to provide positive abnormal returns in both stock indices and options transactions. In other words, the results support the usefulness of technical trading rules and provide strong support for hypothesis 4.

Chapter 6 Conclusions

To conclude, the investigation of high and low equity prices is motived by the fact that closing prices fail to reflect some valuable information that high-low prices convey, and which help to construct a new volatility estimator, predict future high-low prices and facilitate technical trading analysis. The new variance estimator offers additional power to uncover the puzzling risk and return relationship, where the analysis uses data from 48 countries. Initially, the implementation of historical data takes the form of (1) a standard close-to-close variance based on historical closing prices, (2) a new variance estimator constructed from historical high-low prices, and (3) the RA method. On the other hand, high and low prices' prediction models including (1) EG-OLS, (2) EG-NLS and (3) MIDAS are examined in two estimation periods with the direct purpose of capturing more precisely the underlying correlation between the highs and lows. Basically, the fact that the high and low prices follow a random walk process individually while the price ranges exhibit a co-integration relationship suggests the use of the Engle and Granger linear and non-linear prediction models. MIDAS is a novel technique that takes advantage of information hidden due to it being of different data frequencies, which the RA method combines with the non-linear specification.

Empirical results show neither historical closing prices nor historical high-low prices yield the expected positive risk and return trade-off. The more complicated RA method does not outperform the simple market model using historical data as well. On the contrary, forecasting high-low prices' series by means of new volatility estimators shows a significantly positive risk and return relationship, which proves that high-low prices' forecasts generated from the three prediction models are able to better estimate conditional variance. In support of the high efficiency of the new volatility estimators, we conclude that the occurrence of positive risk and return relationships based on forecasts of high and low prices is found more frequent by that means than by historical data.

Alternatively, accurate forecasts of high and low prices, obtained from the previous three prediction models, help generate valuable trading signals in trading both stock indices and options by means of two simple technical trading strategies, namely range-based strategy and midpoint strategy. The analysis of technical analysis is conducted in the U.S. financial market since it is least likely that abnormal returns will occur in that market. Significant positive trading profits not only verify the usefulness of the two simple trading rules, but also suggest that anticipated high and low prices improve trading performance. Particularly, superior investment performance in trading stock indices is more robust when daily data is applied, while monthly data is applicable in options transactions. This study also examines the explanatory power of corporate governance factors, which include investor protection and law enforcement in particular, on the risk aversion coefficients obtained from previous risk and return regressions. We find such factors fail to reach the expected conclusion because most of the volatility parameters are independent of those legal variables, in spite of the intuition that stronger protection through laws against expropriation should to some extent reduce investors' perception towards risky investments.

References

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

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

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, Standard Volatility Models do provide accurate forecasts. *International Economic Review, 39*(4), 885-905. doi: 10.2307/2527343

Andreou, E., Ghysels, E., & Kourtellos, A. (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics, 158*(2), 246-261. doi: http://dx.doi.org/10.1016/j.jeconom.2010.01.004

Baillie, R. T., & DeGennaro, R. P. (1990). Stock returns and volatility. *Journal of Financial and Quantitative Analysis*, *25*(2), 203-214.

Bajgrowicz, P., & Scaillet, O. (2012). Technical trading revisited: False discoveries, persistence tests, and transaction costs. *Journal of Financial Economics, 106*(3), 473-491. doi: http://dx.doi.org/10.1016/j.jfineco.2012.06.001

Barnhart, S. W., McNown, R., & Wallace, M. S. (1999). Non-informative tests of the unbiased forward exchange rate. *Journal of Financial and Quantitative Analysis*, *34*(02), 265-291. doi: doi:10.2307/2676281

Bauer, R., Guenster, N., & Otten, R. (2004). Empirical evidence on corporate governance in Europe: The effect on stock returns, firm value and performance. *Journal of Asset Management*, *5*(2), 91-104.

Beckers, S. (1983). Variances of security price returns based on high, low, and closing pricess. *Journal of Business, 56*(1), 97-112.

Bessembinder, H., & Chan, K. (1995). The profitability of technical trading rules in the Asian stock markets. *Pacific-Basin Finance Journal*, *3*(2–3), 257-284. doi: http://dx.doi.org/10.1016/0927-538X(95)00002-3

Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments* (9th ed.). New York: McGraw-Hill/Irwin.

Bornholt, G. (2013). The failure of the Capital Asset Pricing Model (CAPM): An update and discussion. *Abacus*, *49*(S1), 36-43.

Brenner, M., Ou, E. Y., & Zhang, J. E. (2006). Hedging volatility risk. *Journal of Banking & Finance, 30*(3), 811-821.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance, 47*(5), 1731-1764. doi: 10.1111/j.1540-6261.1992.tb04681.x

Buescu, C., Taksar, M., & KonÉ, F. J. (2013). An application of the method of moments to range-based volatility estimation using daily high, low, opening and closing (HLOC) prices. *International Journal of Theoretical & Applied Finance, 16*(5), -1. doi: 10.1142/S021902491350026X

Cai, B., Cai, C., & Keasey, K. (2005). Market efficiency and returns to simple technical rrading rules: Further evidence from U.S., U.K., Asian and Chinese stock markets. *Asia-Pacific Financial Markets, 12*(1), 45-60. doi: 10.1007/s10690-006-9012-y

Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics, 18*(2), 373-399. doi: http://dx.doi.org/10.1016/0304-405X(87)90045-6

Caporin, M., Ranaldo, A., & de Magistris, P. S. (2013). On the predictability of stock prices: A case for high and low prices. *Journal of Banking & Finance*(0). doi: http://dx.doi.org/10.1016/j.jbankfin.2013.05.024

Chaput, J. S., & Ederington, L. H. (2005). Volatility trade design. *Journal of Futures Markets, 25*(3), 243-279.

Chen, A.-S. (2003). Option straddle trading: Financial performance and economic significance of direct profit forecast and conventional strategies. *Applied Economics Letters, 10*(8), 493.

Cheung. (2007). An empirical model of daily highs and lows. *International Journal of Finance & Economics, 12*(1), 1-20. doi: 10.1002/ijfe.303

Cheung, Cheung, & Wan, A. T. K. (2009). A high–low model of daily stock price ranges. *Journal of Forecasting, 28*(2), 103-119. doi: 10.1002/for.1087

Cheung, Cheung, Y.-W., He, A. W. W., & Wan, A. T. K. (2010). A trading strategy based on callable bull/bear contracts. *Pacific-Basin Finance Journal, 18*(2), 186-198. doi: http://dx.doi.org/10.1016/j.pacfin.2009.11.002

Clements, M. P., & Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data. *Journal of Business & Economic Statistics, 26*(4), 546-554. doi: 10.1198/073500108000000015

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance, 67*(2), 719-760. doi: 10.1111/j.1540-6261.2012.01729.x

Curcio, R., & Goodhart, C. (1992). *When support/resistance levels are broken, can profits be made? Evidence from the foreign exchange market*. Financial Markets Group.

Dennis, Y., & Qiang, Z. (2000). Drift-independent volatility estimation based on high, low, open, and close prices. *Journal of Business, 73*(3), 477.

Deuskar, P., Gupta, A., & Subrahmanyam, M. G. (2011). Liquidity effect in OTC options markets: Premium or discount? *Journal of Financial Markets, 14*(1), 127-160. doi: http://dx.doi.org/10.1016/j.finmar.2010.08.003

Drobetz, W., Schillhofer, A., & Zimmermann, H. (2004). Corporate governance and expected stock returns: Evidence from Germany. *European Financial Management, 10*(2), 267-293. doi: 10.1111/j.1354-7798.2004.00250.x

Easley, D., Kiefer, N. M., O'Hara, M., & Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *The Journal of Finance, 51*(4), 1405-1436. doi: 10.1111/j.1540-6261.1996.tb04074.x

Enders, W. (1995). *Applied econometric time series*. New York: Wiley.

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and error correction: Representation, estimation, and testing. *Econometrica, 55*(2), 251-276. doi: 10.2307/1913236

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

Fiszeder, P., & Perczak, G. (2013). A new look at variance estimation based on low, high and closing prices taking into account the drift. *Statistica Neerlandica, 67*(4), 456-481. doi: 10.1111/stan.12017

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics, 19*(1), 3-29.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *The Journal of Business, 53*(1), 67-78. doi: 10.2307/2352358

Gençay, R. (1998). The predictability of security returns with simple technical trading rules. *Journal of Empirical Finance, 5*(4), 347-359. doi: http://dx.doi.org/10.1016/S0927-5398(97)00022-4

Gençay, R. (1999). Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *Journal of International Economics, 47*(1), 91-107. doi: http://dx.doi.org/10.1016/S0022-1996(98)00017-8

Gharghori, P., Chan, H., & Faff, R. (2007). Are the Fama-French factors proxying default risk? *Australian Journal of Management, 32*(2), 223-249.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS touch: Mixed data sampling regression models. *Anderson Graduate School of Management-Finance UCLA.*

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2005). There is a risk-return trade-off after all. *Journal of Financial Economics, 76*(3), 509-548. doi: http://dx.doi.org/10.1016/j.jfineco.2004.03.008

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics, 131*(1–2), 59-95. doi: http://dx.doi.org/10.1016/j.jeconom.2005.01.004

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews, 26*(1), 53-90.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801. doi: 10.1111/j.1540-6261.1993.tb05128.x

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate governance and equity prices. *The Quarterly Journal of Economics, 118*(1), 107-156.

Gonzalo, J. (1994). Five alternative methods of estimating long-run equilibrium relationships. *Journal of Econometrics, 60*(1–2), 203-233. doi: http://dx.doi.org/10.1016/0304-4076(94)90044-2

Gunasekarage, A., & Power, D. M. (2001). The profitability of moving average trading rules in South Asian stock markets. *Emerging Markets Review, 2*(1), 17-33. doi: http://dx.doi.org/10.1016/S1566-0141(00)00017-0

Hamilton, J. D. (1994). *Time series analysis* (Vol. 2). Princeton: Princeton University Press.

He, A. W. W., & Wan, A. T. K. (2009). Predicting daily highs and lows of exchange rates: A cointegration analysis. *Journal of Applied Statistics, 36*(11), 1191-1204. doi: 10.1080/02664760802578304

Hillier, D., Grinblatt, M., & Titman, S. (2008). *Financial markets and corporate strategy* (European ed.). London Boston: McGraw-Hill Higher Education.

Holmberg, U., Lönnbark, C., & Lundström, C. (2013). Assessing the profitability of intraday opening range breakout strategies. *Finance Research Letters, 10*(1), 27-33.

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. doi: http://dx.doi.org/10.1016/0378-4266(95)00043-7

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control, 12*(2–3), 231-254. doi: http://dx.doi.org/10.1016/0165-1889(88)90041-3

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration — with applications to the demand for money. *Oxford Bulletin of Economics and Statistics, 52*(2), 169-210. doi: 10.1111/j.1468-0084.1990.mp52002003.x

Kao, C., & Chiang, M.-H. (2001). On the estimation and inference of a cointegrated regression in panel data. *Advances in Econometrics, 15*, 179-222.

Kunitomo, N. (1992). Improving the Parkinson method of estimating security price volatilities. *Journal of Business, 65*(2), 295.

Kwon, K.-Y., & Kish, R. J. (2002). Technical trading strategies and return predictability: NYSE. *Applied Financial Economics, 12*(9), 639-653. doi: 10.1080/09603100010016139

La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2006). What works in securities laws? *The Journal of Finance, 61*(1), 1-32.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (2000). Investor protection and corporate governance. *Journal of Financial Economics, 58*(1), 3-27.

Laubie, A. (2010). Innovative option combinations: Enhancing the straddle. *Journal of Trading, 5*(4), 88-97.

LeBaron, B. (1999). Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics, 49*(1), 125-143. doi: http://dx.doi.org/10.1016/S0022-1996(98)00061-0

Lee, B.-S., & Jeon, B. N. (1995). Common stochastic trends and predictability of international stock prices. *Journal of the Japanese and International Economies, 9*(3), 245-277. doi: http://dx.doi.org/10.1006/jjie.1995.1013

Levich, R. M., & Thomas III, L. R. (1993). The significance of technical trading-rule profits in the foreign exchange market: A bootstrap approach. *Journal of International Money and Finance, 12*(5), 451-474. doi: http://dx.doi.org/10.1016/0261-5606(93)90034-9

Liu, M.-H., Margaritis, D., & Tourani-Rad, A. (2008). Monetary policy transparency and pass-through of retail interest rates. *Journal of Banking & Finance, 32*(4), 501-511. doi: http://dx.doi.org/10.1016/j.jbankfin.2007.06.012

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

Miller, J. I. (2011). Cointegrating MIDAS regressions and a MIDAS test. *Department of Economics, University of Missouri, mimeo*.

Mok, D. Y., Lam, K., & Li, W. (2000). Using daily high/low time to test for intraday random walk in two index futures markets. *Review of Quantitative Finance and Accounting, 14*(4), 381-397. doi: 10.1023/A:1008323926951

Parkinson, M. (1977). Option pricing: The American put. *The Journal of Business, 50*(1), 21-36. doi: 10.2307/2352287

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *The Journal of Business, 53*(1), 61-65. doi: 10.2307/2352357

Phillips, P. C. B., & Loretan, M. (1991). Estimating long-run economic equilibria. *The Review of Economic Studies, 58*(3), 407-436. doi: 10.2307/2298004

Ratner, M., & Leal, R. P. C. (1999). Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *Journal of Banking & Finance, 23*(12), 1887-1905. doi: http://dx.doi.org/10.1016/S0378-4266(99)00042-4

Ready, M. J. (2002). Profits from technical trading rules. *Financial Management, 31*(3), 43-61. doi: 10.2307/3666314

Reilly, F. K., & Brown, K. C. (2012). *Investment analysis & portfolio management* (10th ed.). Mason, OH: South-Western Cengage Learning.

Rogers, L. C. G., & Satchell, S. E. (1991). Estimating variance from high, low and closing prices. *Annals of Applied Probability, 1*(4), 504-512.

Stock, J. H. (1987). Asymptotic properties of least squares estimators of cointegrating vectors. *Econometrica, 55*(5), 1035-1056. doi: 10.2307/1911260

Sullivan, R., Timmermann, A., & White, H. (1999). Data-snooping, technical trading rule performance, and the bootstrap. *The Journal of Finance, 54*(5), 1647-1691. doi: 10.1111/0022-1082.00163

Sweeney, R. J. (1988). Some new filter rule tests: Methods and results. *Journal of Financial and Quantitative Analysis, 23*(03), 285-300.

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.

Tian, G., Wan, G., & Guo, M. (2002). Market efficiency and the returns to simple technical trading rules: New evidence from U.S. equity market and Chinese equity markets. *Asia-Pacific Financial Markets, 9*(3-4), 241-258. doi: 10.1023/A:1024181515265

White, H. (2000). A reality check for data snooping. *Econometrica, 68*(5), 1097-1126. doi: 10.2307/2999444

Wooldridge, J. M. (2009). *Introductory econometrics : A modern approach* (4th ed.). Mason, Ohio: South-Western Cengage Learning.

Appendix A:

Summary Country List

Country	Label	TICKER	Start	End	Series
Argentina	ARG	IBGD	1967.01	2013.11	Buenos Aires SE General Index
Australia	AUS	AORDD	1958.01	2013.11	Australia ASX All-Ordinaries
Austria	AUT	ATXTRD	1996.01	2013.11	Vienna SE ATX Total Return Index
Belgium	BEL	BSPTD	1985.01	2013.11	Brussels All-Share Price Index
Brazil	BRA	BVSPD	1972.01	2013.11	Brazil Bolsa de Valores de Sao Paulo
Canada	CAN	TRGSPTSE	1977.01	2013.11	Canada S&P/TSX-300 Total Return Index
Switzerland	CHE	SSMID	1969.01	2013.11	Swiss Market Index
Chile	CHL	IGPAD	1975.01	2013.11	Santiago SE Indice General de Precios de Acciones
Colombia	COL	IGBCD	1992.01	2013.11	Colombia IGBC General Index
Germany	DEU	FWBXXD	1959.1	2013.11	Germany CDAX Composite Index
Denmark	DNK	OMXCPID	1979.01	2013.11	OMX Copenhagen All-Share Price Index
Ecuador	ECU	BVGD	1994.01	2013.11	Ecuador Bolsa de Valores de Guayaquil
Egypt	EGY	EFGID	1993.01	2013.11	Cairo SE EFG General Index
Spain	ESP	SMSID	1993.01	2013.11	Madrid SE General Index
Finland	FIN	OMXHPID	1987.01	2013.11	OMX Helsinki All-Share Price Index
France	FRA	CACTD	1968.1	2013.11	France CAC All-Tradable Index
United Kingdom	GBR	FTASD	1969.01	2013.11	UK FTSE All-Share Index
Greece	GRC	ATGD	1988.1	2013.11	Athens SE General Index
Hong Kong	HKG	HSID	1969.12	2013.11	Hong Kong Hang Seng Composite Index
Indonesia	IDN	JKSED	1983.04	2013.11	Jakarta SE Composite Index
India	IND	BSESND	1979.04	2013.11	Bombay SE Sensitive Index
Ireland	IRL	ISEQD	1987.01	2013.11	Ireland ISEQ Overall Price Index
Israel	ISR	ILTLVAD	1967.01	2013.09	Tel Aviv All-Share Index
Italy	ITA	BCIID	1957.01	2013.11	Banca Commerciale Italiana Index
Jordan	JOR	AMMAND	1992.01	2013.11	Jordan AFM General Index
Japan	JPN	N225D	1955.01	2013.11	Nikkei 225 Stock Average
Kenya	KEN	NSEKD	1991.02	2008.1	Nairobi SE Dyer and Blair All-Share Index
Korea	KOR	KS11D	1962.01	2013.11	Korea Kosdaq

Sri Lanka	LKA	CSED	1985.01	2013.11	Colombo SE All-Share Index
Mexico	MEX	MXXD	1985.01	2013.11	Mexico SE Indice de Precios y Cotizaciones
Malaysia	MYS	KLSED	1980.01	2013.11	Malaysia KLSE Composite
Nigeria	NGA	NGSEIND	1988.11	2013.11	Nigeria SE Index
Netherlands	NLD	AAXD	1980.01	2013.11	Netherlands All-Share Price Index
Norway	NOR	OSEAXD	1983.01	2013.11	Oslo SE All-Share Index
New Zealand	NZL	NZCID	1970.01	2013.11	New Zealand SE All-Share Capital Index
Pakistan	PAK	KSED	1989.01	2013.11	Pakistan Karachi SE-100 Index
Peru	PER	IGRAD	1982.01	2013.11	Lima SE General Index
Philippines	PHL	PSID	1986.01	2013.11	Manila SE Composite Index
Portugal	PRT	BVLGD	1988.01	2013.11	Lisbon BVL General Return Index
Singapore	SGP	FTSTID	1965.07	2013.11	Singapore FTSE Straits-Times Index
Sweden	SWE	OMXSBGI	1995.07	2013.11	OMX Stockholm Benchmark Gross Index
Thailand	THA	SETID	1975.05	2013.11	Thailand SET General Index
Turkey	TUR	XU100D	1987.1	2013.11	Istanbul SE IMKB-100 Price Index
Taiwan	TWN	TWIID	1967.01	2013.11	Taiwan SE Capitalization Weighted Index
Uruguay	URY	BVMBGD	2008.02	2013.11	Bolsa de Valores de Montevideo Index
United States	USA	SPXD	1928.01	2013.11	S&P 500 Composite Price Index
Venezuela	VEN	IBCD	1994.01	2013.08	Caracas SE General Index
South Africa	ZAF	JALSHD	1986.05	2013.11	FTSE/JSE All-Share Index

Notes: This table lists the market indices selected for 48 countries based on the longest availability criterion with corresponding country label provided. Although the starting points of each market index are different, most of them end in November 2013, except Israel, Kenya and Venezuela. Both the names of the series and tickers that represent each country’s market stock index are retrieved from the Global Financial Data website.

Appendix B:

Summary Critical Values

Significance Level	**1%**	**5%**	**10%**
Standard t-test	2.58	1.96	1.65
Dickey-Fuller test	-3.43	-2.86	-2.57
Augmented Dickey-Fuller test	-3.43	-2.86	-2.57
EG-OLS test	-3.73	-3.17	-2.91

Notes: This table compares the critical values on the three most frequently used significance levels for four hypothesis-testing techniques, which are the standard t-statistics, Dickey-Fuller test, Augmented Dickey-Fuller test and EG-OLS test.