THE COINTEGRATING RELATIONSHIP IN ASIAN MARKETS WITH APPLICATIONS TO STOCK PRICES, EXCHANGE RATES AND INTEREST RATES

A thesis submitted for the Degree of Doctor of Philosophy

By

Tippawan Tanonklin

DEPARTMENT OF ECONOMICS AND FINANCE

SCHOOL OF SOCIAL SCIENCES

BRUNEL UNIVERSITY

February 2013

ABSTRACT

The aim of this research is to investigate the long-run co-integrating relationships in the Asian markets. Our research focuses on 4 areas; pair trading, out-of-sample forecasting, testing the unbiased forward exchange rate hypothesis and testing the expectation hypothesis of the term structure of interest rates. The introduction is provided in chapter one. In chapter two, we develop a pairs trading strategy using individual stocks listed in the Stock Exchange of Thailand. Engle and Granger approach is used to identify the potential pairs that are cointegrated. The results show that pairs trading strategy is profitable in this market. Chapter three examines the forecasting performance of the error correction model on daily share price series from the Stock Exchange of Thailand. The disequilibrium term is classified into “correct” and “mix” sign based on Alexander (2008)’s criterion; the results indicate that the error correction component can help to improve the predictability in the long run. Chapter four tests the unbiased forward rate hypothesis of 11 Asian exchange rates using linear conventional regression, ECM and logistic smooth transition regression with the forward premium as the transition variable. Out-of-sample forecasting results also suggest that inferior forecasting performance could be obtained as a result of using linear models. In chapter five, we investigate the expectation hypothesis of the term structure of interest rate for four Asian countries. We employ linear models and nonlinear approaches that allow to capture asymmetric and symmetric adjustments. The result also indicates that the term structure can be better modeled by means of LSTR models. The forecasting exercise also confirms these findings.

Acknowledgement

I would like to acknowledge all the assistance, support and guidance of my supervisor Dr. Fabio Spagnolo, and thank him for his tireless effort on my behalf. I have been very fortunate to have had him as my supervisor. He has not only advised on academic work but also my future career and life throughout my research. With his efforts to explain things clearly and simply, he made econometric fun and interesting for me. He also provided me different ways to overcome the difficulties and cheer me up when I was stressed. I have learned so much from him. I would like to thank him very much for his patience, kindness and encouragement.

I would also like to extend my appreciation to my father and mother, Narong and Wanlapha Tanonklin, for their unconditional love and support in pursuance of my academic interests. They have blessed me with power and willingness. They have always believed that I could reach the goal I had set out to achieve. With all their support, I have had the strength to overcome all obstacles I have come across through all the years of hard work to make them proud of having me as their daughter.

I would like to show my appreciation to all members of the academic and administrative staff at the Department of Economics and Finance of Brunel University for their help towards the completion of this thesis. Finally, I would like to thank all the friends I have known throughout the years in Brunel.

Table of contents

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

The concept of an efficient financial market was firstly proposed by Fama (1970). It says that the security prices always fully reflect the available information; any new information is quickly and instantaneously reflected in prices. The basic assumptions included are; 1) no trading cost and tax; 2) no investors have power to influence the price; 3) no information gathering cost and 4) the new information is rapidly reflected in prices. Moreover, the efficient market hypothesis is often tested in its weak form, in which it is asserted that financial markets incorporate all available past information; thus, the investors cannot outperform the market, on average, by using the historical values.

The common practice of testing this hypothesis is to investigate whether the past value of one variable can help to predict the future value of another variable. As a consequence, the investors can earn excess returns. Moreover, introducing the cointegration concept leads to a different way of testing the efficient market hypothesis. The widely implemented cointegration approach is the Engle and Granger (1987) two steps approach (even though the model restricts to a system of only two or three variables). This approach firstly (i) estimates the long-run relationship between the two non-stationary series; (ii) secondly, tests the linearly combination between the two stocks for the presence of unit root; thus, the two series are cointegrated at the same order if the long-run relationship is stationary. Moreover, Granger (1986) shows that cointegrated time series has an error correction representation. This result implies that, historical values embedded in the error correction term can help to predict the current movement of the series. Therefore, the efficient market hypothesis is violated in the sense that the two variables should not be cointegrated in an efficient market (Granger, 1986).

If the two non-stationary series are cointegrated, the short-run disequilibrium from the long-run cointegrating relationship or error correction mechanism should help to forecast the future price correctly and results in abnormal return. To the best of our knowledge, the previous literatures mainly implement this approach in the advanced economic countries, but rarely in the emerging markets. Therefore, in this research, we attempt to test the efficiency hypothesis in Asian market by applying the concept of cointegration in 4 empirical financial applications. The Asian financial time-series data is used, which consists of individual share prices series from the Stock Exchange of Thailand, spot and forward exchange rates and the Treasury bill rates from Asian countries.

In the first application, to exploit the short-run deviation from a long-run equilibrium pricing relationship between two non-stationary stocks, we implement pairs trading strategy based on Vidyamurthy (2004) methodology in the Stock Exchange of Thailand from 1999 to 2008. Pairs trading strategy is straightforward: buy the under-valued stock and sell the over-valued stock. If the cointegrating relationship exists, the two stocks are tied together in the long-run; thus the short-run deviation will be corrected and reversed back to the long-run equilibrium. However, the critical question is "which pairs of stock are to be traded?" In this study, we develop a pairs trading strategy with an attempt to test our strategy in terms of profitability. Firstly, we identify the trading pairs based on the presence of a cointegrating relationship between the two stocks using the Engle and Granger two steps approach. The previous literature suggested using the stocks in the same category as they are more likely to move together. The possible reasons are that 1) the businesses in the same industry have similar products; therefore are affected by the same shocks; 2) the market risk is alike. Secondly, to select the potential pairs, an error correction model is applied in order to select the cointegrated pair that exhibits strong mean reversion property. Thirdly, the trading rules and pairs trading strategies are implemented using 3 level of trading bands and 3 trading strategies. These 3 strategies are simulated in 4 different experiments dealing with and without trading period constraint and updated beta. In addition, we also attempt to investigate whether the sign of the disequilibrium term matters in pairs trading analysis. For this analysis, the Alexander's (2008) criterion is considered.

The second application considers out-of-sample forecasting. The previous literature has addressed that using error correction mechanisms can improve the forecasting accuracy especially in the longer-forecasting horizons (LeSage, 1990; Lin and Tsay, 1996). Thus, in this research, 20-steps ahead forecasts of the error correction model are compared to those obtained using random walk and random walk with drift models. The accuracy of forecast is assessed in terms of point forecast analysis, direction of change and forecast encompassing. Moreover, the cointegrated pairs are classified into "correct" and "mix" sign groups based on Alexander's (2008) criteria. Thus, our research also assess whether the correct sign of the error correction mechanism is well captured. In addition, the specified and misspecified error correction models are conducted to show whether including insignificant disequilibrium term would help to improve the predictability.

In the third application, the cointegration concept is used to test the efficient market hypothesis in 11 Asian currencies; efficiency implies that the forward exchange rate should be an unbiased predictor of the corresponding spot exchange rate. As a consequence that the available information is fully reflected in the forward exchange rate; thus, the future spot rate is expected to be equal to the current forward rate. A number of works in literature has rejected the forward rate unbiased hypothesis (FRUH) and found that the beta is significantly different from the true value of unity in both advance and emerging currency markets. In particular, the empirical study of Franken and Poonawala (2010) indicates that the forward bias in emerging markets is less pronounced than the industrial markets using linear conventional model. This implies that the bias in emerging markets is too small and not economically significant. Thus, in this application, we use linear and nonlinear frameworks based on conventional regressions and logistic smooth transition regression to examine the relationship between spot and forward currencies. We also attempt to explore the forward bias in emerging Asian countries in term of forecasting performance relative to the developed Asian countries.

The fourth part of the research is related to testing whether the expectation hypothesis of the term structure of Asian interest rates holds in the market. If the expectation hypothesis holds, the market is efficient. This implies that the long-term interest rate is fully reflected in the information revealed by expected future short-term interest rate. In other words, the term structure of interest rates contains no useful information to predict changes in the future short-term rate. The previous literature reports mixed evidence in both advance and emerging countries. The common finding yields positive estimated slope of the term structure using the linear model. However, the estimated slope deviates from the true value, which suggests rejecting the hypothesis. Moreover, using nonlinear model, the evidence from major countries give favorable result toward the expectation hypothesis. Hence, in this application, we test the expectation hypothesis of the Asian term structure of interest rates using linear regressions and nonlinear smooth transition models. Additionally, a forecasting exercise is also conducted to evaluate whether the term structure of Asian interest rates is better described by nonlinear model.

1.1 The aim and objectives of this research

The general aim of this empirical study is to investigate long-run relationships in the Asian market and the implication in terms of market efficiency. We attempt to consider cointegrating relationships in 4 difference areas, which are pairs trading strategy (using share price series from Thailand's stock exchange market), forecasting performance (of individual stock from Thailand's stock exchange market), testing the forward rate unbiased hypothesis (utilizing Asian spot and forward exchange rates) and testing the expectation hypothesis (of Asian 3-month and 6-month Treasury bill rates).

i) In the pairs trading strategy, we utilized the cointegration approach to select the potential pairs of stocks for trading purposes. The aim of this study is to investigate the performance of the pairs trading strategy in emerging markets based on two stocks that tend to move together in the long-run. We also aim to provide insight into the co-movement of the stocks, which would be valuable to an investor to profit from both winner and loser stocks. The objective is to develop a trading rule for pairs trading using the bivariate cointegration approach. The presence of a cointegration relationship between two stocks provides an important fundamental property, namely mean reversion for profitable pairs trading. Another objective is to explore the profitability of the pairs trading strategy in an emerging equity market (Thailand).

ii) In forecasting, we used the cointegration to improve the forecasting ability in the multi-steps forecast of share price series. The aim of this study is to investigate the multiple-steps forecasting performance of simple ECM dealing with 2 non-stationary stocks that found to be cointegrated. We also aim to assess the profitability of obtained prediction in trading simulation.

iii) In testing the forward rate unbiased hypothesis, we aim to test the FRUH in Asian currency markets using linear and nonlinear models. We also aim to investigate whether the small forward bias in this market can be exploited in term of forecasting purpose.

iv) Finally, we aim to investigate the expectation hypothesis of the term structure between 6-month and 3-month interest rates in Asian markets. Moreover, we also attempt to examine whether the term structure is better explained by a nonlinear model than the conventional linear regression.

1.2 Contribution of this research

The main contribution of this research is summarized as follow:

1) We develop a pairs trading strategy using Vidyamurthy (2004)'s method with an attempt to test on the profitability of the pairs trading strategy as Vidyamurthy (2004) has not tested the profitability. The findings confirm that pairs trading strategy is highly profitable in the Stock Exchange of Thailand.

2) Investigating the performance of pairs trading strategy, the findings also confirm that pairs trading strategy is a market neutral investment strategy in which we implement 3 different strategies with different level of risks in 4 different trading simulations. We obtain similar abnormal returns. The conservative strategy is superior to the riskier strategies in term of lower risk with similar return.

3) We attempt to examine whether the sign and size of the speed adjustment coefficient matters in pairs trading strategy. The results indicate that sign and size of disequilibrium term does matter in this analysis as it alters the profitability of the strategy. In particular, the mix sign with low adjustment speed

pairs yields small return, which is not statistically significant. This could be due to no presence of error correction mechanism that helps in making a correction to the long run equilibrium. Surprisingly, we find profitable results from inactive pairs with small size of adjustment coefficient. This finding suggests that the mechanism of ECM works in self-correcting to the equilibrium as long as the pairs has correct cointegration sign.

4) Our findings indicate that updated slope coefficient (β) in trading simulation can be an alternative method to maximize abnormal returns against a given risk when beta increases over time. As Alexander and Dimitriu (2002) point out, the market neutrality in pairs trading strategy does not require beta to be zero to immunize it against systematic risk.

5) In the forecasting study, our findings indicate that ECM can outperform the RW and RWD in the longer horizon while competitively perform in the short forecasting horizon. Surprisingly, the forecasting performance of ECM produces bad forecasts, when the model is used to forecast in the mix sign cointegrated pairs. This finding cast doubts on the cointegration relationship of a pair of stocks that priory was found to be cointegrated. Thus, the result suggests that how crucial it is to identify a correct cointegration relationship before implementing ECM. Otherwise, ECM would be useless for a forecasting purpose where the error correction mechanism is not present. The error correction sign suggested by Alexander (2008) seems to be an alternative criterion to consider as it is helpful in detecting non-cointegration variables.

6) In the application of exchange rate, we test the forward rate unbiased hypothesis on the forward premium of 11 Asian exchange rates. We find that the hypothesis cannot be rejected in 7 out of 11 currencies using the linear conventional Fama regression.

7) We also attempt to test the FRUH in a nonlinear framework. Using a logistic smooth transition model, we find that 6 Asian currencies exhibit nonlinearity. Similar to the previous findings of Sarno, Valente and Leon (2004) and Baillie

and Kilic (2006) that tested in major currencies, the majority of transition variables line in the lower regime where the forward rate unbiased hypothesis is most likely to reject.

8) The estimated slope of the forward premium is mostly positive for developing countries while we obtain negative estimates for developed Asian currencies. Thus, this result is consistent with the previous finding of Frankel and Poonawala (2010) that the forward bias in developing countries is less severe than the major currencies. This implies that the forward bias is too small to be significantly exploited. However, the forecasting performance shows that conventional Fama regression, linear error correction model and logistic smooth transition model are predictable.

9) We test the expectation hypothesis on the term structure of 4 Asian interest rates using linear and nonlinear models. The results indicate that the hypothesis is rejected in all cases. The models include the linear conventional term structure regression, linear ECM, smooth transition models with logistic and exponential functions. Our finding indicates that the term structure of interest rates contains predictive information that helps to forecast the future changes in the short-term rate. However, the result shows that the term structure of Hong Kong and Malaysia are better explained by nonlinear logistic smooth transition model while the linear conventional regression best approximates the term structure of Thailand’s interest rates. Additionally, the estimation result is inconclusive for the Philippines. The forecasting performance also confirms such findings.

1.3 Chapter outline

This research is organized into 6 chapters, which is presented in the following;

Chapter II: in this chapter, I provide the literature review describing the available methods for implementing pairs trading strategy in the literatures. Moreover, the popular pairs trading is developed using cointegration approach. The profitability of pairs trading strategy is tested in 4 different simulations, which consider 3 levels of trading bands and 3 types of strategies involving different levels of risk.

Chapter III: in this chapter, I extend the research from chapter II into the aspect of forecasting. Firstly, I examine the methods and forecasting models that the previous literatures have implemented for forecasting aspect related to a concept of cointegration. The previous literature has shown that using an error correction mechanism can improve the forecasting accuracy especially in the longer-forecasting horizons. Thus, the 20-steps forecast of ECM is conducted. Random walk and Random walk with drift models are used as benchmarks. The accuracy of forecast is evaluated in term of point forecast, directional of change and forecast encompassing.

Chapter IV: in this chapter, the linear and nonlinear models that have been used to capture the relationship between the spot and forward exchange rates and how the forward biased hypothesis has been tested in the previous literatures are reviewed. Then, I implement linear and nonlinear models to explain the behavior of spot and forward relationships. The forward rate unbiased hypothesis is also tested in Asian currency markets. As the previous study of Franken and Poonawala (2010) indicated the smaller bias in the emerging forward exchange rate markets, the forecasting experiment is conducted to examine whether the obtained bias from this sample could be exploited.

Chapter V: in this chapter, I describe the previous evidence of testing expectation hypothesis of the term structure of interest rates in both advance and emerging economies using various models. The term structure of interest rates is examined using linear conventional regression, error correction model and smooth transition models with logistic and exponential transition functions. Moreover, estimated slope coefficient generated from each model is tested to check whether it equals to the theoretical value suggested by the expectation hypothesis. Rejecting the hypothesis implies that the term structure can forecast the future changes in the short term rates. I also conduct small forecasting exercises to confirm whether the interest rate is better approximated by linear or nonlinear models.

Chapter VI: the main findings of this research are summarized in this chapter.

CHAPTER II

PAIR TRADING PERFORMANCE OF COINTEGRATION APPROACH: EVIDENCE FROM STOCK EXCHANGE OF THAILAND

2.1 Introduction

"Pairs trading" is one of the popular quantitative methods of speculation in the financial market. The strategy was initiated in the mid-1980s by Wall Street quant Nuncio Tartaglia after forming a group of mathematicians, physicists and computer scientists to explore arbitrage opportunities in the equity market (Vidyamurthy, 2004). Tartaglia and the group traded with great success in 1987 and the strategy became known as "pairs trading". The popularity of the strategy established it as a common trading strategy, widely implemented by hedge funds and institutional investors (ibid). The concept of pairs trading is straightforward. Identify pairs of stocks whose prices tend to move together when the spread deviates from the long-run equilibrium, short the winner stock and long the loser stock. The contrarian trade is made when the spread reverses back.

The previous literatures have shown some evidence of profitability of the pair trading strategy. Gatev et al (1999) and Nath (2003) employed the distance method on the US market and Do et al (2006) employed residual spread in the US, the UK, and Australia. Their empirical studies showed significant profit even after the transaction costs in the developed markets. Moreover, the recent empirical studies on developing countries have also indicated profitability in pairs trading. Perlin (2007) employed the distance method on the Brazilian financial market and his findings confirm that pair trading is profitable. In general, there are four main methods identified in the literature: the distance method, the stochastic spread method, the stochastic residual spread method and the cointegration method.

Previous literatures have tested the profitability of pairs trading in developed countries and have indicated anomaly return, but there have not been many empirical studies conducted on developing countries. Although the strategy seems to be profitable in both developed and developing economies, developing markets are less efficient than developed markets and this might lead to the pairs trading strategy yielding better results in the latter. We are particularly interested in studying the stock exchange of Thailand (SET) because Thailand is an emerging country with a wealthy economic condition among other Asian countries. In particular, the SET index is the best performing stock market in Asia and the top 10 world's best performing stock market (Kawa, 2012). Thus, it is beneficial to investigate the characteristic of the market using cointegration approach to gain further insight and explore the investment opportunities in this market.

The aim of this empirical study is to investigate the performance of pair trading strategy with the objective of exploring the profitability of the strategy in Thailand. The methodology is adopted from Vidyamurty's (2004) study that applies Engle and Granger's cointegration approach for the pair's selection process and the error correction model for selection of the quality pairs that have a strong mean reversion property. Moreover, three trading strategies are conducted in three different simulations with three levels of trading boundaries.

The remainder of this paper is organized as follows. Section 2.2 describes the various pair trading methods in the literatures. The empirical framework is explained in section 2.3, which includes Engle and Granger's cointegration approach and error correction model on how one selects the cointegrated pairs and - later in this section - how we conduct trading simulations. In section 2.4, we describe ten years data that were employed in this study. Next, the economic outlook is described in section 2.5. In section 2.6, the empirical results are analyzed. Finally, section 2.7 presents concluding remarks.

2.2 Literature review

"Pairs trading" is a popular quantitative method of speculation, which was initiated by Wall Street quant Nuncio Tartaglia in the mid-1980s. This strategy is widely known and implemented by hedge funds and institutional investors (Vidyamurthy, 2004). The concept of pairs trading is simple: select a pair of stocks that are linearly combined, which tend to move together in the long-run. When the spread of this pair deviates substantially from the long-run equilibrium, we sell the over-valued stock and buy the under-valued stock. The contrarian trade is made when the spread reverses back to the equilibrium. The presence of a cointegrating relationship between the two stocks implies that these two stocks share a long-run equilibrium relationship; the short-term disequilibrium is expected to return to zero in future periods.

Four main methods that have been implemented for the pairs trading strategy in the current literature: the distance method, the stochastic spread method, the stochastic residual spread method and the cointegration method.

2.2.1 The distance method

Matching pairs that minimize the sum of squared deviation between two normalized historical price series is the essence of the distance method implemented in pairs trading. The trading signal is emitted when the distance between pairs reaches a certain threshold as considered over a sample period of study. If the distance is greater than a specified threshold, then there is an arbitrary opportunity to explore the profit or execute the trading short/long positions when the distance is less than a specified threshold.

In the Gatev, Goetzmann, and Rouwenhorst (1999) empirical study, the authors applied a pair trading strategy to daily US security from 1962 to 2002. The first twelve-month sample period is used in formation period where they formed trading pairs. These pairs are traded over the trading period of the last six-month. In the formation period, they first screened out illiquid stocks from the Center for Research in Security Prices (CRSP) daily files that had one or more days with no trade in historical data (Gatev et al, 1999). Second, they constructed a cumulative total returns index for each stock over a twelve-month sample period. Third, they selected matching pairs for each stock by finding the security that minimizes the sum of squared differences between the two normalized price series, where price includes reinvested dividends.

In addition, the study of unrestricted pairs yields the results by sector. They restrict stocks to belong to the same industry categories defined by Standard and Poors, which are Utilities, Transportation, Financial and Industrials. In the trading period, Gatev et al (1999) tested the pairs trading strategy over the 6-month trading period on the top 5 and 20 pairs that have a minimum historical distance measure. Gatev et al (1999) based their trading rules on a standard deviation metric where they open long/short positions when the prices have deviated by a certain amount and close the long/short positions when the share prices have reverted back. Using a six-month trading period, they enter a long/short position when prices diverge more than two historical standard deviations and exit at the next crossing or convergence of the share prices. If the prices do not cross within the 6-month trading period, they close the pairs trading at the end of the trading day of that period. In addition, historical standard deviations are estimated during the pair’s formation period.

The empirical findings of Gatev et al (1999) confirmed that this popular Wall Street investment strategy is significantly profitable even after taking in account the transaction costs. The average excess returns of the top 5 and top 20 pairs are respectively 1.31% and 1.44% per month. In addition, over a six-month trading period, they achieved profit levels of approximately 436 to 549 basis points. The average net profit ranged from 113 to 225 basis points after the transaction costs of 162 basis points multiplied by 2 rounds trips per pair. The results suggest that pairs trading are profitable.

Moreover, the statistic shows that the top 5 pairs enter the position during the trading period on average 4.81 times and an average of 2.02 round trips per pair. The position is held on average for 3.75 months. Hence, these statistical results indicate that pairs trading in this empirical research are a medium term investment strategy.

Furthermore, these anomaly profits are uncorrelated with the S&P 500. The result of excess return comparison shows that the excess return to pairs trading has been twice as large as the excess return on the S&P 500 (Gatev et al, 1999). In addition, the sharp ratios of pairs trading are approximately 4 to 6 times larger than the U.S. market. Thus, pair trading seems to have outperformed the market. Moreover, these abnormal profits are essentially different from a pure mean-reversion strategy. Gatev et al (1999) conducted a bootstrap test to compare the performance of pairs to random pairs. The outputs of the bootstrapped pairs yield lower returns and larger standard deviations than the strategies' pairs. Thus, the results indicate that bootstrapped pairs are poorly matched, and the pairs trading strategy does not reflect mean reversion (Gatev et al, 1999).

Under the distance method, Nath (2003) also employs a measure of distance in the liquid secondary U.S. market to identify potential co-movement securities. The Treasury securities used in this study include bills, notes and bonds from the period January 1994 to December 2000. The author records the distance between each pair in the universe of securities. The record is kept in the form of the empirical distribution. Thus, long/short trading is open when the distance between the securities widens to reach or cross a trigger level (15 percentile), which is defined as a percentile of the empirical distribution of distances observed over the training period. Moreover, he adopts a stop loss trigger to close the trading position, in which a pair trading is closed when it meets one of the three conditions below:

1) The spread of the distance narrows and reaches or crosses its median distance.

2) The last day of the trading period is reached.

3) The spread of distance widens to hit a risk management trigger.

If the pair trading meets the first condition, the pair trading strategy leads to a profit. The second condition may lead to a profit or a loss. The last condition always leads to a loss.

In order to appraise the performance of the pair trading strategy, Nath (2003) attempts to create a duration-matched benchmark and Gain-Loss ratios. In addition, a more comprehensive comparison is provided by including the Salomon Brothers Treasury Index, S&P 500 Composite and the risk-free rate. The author finds that pairs trading returns performed better than the equity and bond index, in which the Sharpe Ratio's value of the pair trading strategies is higher than the benchmarks. Gain-Loss ratio also confirms that the pairs trading strategies almost always yield a better result than other benchmarks. In addition, the return distribution of P1505Z (pairs trading strategy with 15% of open trigger, 5% of stop-loss trigger and without transaction costs) has a much narrower range than Salomon Brothers Treasury Index and S&P 500 Composite, which highlights the fact that P1505Z has a limited upside and downside return.

There are some important differences between the empirical research of Gatev et al (1999) and Nath (2003). Firstly, the Gatev et al (1999) approach has only one matching partner for a particular security. This implies that security A can only match with security B. Conversely, there is the possibility that one particular security has multiple matches under the Nath (2003) approach. For example, security A matches with security B and, at the same time, security A also matches with security C. Secondly, empirical research by Gatev et al (1999) does not attempt to include any risk management measures to prevent substantial losses for the pairs trading strategy. On the other hand, Nath (2003) proposes a trading rule that includes a stop-loss trigger to close the long/short position when the distance widens to cross the trigger point at 5%, which aims to limit the massive loss of the strategy.

More recent empirical research also confirms the profitability of the pair trading strategy. Perlin (2007) employs the minimum squared distance rule on the Brazilian financial market from 2000 to 2006 and tests different frequencies of stock data (i.e. daily, weekly and monthly). The author states that the logic behind the expected profit of pairs trading strategy is (Perlin 2007):

> "*if the correlated movement between the pairs is going to continue in the future then, when the distance between an asset and its pairs is higher than a particular threshold value, there is a good possibility that such price is going to converge in the future and this can be explored for profit purpose*".

Hence, the pairs trading rule implemented in this research is based on the logic that a trading signal is emitted when the absolute distance between pairs normalized price of assets is greater than the threshold value and maintain the trade positions until absolute distance is less than the threshold. For instance, if the absolute distance is positive and higher than the threshold value, the investor shorts the winner stock A and longs the loser stock B and maintains the position until the distance is lower than the threshold; then the trade is executed in long stock A and short stock B.

Moreover, Perlin (2007) evaluates the performance of the pairs trading strategy against a naïve approach and concludes that pairs trading strategies perform better than weighted naïve portfolio in most cases, especially in the daily and weekly share price series. This seems to suggest that pairs trading strategies can take advantage of market inefficiency. Also, the long position yields are far more profitable than the short position when applied to the upward-trending Brazilian financial market at all difference frequencies.

Additionally, Perlin (2007) finds the correlation of threshold value and number of trades to be negative, which implies that the investor can lower the transaction cost by increasing the threshold value hence reducing the number of trades. Moreover, the beta is close to zero and not significant at 10% level, which indicates that the pairs trading strategy is a market neutral rule. In other words, pairs trading strategy can perform well no matter if the stock market is in a bull or bear period.

2.2.2 The stochastic spread method

Another interesting pairs trading approach is the study of the mean reverting behavior of the spread in a continuous time setting, which is explicitly described in the empirical research of Elliott, van der Hoek, and Malcolm (2005). The spread is the difference between the two security prices, which is driven by a latent state variable x and, additionally, the spread between the two security prices is assumed to follow a Vasicek process:

$$dx_t = k(\theta - x_t)d_t + \sigma dB_t \tag{2.1}$$

where dB_t is a standard Brownian motion on some probability space. The state variable is known to revert to its mean θ at the rate k. Elliott et al (2005) assume the observation process $\{y_t\}$ of $\{x_t\}$ equal to the state variable plus a Gaussian noise:

$$y_t = x_t + H\omega_t \qquad (2.2)$$

where $\{\omega_t\}$ are iid[1] Gaussian N(0,1). The trader declares that the observed spread is driven mainly by a mean reverting process, plus some measurement error. The trader can enter the position when the spread $\{y_t\}$ is greater than $\hat{x}_{t|t-1}$ by some threshold value. In contrast, short the position when $y_t < \hat{x}_{t|t-1}$.

There are some major advantages of the Elliott et al (2005) stochastic spread model from the empirical perspective. Firstly, the stochastic spread model captures mean reversion, which emphases pairs trading. Do et al (2006) point out that Elliott et al (2005) have ambiguously defined the spread that can have negative value. Hence, they propose to identify the spread as the difference in logarithms of the prices $\log(p_t^A) - \log(p_t^B)$. In general, the long term average of the level difference in two stocks should not be constant, but widen as they go up and narrows as they go down. Moreover, Schmidt (2008) cast doubt on the previous researches in that simply taking logarithms should not give any result in a mean reverting series if the spread series does not exhibit mean reversion. The logarithm function seems to force the spread series to appear to converge, whereby large deviations appear less pronounced. For this reason, the spread series' appearance seems to have a mean reverting property but no relevant support for such an occurrence. Schmidt (2008) also mentions that the spread of an arbitrary pairs trading is not expected to exhibit a long-run relationship - also known as mean reversion - if those securities are not cointegrated.

Secondly, the stochastic spread model has the advantage of being completely tractable, plus the parameters are easily estimated by the Kalman filter in a state space setting. The maximum likelihood estimator is implemented, which yields the optimal result in the sense of minimum mean square error (MMSE). In a state space setting, (2.1) can be

[1] "independently and identically distributed"

present in a discrete time transition equation, motivated by the fact that the solution to (2.1) is Markovian:

$$x_k = E[x_k | x_{k-1}] + \varepsilon_k \tag{2.3}$$

k=1, 2…, and ε is a random process with zero mean and variance equal to $v_k = VAR[x_k | x_{k-1}]$. Both conditional expectation and variance can be computed clearly and the above equation can be written as:

$$x_k = \theta(1 - e^{-k\Delta}) + e^{-k\Delta} x_{k-1} + \varepsilon_k \tag{2.4}$$

where Δ denotes the time interval (in years) between two observations and the variance of the random process and ε happens to be a constant $v = \dfrac{\sigma^2}{2K(1 - e^{-2k\Delta})}$. Additionally, it indicates that the conditional distribution of x_k is Gaussian. Then, the discrete time measurement equation becomes:

$$y_k = x_k + \omega_k \tag{2.5}$$

Therefore, the transition and measurement equation of a state space system has a linear equation and is a Gaussian function such that the Kalman filter recursive procedure gives optimal estimates of the parameters Ψ= {θ,K,σ,ħ}.[2]

Although the stochastic spread model exhibits some advantages, this approach does have a fundamental limitation in that it poses restrictions on the long-run relationship between the two stocks to one of return parity (Do et al, 2006). It implies that the security pairs chosen must give the same return in the long-run, and thus any departure from it will be expected to be corrected in the future.[3] This is a severe limitation as, in practice; there is a small probability of finding two securities with identical return series. Regarding the risk and return models such as Arbitrage Price Theory (APT) and Capital

---

[2] For introduction to the state space model and Kalman filter, see Durbin and Koopman (2001)

[3] Do, Faff and Hamza (2006) provide a proof in page 8 as follow:-

Assume both stock A and B return (r) in 1 unit of time so that $p^A_{t+1} = p^A_t e^r \text{ and } p^B_{t+1} = p^B_t e^r$.

The log difference is

$$\log(p^A_{t+1}) - \log(p^B_{t+1}) = (\log(p^A_t) + r) - (\log(p^B_t) + r)$$
$$= \log(p^A_t) - \log(p^B_t)$$

Asset Pricing Model (CAPM), the two stocks that bear the same risk are expected to have the same return (Schmidt, 2008). However, this assumption does not hold in practice because there are essential firm-specific risks that make companies with the same risks yield different returns.

Moreover, the concept of diversification does not apply in this case because the pairs trading portfolio is not sufficient to diversify the unsystematic risk. Regardless of the limitation of the stochastic spread model, the Elliott et al (2005) approach is appropriate for implementing with two types of companies; a dual-listed company and crossed listing company (Do et al, 2006).

Firstly, the stochastic spread model can possibly be implemented where the company has a dual-listed company (DLC) structure (or 'Siamese twin'). According to Bedi, Richards and Tennant (2003), DLC structures are:

> "*..... Effectively mergers between two companies in which they agree to combine their operations and cash flows and make similar dividend payments to shareholders in both companies, while retaining separate shareholder registries and identities*".

There are a few dual listed companies - Unilever NV/PLC, Royal Dutch Petroleum/Shell, BHP Billiton Ltd/PLC and Rio Tinto Ltd/PLC. In a DLC structure, the shareholders of twin companies are entitled to exactly the same voting power and cash flows; one might have expected that DLC twins should have traded at the same price. The empirical research by Froot and Dabora (1999) has verified that DLC twins have large and variable price difference even though the share prices are highly correlated. Indeed, the shares cannot be exchanged for each other, which protect them from riskless arbitrage even though there is an opportunity for pairs trading.

Secondly, the stochastic spread model can be applied to the cross listed company. A cross listing occurs when an individual company establishes a secondary listing on a foreign stock exchange in addition to its domestic exchange, the most prominent arrangement being via American Depositary Receipts (ADRs). Moreover, the companies can cross list within different stock exchanges within a country such as the NASDAQ and NYSE in America (Do et al, 2006).

2.2.3 Stochastic residual spread method

Despite the existing approaches that address the mis-pricing between two stocks at a given price level, Do, Faff and Hanmza (2006) propose a stochastic residual spread method that models the spread between two stocks at the return level.

Do et al (2006) assume that there exists some equilibrium in the relative valuation of the two stocks, which measured by some spread. This mis-pricing is therefore constructed as the state of disequilibrium, which is quantified by a *residual spread function* $G(R_t^A, R_t^B, U_t)$ (Schmidt, 2008). U indicates some exogenous vector potentially present in formulating the equilibrium. The term "residual spread" indicates that the function captures any excess over and above the long term spread and may take non-zero values depending on the formulation of the spread (Do et al, 2006). The market is assumed to affect the mean-reversion process of the spread to reverse back in the long-run. Similar to previous pairs trading approaches, the pair traders can enter the trading position when the disequilibrium is sufficiently large and the expected correction time is sufficiently short; thus, the pair trade can be executed for profit.

Similar to Elliott et al (2005)'s modeling framework, Do et al (2006) use one factor stochastic model to explain the state of mis-pricing or disequilibrium. The model also lets some noise contaminate its actual observation being measured by a function G. In this case, x represents a state of mis-pricing or residual spread with respect to a given equilibrium relationship, where the dynamic is governed by a Vasicek process as follow:

$$dx_t = k(\theta - x_t)dt + \sigma dB_t$$

The observed mis-pricing is:

$$y_t = G_t = x_t + \omega_t \tag{2.6}$$

These two equations form a state space model of relative mis-pricing with respect to some equilibrium relationship between two assets. Moreover, Do et al point out that the state space of mis-pricing in this model is not fully observed but it can detect up to some measurement noise.[4] Additionally, Do et al (2006) do not consider some measurement noises such as the presence of bid-ask spread and human error in data handling, which have an insignificant impact on the residual spread result. In this study, measurement noise is set to capture the uncertainty in equilibrium relationship that embedded in the residual spread function G. In summary, the state space of mis-pricing is not fully observed because the equilibrium relationship is unknown and needs to be estimated. Moreover, the equilibrium relationship or the residual spread is motivated by the Arbitrage Pricing Theory (APT) (Ross, 1976). The APT asserts that the return on a risky asset, over a risk free rate, should be the sum of risk premiums multiplied by exposure (ibid). Additionally, the specification of the risk factors is flexible and may form as the Fama-French three factor model below:

$$R^i = R_f + \beta r^m + \eta^i$$

where $\beta = [\beta_1^i \beta_2^i \ldots \beta_n^i]$ and $r_m = [(R^1 - r_f)(R^2 - r_f) \ldots (R^n - r_f)]^T$, R^i denotes the actual return on the i[th] factor. The residual (η) has expected value of zero, which indicates that APT works on a diversified portfolio where unsystematic or firm-specific risks are not rewarded, although the actual value can be non-zero.

A relative APT on stock A and B can be written as:

$$R^A = R^B + \Gamma r^m + e$$

where $\Gamma = [(\beta_1^A - \beta_1^B)(\beta_2^A - \beta_2^B) \ldots (\beta_n^A - \beta_n^B]$ is a vector of exposure differentials and e is a residual noise term. Do et al (2006) make the assumption that the above relationship holds true in all time periods, therefore the equation can be written as:

$$R_t^A = R_t^B + \Gamma r_t^m + e_t$$

Thus, from the above equilibrium model, they specified the residual spread function G as follow:

[4] The measurement noise is used to apply in dynamic asset pricing studies, which capture the pricing error occurring across a cross-section of assets.

$$G_t = G(p_t^A, p_t^B, U_t) = R_t^A - R_t^B - \Gamma r_t^m \tag{2.7}$$

At the final point, the residual spread function G is fully observable when Γ is known and r_t^m is specified. As a corollary, the model of mean reverting relative pricing for two stocks is completely tractable and ready to be applied for pairs trading. In addition, in a discrete time, the transition equation can be written as:

$$x_k = \theta(1 - e^{-K\Delta}) + e^{-K\Delta} x_{k-1} + \varepsilon_k \tag{2.8}$$

The measurement equation can be written as:

$$y_k = x_k + H\omega_t \tag{2.9}$$

The model above is similar to the Elliott et al (2005) model when Γ is a zero vector. However, when the observation function G_k is not able to observe as Γ is not known, this state space model still has a problem. The first solution for this problem can be supplied by firstly estimating Γ by standard linear regression with the return difference of stock A and B (R^A-R^B) as the dependent variable and the excess return factors as the independent variables. Secondly, residual spread time series can be constructed, using the calculated residuals from the regression. The above time series becomes the observation for the state space model.

Another alternative solution is proposed by Do et al (2006) such that the observation $y = R^A - R^B$ is redefined. Hence, the measurement equation is rewritten as:

$$y_k = x_k + \Gamma r_k^m + H\omega_k \tag{2.10}$$

As a result, the mis-pricing dynamics and the vector of exposure factor differentials Γ can be identified simultaneously by estimating the state space model (Schmidt, 2008). This formulation also helps to avoid the increase of estimation errors that would arise from the two-step procedure. As a final point, equations (2.8) and (2.10) give rise to a stochastic residual spread model for pairs trading strategy. This is a linear and Gaussian state space model, which can be estimated by Maximum Likelihood Estimation (MLE).

Do et al (2006) applied residual spread model to 3 pairs stocks: BHP-Rio and Tinto, Target and Wal-mart and Shell and BP, which are the top two miners in Australia, the second top retailers in the U.S and the largest energy companies in the UK, respectively. The estimation is performed using weekly returns over two years. The performance of each pair is compared against their own market index, which are the S&P 200 index for the Australian pair, the S&P 500 for the US pair and the FTSE All Shares index for the UK pair.

In conclusion, the empirical results of Do et al (2006) show strong mean reversion in the residual spread across 3 pairs of top players in the mining, retail and energy industries. Moreover, the level of mean reversion is strong, which is reflected by the large value of speed of reversion to its mean (k coefficient). Do et al (2006) point out that the mean reversion may be too strong, in which the profit opportunities of pair trading can quickly disappear. Moreover, Do et al (2006) find the model retains some residual risk as the mean coefficient (θ) is not zero. In addition, during two years testing of Target and Wal-mart, the long run spread was slightly up for Target and slightly down for Wal-mart. Do et al (2006) identified in their study that Target and Wal-mart pair is risky and should be avoided because this pair moves together in the short run and then deviates in the long run.

2.2.4 The cointegration method

Another noteworthy pairs trading approach is the study of statistical relationships where two share price series are linearly combined to produce a single time series, which is stationary. The process is the so called the cointegration method, and is reviewed in Vidyamurthy's (2004) book. Vidyamurthy attempts to parameterize pairs trading by exploring the possibility of applying the popular Engle and Granger approach.

If a specific linear combination of the two non-stationary time series is stationary, the two time series are cointegrated. Let y_t and x_t be 2 non-stationary time series or $I(1)$. If z_t is a linear combination of the two $I(1)$ time series, and z_t is $I(0)$ or a stationary process with mean of zero and constant variance, then, y_t and x_t are identified as cointegrated. In the other words, when two $I(1)$ series are cointegrated, they tend to move together.

Hence, the zero mean and constant variance of their cointegrated linear combination prevents them from deviating too far apart (Johnston and Dinardo, 1997).

Moreover, cointegrated time series can be represented in an error correction model (ECM). The idea behind an ECM is that the cointegrated time series has a long-run equilibrium, which is the long-run mean of the linear combination of the two time series. If there is a deviation from the long-run equilibrium, then one or two time series will adjust themselves or revert to the long-run equilibrium (Vidyamurthy, 2004). In other words, the dynamics of one time series at the current time is a correction of previous period's divergence from the equilibrium (called the error correction part) and some lag dynamics (white noise part) (Do et al, 2006).

In Engle and Granger cointegration approach, the first step is to estimate the long run relationship between the two stocks. Thus, the log price of stock A is regressed against the log price of stock B:-

$$\log(p_t^A) - \gamma \log(p_t^B) = \mu + \varepsilon_t \tag{2.11}$$

where γ represents the cointegration coefficient and μ is a constant, in which captures some sense of premium in stock A versus stock B.

Then, the second step is to test the long run equilibrium for stationarity. The augmented Dickey-Fuller test (ADF) is applied to detect the presence of unit root in the estimated residual series. However, it should be noticed that the result from this procedure is sensitive to the ordering of the variables; if the log price of stock B on log price of stock A is regressed in a reverse of the equation mentioned above, the regression will produce different residual time series.

Vidyamurthy applied the error correction procedure in an attempt to find an indication of mean reversion in the spread time series. If the γ coefficient is significantly different from zero, the long run equilibrium series has a mean reverting property. Subsequently, Vidyamurthy created the pairs trading strategies where the trades are entered and existed on the deviation of the spread (Δ) above or below the long run equilibrium (μ). Thus, the author bought the portfolio when the time series was below its long-run equilibrium (μ-

Δ) and sold the portfolio when the time series was above its long-run equilibrium (μ+Δ). Once, the portfolio mean reverts back to its long-run equilibrium, the position can be executed and earn 2Δ[5].

Then he examined the residuals for mean reversion by employing both parametric and non-parametric methods. The first approach is to model the residuals as a mean reverting process such as the ARMA process. The second approach is to construct an empirical distribution of zero crossings from the data sample. The zero crossing approach appears to be favored by Vidyamurthy (2004) as it is model-free. Therefore this will avoid the mis-specification problem. In addition, the zero crossing approach is a popular method for mean reversion testing even though how to define the trigger point of the approach is still not clear.

Moreover, the major concern is the validation of the cointegration method as it is difficult to relate the cointegration model to asset pricing theories and it is necessary as well as to keep an eye on the fundamental driving the values of the assets. Vidyamurthy attempts to relate the cointegration approach to Arbitrage Pricing Theory (APT) (Ross, 1976) and advocates that the cointegration coefficient (γ) may have the meaning of constant risk exposure proportionality. In other words, if 1 unit exposure by stock B to all risk factors and stock A exposes to γ units, then stock A and B meet the condition of cointegration in the APT framework. Therefore, the individual series is the sum of the common trend (random walk component) and specific component (stationary) or so called Common trend model of Stock and Watson (1988).

$$\log(p_t^A) = n_t^A + u_t^A$$

$$\log(p_t^B) = n_t^B + u_t^B$$

Differencing the logarithm of stock price gives the return time series:

$$R_t^A = R_t^{c.A} + R_t^{s.A}$$

$$R_t^B = R_t^{c.B} + R_t^{s.B}$$

[5] See Vidyamurthy (2004) page 82

where R^c is the return component due to the non-stationary trend component and R^s is the return component due to stationary specific component. If the two time series are cointegrated, both common trends must be identical up to a scalar or $R_t^{c.A} = \gamma R_t^{c.B}$, therefore:

$$R_t^A = \gamma R_t^{c.B} + R_t^{s.A} \tag{2.12}$$

Vidyamurthy shows that the APT theory holds for cointegrated system if the factor exposure vectors of the two stocks are identical up to a scalar:

$$R_t^A = \gamma\left(r_{1,t}b_1 + r_{2,t}b_2 + \cdots + r_{n,t}b_n\right) + R_t^{s.A}$$

$$R_t^B = \left(r_{1,t}b_1 + r_{2,t}b_2 + \cdots + r_{n,t}b_n\right) + R_t^{s.B}$$

where r_1, r_2,…r_n represent the excess returns from exposure to risk factors and b_1, b_2,…b_n represent the degree of exposure or beta.

Moreover, Lin, McCrae and Gulati (2006) have practiced pairs trading by using a cointegration approach to yield a minimum profit constraint. The empirical findings suggest that it is feasible to employ the pairs trading strategy and yield minimum conservative return for the strategy. Lin et al (2006) applied a cointegration approach on two Australian Stock Exchange quoted bank shares, namely the Australia New Zealand bank and the Adelaide bank from January 2001 to August 2002. They estimated a cointegration relationship using the 1st year and found the spread to be stationary. Lin et al's empirical study suggested that altering the open and close criterion value affects the number of trades for any given minimum profit per trade level. When the open value is closer to the mean, the average trade number is increased. Moreover, the limit on the total dollar investment budget allowed per trade affects the rate of return. This empirical study indicated very small return due to investment budget constraints and the requirement to meet minimum profit per trade. However, the main objective of Lin et al's study is not to maximize the profit but to ensure that the strategy yields minimum profit.

More recent empirical study also found profitability in pairs trading. Schmidt's (2008) empirical study has applied the cointegration approach to the 17 financial stocks listed on the Australian Stock Exchange and found 5 pairs from possible 136 trading pairs that resulted in strong cointegration. In order to overcome the drawback of the Engle and Granger 2-step method adopted by Vidyamurthy (2004), Schmidt (2008) attempted to develop an alternative approach for selecting trading pairs. Thus, Schmidt adopted the Johansen approach to test for cointegration, which is based on the vector error correction model. In this study, Schmidt also considered the illiquidity risk of the sample that would exist when implementing the pairs trading strategy. Hence, Schmidt selected 17 securities amongst the largest and most active trading stocks. The result indicated that the speed of adjustments to coefficients must be significantly different from zero, in order to ensure that the mean reverting system following a deviation from its long-run equilibrium. In addition, one can conclude that when shocks occur to one of the time series, there is also a contagion effect on the other time series. Nonetheless, the purpose of Vidyamurthy and Schmidt's studies in bivariate and multivariate setting were not to test the profitability of the pairs trading strategy. Therefore, how to maximize the return from pairs trading strategy against a given risk still remains an open question.

2.3 Empirical framework

In this study, the Engle and Granger (EG) approach to share prices is applied to the five main sectors from a primary stock index of Thailand (SET100)[6]. The EG approach is selected for cointegration testing due to the simplicity of the approach and since it is suitable for a study where testing is needed on a pair of stocks. In the EG approach, it does not matter which stock is taken as the dependent or independent variable. The OLS regression will produce the same cointegrating vector regardless of the regression of $\{y_t\}$ on $\{x_t\}$ or the regression of $\{x_t\}$ on $\{y_t\}$ (Enders, 1995).

In addition, the property of non stationary cointegrated time series results in OLS estimation that produces super-consistent cointegrating parameters. According to Stock (1987), the OLS estimator of the cointegrating parameter responds faster than the OLS

[6] SET100 indices are the top 100 active companies that listed in Thailand stock index. SET100 indices estimated from the share prices in terms of large market capitalization and high liquidity.

estimator of stationary variables (Enders, 1995). Moreover, the EG approach seeks a stationary linear combination that has minimum variance (Alexander, 2008). Thus, from a risk management point of view, the Engle and Granger's criterion of minimum variance or minimum risk is favorable (ibid).

The methodology will be divided into four subsections. In the identification of trading pairs will be considered employing the EG approach in section 2.3.1. Moreover, the process of EG's two step approach will be described in detail in section 2.3.2. Subsequently, the error correction model (ECM) will be applied on share returns to investigate how short term deviations from the long run equilibrium are corrected in section 2.3.3. Lastly, trading rules, trading strategies, the return on pairs trading and transaction costs are included in section 2.3.4.

2.3.1 Identification of Trading Pairs

"Which pairs of stocks should we trade?" This is a crucial question that traders have to consider as mismatched pairs would make pair trading strategy unprofitable. In this study, we will select a trading pair based on co-movement of two share price series in the long run and the speed of adjustment of the disequilibrium term. Firstly, we apply EG approach to examine the long-run equilibrium between each potential pair in five sectors. Although share price series are more likely to be cointegrated within the same sector, an attempt is also made to match cross sectors. Thus, two top leading share price series are selected from each sector to test for a cointegration relationship. Secondly, we use the ECM to examine the speed of adjustment of short-term disequilibrium.

2.3.2 The Engle-Granger's two step approach

Engle and Granger (1987) proposed a straightforward approach, which is the estimation of the long run equilibrium relationship between two non-stationary series. If the deviation of long run equilibrium is found to be stationary, the two non-stationary series or $I(1)$ series will be cointegrated of order (1, 1) or CI(1, 1). By definition of cointegration, the variables to be integrated must be of the same order. Hence, if time series of different order are integrated, it is possible to conclude that these 2 time series are not cointegrated (Enders, 1995).

Despite the fact that the OLS estimator is normally applied to stationary time series and yields consistent parameters, the OLS estimator also can be applied to non stationary variables to get consistent parameters as long as the residual series is stationary (Alexander, 2008). There are two main steps in Engle and Granger approach, which are described below:

Step 1: C*ointegrating regression*

By the definition of cointegration, it is necessary that the cointegrated variables are of the same order. We need to conduct the pretest to determine the order of integration. This is done by employing the augmented Dickey-Fuller test (ADF). Moreover, Aikaike's Information Criterion (AIC) is used to determine appropriate lags that will minimize the residuals in the unit root test.[7] Therefore, the ADF test is applied to the log share price series to determine whether each of the series contains the unit root (Enders, 1995).

$$H_0 : X_t \sim I(1)$$
$$H_a : X_t \sim I(0)$$

If the result of ADF test indicates that the log share price series is a $I(0)$ series, the particular stationary series has to be excluded from the analysis because the cointegration of stationary and non stationary series would yield spurious regression results. Therefore, if $\{y_t\}$ and $\{x_t\}$ series are found to be $I(1)$ processes, then we estimate the long run relationship between the log of y_t and the log of x_t using ordinary least square estimator (OLS):

$$y_t = \beta_0 + \beta_1 x_t + e_t \tag{2.13}$$

where β_0 is a constant and β_1 is the cointegration coefficient.

[7] We run the unit root and choose AIC's automatic lag selection starting from 26 lags.

Step 2: *Test residual series for stationary*

The unit root test is applied to the estimated residual series $\{\hat{e}_t\}$ obtained from equation (2.13) as the cointegration framework requires the long run relationship to be stationary:

$$\hat{e}_t = y_t - \beta_0 - \beta_1 x_t \tag{2.14}$$

The ADF test is used to verify that the residual series obtained is stationary. Therefore, the unit root test has to reject the null hypothesis of non stationary and accept an alternative hypothesis of stationary. In other words, the two variables are not cointegrated if the residual process in equation (2.14) is non stationary.

2.3.3 Error Correction Model (ECM)

The Granger representation theorem states that when the two time series are cointegrated, a vector autoregressive model on the differences will be mis-specified (Granger, 1986). However, this can be solved by including the previous disequilibrium term as an explanatory variable and, in this way, the model becomes well-specified.

The ECM is a dynamic model of the correlation in the share price returns or the first difference. After obtaining the disequilibrium term from equation (2.14), the ECM is applied to two cointegrated log return series $\{y_t\}$ and $\{x_t\}$.

$$\Delta x_t = \alpha_1 + \gamma_1 z_{t-1} + \varepsilon_{1t} \tag{2.15}$$

$$\Delta y_t = \alpha_2 + \gamma_2 z_{t-1} + \varepsilon_{2t} \tag{2.16}$$

where z is the disequilibrium term given by equation (2.13), $z = y_t - \beta_0 - \beta_1 x_t$, α_1 and α_2 represent constant while γ_1 and γ_2 represent the speed of adjustment coefficients of the equilibrium.

We apply OLS regression on equation 2.15 (and 2.16) by running the regression of the first difference of x_t on the first lagged disequilibrium term. Lags are added to the ECM to ensure that the residuals display no signs of autocorrelation.

$$\Delta x_t = \alpha_1 + \sum_{i=1}^{m} \beta_{11}^{i} \Delta x_{t-i} + \sum_{i=1}^{m} \beta_{12}^{i} \Delta y_{t-i} + \gamma_1 z_{t-1} + \varepsilon_{1t} \tag{2.17}$$

$$\Delta y_t = \alpha_2 + \sum_{i=1}^{m} \beta_{21}^{i} \Delta x_{t-i} + \sum_{i=1}^{m} \beta_{22}^{i} \Delta y_{t-i} + \gamma_2 z_{t-1} + \varepsilon_{2t} \tag{2.18}$$

In addition, Alexander (2008) suggests the appropriate signs of the speed of adjustment coefficients for the error correction mechanism. Recall that $z = y_t - \beta_0 - \beta_1 x_t$, when $\beta_1 > 0$, the ECM will correct itself when $\gamma_1 < 0$ or $\gamma_2 > 0$. Similarly, when $\beta_1 < 0$, the appropriate signs to capture the error correction mechanism must be $\gamma_1 < 0$ or $\gamma_2 < 0$.[8]

The speed of adjustment (γ_1 and γ_2) also indicates how fast the short term deviation will move back to the long term equilibrium following an exogenous shock (Alexander, 2008). The larger γ_1 or γ_2 is, the quicker the response of the dependent variable to the deviation from long run equilibrium of the previous period's disequilibrium (Enders, 1995). Moreover, the large value of coefficient is an indication of a highly stationary disequilibrium term (Alexander, 2008). At the opposite extreme, when these coefficients are small, the speed of adjustment is slow, in which the dependent variable does not respond to the previous period's disequilibrium.

In summary, the sign and size of the disequilibrium term plays an important role as an indication of the mean reversion characteristic and the convergence speed of the cointegrated pairs. Hence, the potential cointegrated pairs will be selected based on these two criteria - that the pairs have the correct sign (as mentioned above) and a high value of the adjustment coefficient.

2.3.3.1 Granger causality

The error correction model can be used to model the long run and short run Granger causal flows in the system of cointegrated share price series (Alexander, 2008). Consider equation (2.17) and (2.18), the speed of adjustment coefficients (γ_1 and γ_2) are

[8] See more details on how equations (2.17) and (2.18) define the Error Correction Mechanism - clearly set out in Alexander (2008, p244).

expected to capture the adjustment of the return of stock x (Δx_t) and return of stock y (Δy_t) toward long run equilibrium:

$H_0: \beta_{11}^1 = \beta_{12}^2 = \cdots = \beta_{1i}^i = \gamma_1 = 0$ or y does not granger cause x

$H_a: \beta_{11}^1 \neq \beta_{12}^2 \neq \cdots \neq \beta_{1i}^i \neq \gamma_1 \neq 0$ or y granger causes x

$H_0: \beta_{21}^1 = \beta_{22}^2 = \cdots = \beta_{2i}^i = \gamma_2 = 0$ or x does not granger cause y

$H_a: \beta_{21}^1 \neq \beta_{22}^2 \neq \cdots \neq \beta_{2i}^i \neq \gamma_2 \neq 0$ or x granger causes y

In equation (2.17), y Granger causes x if the joint significance test of all variables containing lagged y and γ_1 are different from zero - meaning that the past value of y helps to predict current or future values of x better than a past value of x alone (Alexander, 2008). While equation (2.18), x Granger causes y if the joint significance test of all variables containing lagged x and γ_2 is different from zero. Importantly, there must be one-way or bidirectional Granger causality flow in one cointegrated system. Therefore, at least one of the speeds of adjustment coefficients must be nonzero. If both γ_1 and γ_2 are equal to zero, the long run Granger causality is not present and the model is neither an error correction nor a cointegration model (Enders, 1995).

Besides the Granger causality flow indicating the direction of one variable affecting the other variable, the ECM can also distinguish between short run and long run Granger causality. The short run causation involves estimating whether the coefficients of lagged values of y $(\beta_{11}^1 = \beta_{12}^2 = \cdots = \beta_{1i}^i = 0)$ in equation (2.17) - or the coefficients of lagged values of x $(\beta_{21}^1 = \beta_{22}^2 = \cdots = \beta_{2i}^i = 0)$ in equation (2.18) - are jointly significant and then to reject the null hypothesis if they are (Arize and Malindretos, 2008). In this case, the lagged value of Δy_t $(and\ \Delta x_t)$ can help to forecast the price of x (and y) in the short term. On the other hand, the long run causation is to determine whether the speed of the adjustment coefficient of each equation (γ_1 and γ_2) is non zero. Moreover, the joint test of both short run and long run causality will identify which variable is the main cause of short run deviation that has to adjust towards long run equilibrium. Arize and Malindretos (2008) referred to this case as strong Granger causality where the joint null hypothesis is rejected. In other words, if y Granger causes x in equation (2.17)

($\beta_{12}^{i} \neq 0 \; and \; \gamma_1 \neq 0$), the past value of y can help to predict the price of x in the short and long term.

2.3.4 Trading rule formulation

The key requirement in the pairs trading strategy is the stationary state of the long run equilibrium or the spread. Once I select cointegrated pairs that have a strong mean reversion property, I will enter the pairs trading positions when the spread diverges sufficiently from the equilibrium value, betting that the disequilibrium spread will correct itself and move back to the equilibrium (ibid).[9]

In this section, I will describe the trading rules, trading strategies with different bands that will apply to explore the profitability of the cointegration relationship in different simulations, which are: unlimited trading period with constant beta; unlimited trading period with updated beta; and two extreme cases, which are a limited trading period with constant beta and limited trading period with updated beta. The transaction costs also discuss in the later part of this section.

2.3.4.1 Trading Rules

The pairs trading strategy employs different trading bands, based on 1, 1.5 and 2 standard deviations. The variation of trading bands allows us to explore the relationship of trading bands with the number of trades, transaction costs and abnormal return from the strategies. When the position is entered, I keep the position until the execution indicates either that the spread has reversed back to its mean of zero or that the spread has reached the stop loss trigger. The stop loss is exercised when the spread is not going in the direction that we expected. The stop loss bands are shown below as follow:

[9] In this section, I conduct the pairs trading simulations using Gauss. The program will estimate long run spread for every trading day starting from January 2004 to December 2008.

Trading bands (Standard deviation / σ)	**Stop loss (Standard deviation / σ)**
1	2
1.5	2.5
2	3

Moreover, the trading period is 5 years from January 2004 to December 2008, which consists of 1,225 trading days excluding holidays and weekends. Importantly, β_o and β_1 coefficients from equation (2.13) are re-estimated every six months.

2.3.4.2 Trading Strategy

Once I have the cointegrated pair of stocks, the important question is when to buy and sell the pairs trading position. Thus, I implement three pairs trading strategies that bear different level of risks in order to determine when to enter and exit the position and to test the performance of my forming strategies. The three trading strategies will be described in detail in this section.

Strategy 1

In this strategy, I decide to enter the pairs trading position when the spread is actually out of the band. As the spread is wider than the band, there is a bigger gap from which the pair trading strategy can make abnormal profits. However, strategy 1 is risky in term of the unpredictability of the spread's direction i.e. the spread could continue to deviate further from the mean and possibly result in a massive loss.

Table 2.1: Pair trading strategy 1			
Trading band	**Open**	**Close**	**Stop loss**
1SD	$z_t > 1\sigma \; and \; z_{t-1} < 1\sigma$	$z_{t+i} < 0$	$z_{t+i} > 2\sigma$
	$z_t < -1\sigma \; and \; z_{t-1} > -1\sigma$	$z_{t+i} > 0$	$z_{t+i} < -2\sigma$
1.5SD	$z_t > 1.5\sigma \; and \; z_{t-1} < 1.5\sigma$	$z_{t+i} < 0$	$z_{t+i} > 2.5\sigma$
	$z_t < -1.5\sigma \; and \; z_{t-1} > -1.5\sigma$	$z_{t+i} > 0$	$z_{t+i} < -2.5\sigma$
2SD	$z_t > 2\sigma \; and \; z_{t-1} < 2\sigma$	$z_{t+i} < 0$	$z_{t+i} > 3\sigma$
	$z_t < -2\sigma \; and \; z_{t-1} > -2\sigma$	$z_{t+i} > 0$	$z_{t+i} < -3\sigma$

Note that z_t , z_{t-1} and z_{t+i} represent the spread at the opening position, the spread over the previous period and the spread at the closing position respectively and i is the number of days it takes for the spread to revert back to the mean. SD and σ represents standard deviation.

In table 2.1, I enter the trading positions when the positive spread hits the trading band for the first time. In other words, the spread crosses over the band from inside to outside the band. For example, when the spread is at time t across 1 standard deviation band, I expect that the current positive value of spread will decrease to its mean so that I can execute the trade. However, if the spread continues to increase until hitting the stop loss trigger of 2SD at time t+i, the particular trade has to be closed. Moreover, the same process is applied to different trading boundaries and when the spread has a negative value.

Strategy 2

If the spread fluctuates and does not reach stop loss trigger and has not yet converged to the mean, the open position has to be held longer until the spread moves back to the mean. Moreover, the same amount of profit with a long holding period and uncertainty of the spread make pairs trading strategy 1 unprofitable economically. Therefore, in strategy 2, I increase number of trade by entering the trading position everyday as long as the spread deviates between the restrictions of each band.

Table 2.2: Pair trading strategy 2			
Trading band	**Open**	**Close**	**Stop loss**
1SD	$1\sigma < z_t < 1.5\sigma$	$z_{t+i} < 0$	$z_{t+i} > 2\sigma$
	$-1\sigma > z_t > -1.5\sigma$	$z_{t+i} > 0$	$z_{t+i} < -2\sigma$
1.5SD	$1.5\sigma < z_t < 2\sigma$	$z_{t+i} < 0$	$z_{t+i} > 2.5\sigma$
	$-1.5\sigma > z_t > -2\sigma$	$z_{t+i} > 0$	$z_{t+i} < -2.5\sigma$
2SD	$2\sigma < z_t < 2.5\sigma$	$z_{t+i} < 0$	$z_{t+i} > 3\sigma$
	$-2\sigma > z_t > -2.5\sigma$	$z_{t+i} > 0$	$z_{t+i} < -3\sigma$

Note that z_t and z_{t+i} are the spread at open position and the spread at close position and i is the number of days it takes for the spread to revert back to the mean. SD and σ represents standard deviation.

In table 2.2, the positive spread case, I enter the trading position when the spread at time t is greater than the 1st trading band but less than the 2nd trading band. Then, I close the position when the spread reverts to its mean or hits the stop loss trigger. A similar procedure is applied to all other trading bands. In this strategy, the pairs trading strategy will yield a higher return out of the bigger gap of the spread, which is a trade-off against the risk of uncertainty. However, this strategy is risky in term of investment cost but higher risk will trade off against higher return.

Strategy 3

In strategy 3, I decide to follow a conservative strategy, which has lower risk than the other two strategies mentioned above. In this case, I will not enter the trade when the deviation is getting wider. Thus, I enter the position when the spread already converges and is on the way back to the mean. From the risk and return perspective, the lower risk strategy would yield lower profitability. However, pair trading is a market neutral strategy; therefore, the conservative strategy should perform in a relatively similar way to the other two risky strategies.

Table 2.3: Trading strategy 3 (Conservative strategy)

Trading band	Open	Close
1SD	$z_t < 1\sigma \ and \ z_{t-1} > 1\sigma$	$z_{t+i} < 0 \ and z_{t+i-1} > 0$
	$z_t > -1\sigma \ and \ z_{t-1} < -1\sigma$	$z_{t+i} > 0 \ and z_{t+i-1} < 0$
1.5SD	$z_t < 1.5\sigma \ and \ z_{t-1} > 1.5\sigma$	$z_{t+i} < 0 \ and z_{t+i-1} > 0$
	$z_t > -1.5\sigma \ and \ z_{t-1} < -1.5\sigma$	$z_{t+i} > 0 \ and z_{t+i-1} < 0$
2SD	$z_t < 2\sigma \ and \ z_{t-1} > 2\sigma$	$z_{t+i} < 0 \ and z_{t+i-1} > 0$
	$z_t > -2\sigma \ and \ z_{t-1} < -2\sigma$	$z_{t+i} > 0 \ and z_{t+i-1} < 0$

Note that z_t, z_{t-1}, z_{t+i} and z_{t+i-1} are the spread at the opening position, the spread over the previous period, the spread at the closing position and the spread on previous day before the closing position respectively and i is the number of days it takes for the spread to revert back to the mean. SD and σ represents standard deviation.

In table 2.3, I enter the position when the spread crosses the trading band on the way back to the mean. In the positive spread case, I enter the trading position when the spread of today is lower than the trading trigger and the spread of yesterday is higher than the trading trigger. Similarly, I close the trading position when the spread crosses the mean.

A similar technique is also applied when the spread is at a negative value: I open the position when the spread at time t is greater than negative standard deviation but the previous spread is less than negative standard deviation. The position is also closed when the spread reverts back and across its mean. In this case, I expect the spread to increase to the mean level of zero. In addition, strategy 3 is a more conservative pairs trading strategy than the other two strategies mentioned above. Therefore, I will not apply a stop loss trigger in order to explore the performance of a conservative strategy.

2.3.4.3 Pairs Trading

In this section, the different simulations conducted in this research will be explained in addition to the crucial decision of which stocks to buy and sell and the calculation of the return.

Simulation A: unlimited trading period with constant beta

In simulation A, I allow the spread to take time to converge back to the mean within 5 years. Therefore, the open position can be closed at any time that the spread gets to zero or reaches a stop loss trigger. Moreover, all the remaining open positions have to close at the end of a 5-year trading period. In addition, I restrict to buying or selling the same beta units to both the open and close positions as shown below.

$$open: y_o - (x_o * \beta_o)$$

$$close: -y_c + (x_c * \beta_o)$$

For example, I open the pairs trading position by selling 1 unit of stock y_o and buying β_o (beta at open) units of stock x_o. Conversely, I buy 1 unit of stock y_c and sell β_o (the same beta at open) units of stock x_c when I execute the trade as I assume constant beta in this simulation.

Simulation B: unlimited trading period with updated beta

As above, this simulation has an unlimited trading period but I allow the beta to change over time. Thus, I aim to test how different levels of risk would affect the profitability of the strategies. Therefore, in simulation B, all the open positions can be closed at any time when the close signal or stop loss signal is shown. Also, I update the beta as described below.

$$open: y_o - (x_o * \beta_o)$$

$$close: -y_c + (x_c * \beta_c)$$

For example, when an open signal is emitted; I sell 1 unit of stock y_o and buy β_o (beta at open position) units of stock x_o. When the close signal is shown, I buy 1 unit of stock y_c and sell β_c (beta at close position) units of stock x_c.

Simulation C: limited trading period with constant beta

Simulation C is an extreme case where I restrict the trading period to six months and assume a constant beta over time. I aim to study how the pairs trading strategies would perform in a limited trading time. Hence, all open trading positions have to close at the end of six months if there is no signal to close either because of the spread converging to the mean or hitting stop loss. Moreover, I apply the same beta at the open and close positions, as in simulation A.

Simulation D: limited trading period with updated beta

As in simulation C, the trading period is limited to six months but, in this simulation, we allow the beta to change over time. I aim to test whether an updated beta helps to improve the profitability of pairs trading even though I employ a trading period constraint. Therefore, in simulation D, the open and close trading positions are performed within a 6-month period but with beta updated daily.[10]

When the enter signal is emitted, it is essential to determine which stock to buy and sell. Firstly, I have to identify which stock is the dependent variable and independent variable from OLS regression in equation (2.13). Secondly, the sign of the equilibrium spread will be identified. If the spread is in a positive value at the time of entering the position, I expected the spread to reduce. Therefore, I sell dependent variable (y) and buy β units of independent variable (x). On the other hand, I buy dependent variable (y) and sell β unit of independent variable (x) when the spread is in a negative value based on an expectation that the spread will increase.

In summary, I enter short/long positions as described above on the next trading day after the enter signal is emitted. Then, I maintain the position until the execution signal is

[10] In simulation A, B and C, I updated beta every 6-month period. Hence, every trade position that opens in the same period will apply the same beta. However, this is not a case in simulation D where I limited trading period to 6 months and updated beta daily.

emitted and close the trade by taking the reverse position on the next trading day. Moreover, the percentage of the total return of each pair trading can be calculated as follows:

$$\text{Total Return (\%)} = \text{Return on y} + \beta \text{ Return on x}$$

The percentage of total return when the spread has a positive value and expectation is that it will decrease:

$$R \; in \; \% = [(\log y_o - log y_c) + \beta(-log x_o + log x_c)]$$

The percentage of total return when the spread has a negative value and expectation is that it will increase:

$$R \; in \; \% = [(-\log y_o + log y_c) + \beta(log x_o - log x_c)]$$

where: $log y_c, log x_c$ are the log price of y and x at close period.

$log y_o$, $log x_o$ are the log price of y and x at open period.

2.3.4.4 Transaction cost

The transaction cost is a crucial factor that alters the profitability of the trading strategy. Thus, in order to demonstrate the performance of our pairs trading strategy, the transaction cost cannot be ignored. Normally, investors review the market frictions only considering explicit trading costs (i.e. commission and tax), while the market fictions actually include implicit costs (i.e. bid-ask spreads), which is crucial as this cost can significantly impact the performance of our pair trading strategy. In order to simplify our trading calculation, we firstly account for explicit transaction cost, which is set equal to 0.1605 % (commission and tax) for each round of trading.[11] In other words, transaction costs have to be added when we open and close the pairs trading positions. Therefore, the results will be reported after accounting for the explicit transaction cost. However, in this section, the implicit transaction cost such as bid-ask spread will be

[11] 0.1605 % transaction cost consists of Kim Eng Thailand commission fee of 0.15% of price*units and 7% VAT of commission fee.

discussed along with how this spread would affect our pair trading strategy in the stock exchange of Thailand.

The bid-ask spread is the difference between the lowest available quote to sell the stock (ask or offer), and the highest available quote to buy the same stock (bid). This bid-ask spread represents one component of the transaction cost that investors, who desire immediately trading the stock, have to handle (Choi, Salandro and Shastri, 1988). In general, the bid-ask spread of emerging market is wider than the developed market. This reflects lower liquidity, smaller market capitalization and higher trading cost. Previous studies (see Tinic and West, 1972; Stoll, 1978) found that the bid-ask spread is negatively correlated with price level, trading volume and the number of market makers but the bid-ask spread has a positive relationship with volatility.

In Thailand, the stock exchange of Thailand has attempted to improve the liquidity, reduce the transaction cost and to protect the investors from excessive volatility by implementing daily price limits and tick size rules[12]. In 2001, the tick size rule has been changed for the stock that is less than 25 baht in an attempt to reduce the transaction cost and induce trading activities (Pavabutr and Prangwattananon, 2008). The recent empirical study, Pavabutr and Prangwattananon (2008) have investigated the impact of this tick size reduction on the transaction costs and liquidity in the SET. The empirical results showed that the tick size reduction has positive impact on the size of the bid-ask spread reduction[13]. In table 2.4, the current stock tick size rule or the spread between the bid and ask quotes is shown. Each group (in column 1) is associated with different price range (in column 2), indicating the allowance of minimum price change or tick size (in column 3). In column 4 and 5, I calculate the percentage of bid-ask spread that is likely to cost in each price range as follows:

[12] The SET implemented both price limits and the circuit breaker in order to protect investors from excessive market volatility. A 30% price limit on daily price fluctuation relative to the previous day's closing price. Moreover, the circuit breaker is also used to create a timeout from the trading process or trading halt. If the SET index falls 10% from previous day's closing, the market will be closed for 30 minutes and if the SET index continues to drop by 20%, the market will be closed for 1 hour (The stock exchange of Thailand, 2013).

[13] See the empirical study of Pavabutr and Prangwattananon (2008) for more detail.

$$\left(\frac{Tick\ size\ or\ the\ bid-ask\ spread}{Minimum\ or\ Maximum\ price}\right)*100$$

In our study, we engage in a pair of stocks, which are EGCO and LANNA from the resource sector. During the trading period (from 2004 to 2008), the price of EGCO was between 50 to 100 baht (group 6), while the price of LANNA was between 5 to 10 baht (group 3). By trading this pair, the trading performance of these stocks would be affected by the bid-ask spreads of approximately 1 to 2% per trade. These bid-ask spreads would have large impact to our result, if frequently engaged in trading. In fact, the higher number of trades, the higher transaction costs. As the SET index uses uniform tick size, the stocks with high or low price would have relatively similar trading cost implied by the tick size. Thus, the bid-ask spread should not be of a particular concern in this market as the spread is still low and bounded by the tick size rule.

Table 2.4: The securities tick size

Group	Price range (THB)	Tick size (THB)	Bid-ask spread
I	Lower than 2	0.01	>0.5%
II	2 - 5	0.02	0.4 - 1%
III	5 - 10	0.05	0.5 - 1%
IV	10 - 25	0.10	0.4 - 1%
V	25 – 50	0.25	0.5 - 1%
VI	50 – 100	0.50	0.5 - 1%
VII	100 – 200	1.00	0.5 - 1%
VIII	200 – 400	2.00	0.5 - 1%
IX	400 – 800	4.00	0.5 - 1%
X	More than 800	6.00	<0.75%

Note that Thai stocks are categorized into 10 groups based on the price range (in Thai baht) with associated tick size or the spread between bid and ask prices. Moreover, the percentage of bid-ask spread is calculated for lower and higher price limit in each group. For example, group 1 with a tick size of 0.01 and the high price limit at 2; thus, the bid-ask spread is (0.01/2)*100 = 0.5%.

2.4 Data

The sample employed in this study consists of individual share prices listed in SET100. The five main industry categories of the Stock Exchange of Thailand (SET) to be investigated are Resources, Financials, Services, Property & Construction and Technology. The data span for this research is 10 years starting from the beginning of January 1999 to the end of December 2008, which consists of 2,454 trading days excluding holidays and weekends. Share price series are converted into logarithmic form. The Thai stock market was volatile over this period as a consequence of political instability and also a contagion effect from global financial crisis. If pairs trading strategy is market neutral, then the instability should have no effect on the pairs trading strategy [see Alexander (1999)].The data of individual share prices listed in SET is available from DataStream.

The cointegration approach is tested using the whole sample period in order to identify possible pairs that have a long-run equilibrium relationship. Then, the sample is divided into two parts; the first part is the training period, which lasts from 1999 to 2003. In this period, we run the regression on the first 5 years of the sample to obtain a criterion for the trading boundary and this will be updated every six months. The second part is the testing period, which lasts from 2004 to 2008, where our trading strategies will be tested.

The share price series are matched to the same industry categories as there is a greater possibility of cointegration due to the common factor that drives both stocks in the long run such as EGCO and LANNA from the resource sector[14]. However, we also attempt to explore pairs trading possibilities on crossed sectors.

Illiquidity risk is also a concern. Therefore, it is necessary to screen inactive stocks out from our analysis that would alter the robustness of the pairs trading strategy. However, inactive stocks will not be considered because the pairs trading strategy was applied to share prices listed in SET100, which are the top 100 companies trading in the Stock

[14] EGCO and LANNA is the name of the stock, which is classified into the resource sector, actively trade in SET100. For more detail of the stocks please see Appendix A2.

Exchange of Thailand. Besides, the research used data over 10 years. Thus, some stocks that have not been listed in SET100 for at least 10 years are excluded from the analysis. Nonetheless, we are still interested in knowing the pairs trading performance of inactive stock. Hence, in this study, we also determine the pairs trading strategy on inactive stocks that have traded in Stock Exchange of Thailand for at least 10 years but are not listed in SET100.

2.5 Economic outlook in Thailand

Prior to the 1997 financial crisis, Thailand had been one of the "hottest" economies in the world. From 1985 to 1995, the average of Gross Domestic Product (GDP) economic growth was remarkably high at 9.04%, with a peak growth rate at 13.28% in 1988 (Fray, 2004).[15] Thailand is one of the largest and wealthiest economies in Southeast Asia but it is in a recovery process after the financial crisis when GDP growth was -10.51% in 1998. The economy is heavily dependent on exports. The major export products are automobile parts and electronic goods. From 1999 to 2008, the average GDP growth was approximately 4.75%, with the highest peak at 7.4% in 2003 (Index Mundi, 2010).

In addition, the Stock Exchange of Thailand was the world's top performing stock market. In particular, the SET index price increasing from 357.81 in 2002 to 773.40 in 2005, which is a 116% increase (Bank of Thailand, 2008). The high GDP growth and the good performance of SET in 2005 indicated that foreign investors regained confidence in Thailand's economic future.

Despite these good figures, the Thai economy has declined again since 2006 mainly due to the political instability and the separatist movement in the south of Thailand (Pisit, 2008). The GDP growth rate has dropped from 2006 to 2008 (5.22%, 4.92% and 2.59% respectively) (Index Mundi, 2010). In addition, there was a sharp decline of 47% of the SET index from 870.12 in 2007 to 458.85 in 2008 (Bank of Thailand, 2008). The total "buy – sell" values of foreign investors in SET index also declined from 55,729.36 in 2007 to -162,357.05 billion Baht in 2008, which indicated that foreign investors had lost

[15] See Appendix A1 for Economic outlook data.

their confidence in the Thai economy (Stock Exchange of Thailand, 2009). Even though the rapid decrease in the SET index made Thai share prices become under-valued foreign investors were still not encouraged to invest (Pisit, 2008).

In summary, our 10 years share price data can be broadly classified into two periods. The first period is the recovery period after the financial crisis, which covers 1999 to 2003. The second period from 2004 to 2008 is the fluctuation period, which included the high performance of the SET and the sharp decline due to political problems and the separatist movement in the south of the country. Clearly, it is beneficial to investigate in the stock exchange of Thailand, not only test the performance of pair trading strategy in fluctuation period, but also gain further insight of the characteristic of Thai stock series using cointegration approach. Thailand is an emerging market with wealthy economic background among other Asian countries. Thus, we expected to see positive returns from the pairs trading strategies.

2.6 Empirical results

In this section, the main findings will be analyzed, starting with the identification of trading pairs that we employed to identify cointegrated pairs and the error correction model to quantify the speed of disequilibrium. Hence, we select the trading pairs that have a cointegration relationship and a high value for the speed of adjustment coefficient. In a subsequent chapter, the pairs trading performance of our strategies will be presented.

2.6.1 Identification of Trading Pairs

The results of the Engle and Granger approach and the error correction model (including both active and inactive share prices) are presented below.

2.6.1.1 Engle and Granger's Cointegration Approach

Table 2.5 is the summary of the ADF test on each log share price series in five sectors. The majority of log share price series are non stationary processes i.e. $I(1)$ as t-statistic falls outside the 5% critical region. Therefore, the null hypothesis that the log share price series have a unit root cannot be rejected. However, some stocks are found to be stationary and therefore have to be excluded from further analysis.

Table 2.5: ADF test of individual log share price from 10 years data in 5 sectors

Sector/log price series	t-Stat	Unit root	No unit root	Sector/log price series	t-Stat	Unit root	No unit root
Resource sector				**Property and construction sector**			
LBANPU	-0.6990	✓		LAMATA	-1.6947	✓	
LEGCO	-0.9958	✓		LCK	-1.3071	✓	
LIPRC	-1.7627	✓		LCPN	-1.4889	✓	
LLANNA	-1.2112	✓		LEMC	-1.4031	✓	
LPTTEP	-0.5223	✓		LITD	-1.3588	✓	
{LSUCCO}	-2.1228	✓		LLH	-1.4858	✓	
Financial sector				LLPN	-1.8343	✓	
LACL	-1.7459	✓		LSCC	-1.0026	✓	
LASP	-1.2586	✓		LSCCC	-3.1995**		✓
LBAY	-1.7254	✓		LSPALI	-1.7222	✓	
LBBL	-1.4017	✓		LSTEC	-1.7041	✓	
LKBANK	-1.3246	✓		LTPIPL	-1.0156	✓	
LKK	-2.2182	✓		{LESTAR}	-2.8854**		✓
LKTB	-1.6971	✓		{LKC}	-0.8996	✓	
LSCB	-1.8957	✓		{LQH}	-2.9463**		✓
LTMB	-0.2136	✓		{LNPARK}	-1.3299	✓	
{AYUD}	-1.0628	✓		{LPAE}	-1.5604	✓	
{BKI}	-1.4569	✓		{LTIW}	-2.8378*		✓
Services sector				**Technology sector**			
LBGH	-1.1319	✓					
LBH	-1.0516	✓		LADVANC	-1.8350	✓	
LBIGC	-1.6993	✓		LTRUE	-0.4035	✓	
LERAWAN	-2.2333	✓		{LMSC}	-2.5394	✓	
LLOXLEY	-2.2712	✓		{LPT}	-2.0392	✓	

Note that t-statistic is reported for augmented Dickey Fuller test. ** and * represent significant at 5 and 10%.

The first step in the Engle and Granger approach is to estimate the long-run relationship of each matched pair from the five sectors listed in the Stock Exchange of Thailand. OLS regression is applied on daily log share price series using 10 years data to distinguish the possible pairs that have a cointegrated relationship over the whole sample period. Then, we conduct the unit root test on each pair's residual series.

The result of Engel and Granger's cointegration test is summarized in tables 2.6 to 2.10, which are Resources, Financial, Property and Construction, Services and Technology sectors, respectively[16]. In addition, the stock in parenthesis {-} represents inactive stock.

In table 2.6, the cointegration test in the resources sector shows that 2 out of 14 pairs lead to rejection of the null hypothesis of a unit root on the basis of ADF tests. We can conclude that the long run relationships between these two pairs are meaningful and statistically significant. In addition, the matched pairs of inactive stocks are not cointegrated in the resource sector.

In table 2.7, the results from the financial sector indicate that out of 55 potential pairs, there are 10 pairs that justified rejecting the null hypothesis of a unit root. Moreover, 2 out of 10 cointegrated pairs are the combination of active and inactive stocks. However, these 2 inactive cointegrated pairs are marginally significant at a 10% confident interval.

[16] The results of Engle and Granger tests are similar, thus, only selected results are reported in this research. The estimation of all matched pairs is available upon request.

Table 2.6: Engle and Granger output of identified pairs from Resource sector (10 Years data)

Pairs	Beta Coefficient	ADF (t-statistic)	Cointegration
LBANPU/LEGCO	2.236790	-2.725798	*
LBANPU/LIRPC	0.893268	-0.472270	
LBANPU/LLANNA	1.551624	-2.218877	
LBANPU/LPTTEP	1.365451	-2.230044	
LBANPU/{LSUCCO}	-0.002421	-0.700640	
LEGCO/LLANNA	-0.626454	-3.387840	**
LEGCO/{LSUCCO}	0.072883	-0.976477	
LIPRC/LLANNA	0.555906	-1.933634	
LIRPC/{LSUCCO}	0.724164	-1.815413	
LLANNA/{LSUCCO}	-0.113342	-1.322341	
LPTTEP/LEGCO	1.554751	-2.334260	
LPTTEP/{LSUCCO}	-0.295547	-0.769729	
LPTTEP/LIRPC	0.681769	-0.793239	
LPTTEP/LLANNA	1.082777	-2.511802	

Note that LBANPU, LEGCO, LIRPC, LPTTEP and LSUCCO are the log share price series where the log share price in parenthesis {-} sign represents inactive stock. Moreover, the residual series of each pair is tested for stationarity using augmented Dickey Fuller test (ADF). *, **, *** indicates the significant level at 10%, 5% and 1%, respectively.

Table 2.7: Engle and Granger output of identified pairs from Financial sector			
Pairs	**Beta Coefficient**	**ADF (t-statistic)**	**Cointegration**
LACL/LASP	0.505353	-1.984669	
LACL/LBAY	-0.186300	-1.869383	
LACL/LBBL	-0.286180	-2.041474	
LACL/LKBANK	-0.302732	-2.058765	
LACL/LKK	0.463097	-2.345927	
LACL/LKTB	0.979761	-2.442438	
LACL/LSCB	-0.358182	-2.358684	
LACL/LTMB	0.537461	-3.253806	**
LASP/LBAY	0.329254	-1.161631	
LASP/LBBL	0.417027	-1.107490	
LASP/LKBANK	0.348174	-1.142970	
LASP/LKK	0.978291	-3.137895	**
LKBANK/LSCB	0.911874	-4.080385	***
LKBANK/LTMB	-0.345176	-1.757904	
LKK/LKTB	0.293474	-3.895147	***
LKK/LSCB	1.054605	-2.049283	
LKK/LTMB	0.147665	-2.664009	*
LKTB/LSCB	-0.104887	-1.225044	
{LAYUD}/LBBL	0.498268	-2.850766	*
LBAY/LSCB	0.891970	-3.219044	**
{LAYUD}/LKBANK	0.466448	-1.922101	
{LAYUD}/LKK	0.277420	-1.544728	
{LAYUD}/LKTB	-0.318482	-1.021468	
{LAYUD}/LSCB	0.451938	-2.668361	*
LBAY/LBBL	0.870169	-1.835930	
LBAY/LKBANK	0.976963	-2.592276	*
LBAY/LKK	0.392893	-1.367450	

Note that LACL, LKBANK, LKK, LKTB, LBAY, LBBL, LAYUD, LSCB and LTMB are the log share price series where the log share price in parenthesis {-} sign represents inactive stock. Moreover, the residual series of each pair is tested for stationarity using augmented Dickey Fuller test (ADF). *, **, *** indicates the significant level at 10%, 5% and 1%, respectively.

Table 2.8: Engle and Granger output of identified pairs from Property and construction sector (10 Years data)			
Pairs	**Beta Coefficient**	**ADF (t-statistic)**	**Cointegration**
LAMATA/LCPN	1.211171	-.1955818	
LAMATA/LITD	1.159287	-2.856546	*
LAMATA/{LPAE}	0.555268	-1.888190	
LAMATA/LSCC	1.730514	-3.249885	**
LAMATA/LTPIPL	0.666586	-1.270476	
LAMATA/{LTSTH}	1.563130	-3.615757	***
LAMATA/LCK	1.045061	-3.065014	**
LAMATA/LEMC	0.418481	-3.127835	**
LCK/LLPN	0.463567	-2.523916	
LCPN/{LTSTH}	1.123644	-3.211929	**
LEMC/LLPN	1.072313	-2.602923	*
LEMC/{LNPARK}	-1.051428	-3.543688	***
LITD/LSCC	0.863427	-2.778859	*
{LKC}/{LNPARK}	-0.639136	-4.124383	***
LLH/LSPALI	0.725476	-2.917559	**
LLH/LSTEC	0.665578	-2.962701	**
LLH/LTPIPL	0.532649	-1.252821	
LLH/{LTSTH}	0.740257	-3.119587	**
LLPN/{LNPARK}	-0.644666	-1.340072	
LLPN/{LTSTH}	1.435990	-3.673175	***
{LNPARK}/{LPAE}	-1.013871	-2.775834	*
LSCC/{LTSTH}	0.906260	-3.189544	**
LSPALI/{LTSTH}	0.980593	-3.609414	***

Note that LAMATA, LCK, LCPN, LEMC, LLPN, LSCC, LLH, LTSTH, LNPARK and LSPALI are the log share price series where the log share price in parenthesis {-} sign represents inactive stock. Moreover, the residual series of each pair is tested for stationarity using augmented Dickey Fuller test (ADF). *, **, *** indicates the significant level at 10%, 5% and 1%, respectively.

The estimation in the Property and Construction sector in table 2.8 also found 24 out of 105 potential pairs that have a stationary long-run cointegration relationship, which consists of 13 pairs from active stocks and 11 pairs from inactive stocks.

Table 2.9: Engle and Granger output of identified pairs from Services sector (10 Years data)

Pairs	Beta Coefficient	ADF (t-statistic)	Cointegration
{LAHC}/{LBJC}	1.418896	-3.140146	**
{LAHC}/LERAWAN	1.188678	-2.092256	
{LAHC}/LLOXLEY	0.450001	-2.072339	
{LAHC}/LMAKRO	0.759329	-2.567337	
LBGH/LBH	0.753896	-3.500745	***
LBGH/LBIGC	2.450827	-1.564195	
LBGH/LROBINS	1.926341	-2.575386	*
LBGH/{LSINGER}	0.877918	-1.435123	
LBGH/{LSPC}	1.515616	-3.328851	**
LBH/{LSPC}	2.872311	-3.328851	**
LBIGC/{LBJC}	0.270473	-1.784472	
LBIGC/LERAWAN	0.601051	-2.468863	
LBIGC/LMAKRO	1.020977	-5.056636	***
LBIGC/LROBINS	0.675728	-4.665083	***
LBIGC/{LSINGER}	-0.463720	-2.638159	*
LBIGC/{LSPC}	0.644826	-2.261068	
{LBJC}/LERAWAN	0.223676	-2.707222	*
{LBJC}/LLOXLEY	0.268626	-2.355810	
LERAWAN/LMAKRO	1.011860	-2.944385	**
LERAWAN/LROBINS	0.910766	-3.374528	**
LMAKRO/ LROBINS	0.420276	-3.763871	***

Note that LBGH, LBH, LBIGC, LLOXLEY, LERAWAN, LROBINS, LMAKRO, LSINGER, LSPC and LBJC are the log share price series where the log share price in parenthesis {-} sign represents inactive stock. Moreover, the residual series of each pair is tested for stationarity using augmented Dickey Fuller test (ADF). *, **, *** indicates the significant level at 10%, 5% and 1%, respectively.

In table 2.9, results of cointegration tests for Services sector show that 14 out of 55 potential pairs are cointegrated and 7 of them are the combination of inactive pairs. In addition, we find only 1 cointegrated pair out of 9 potential pairs in the Technology sector. However, this pair is the combination of inactive stocks and the long-run relationship is marginally significant at 10%. These results are presented in table 2.10.

Table 2.10: Engle and Granger output of identified pairs from Technology sector (10 Years data)

Pairs	Beta Coefficient	ADF (t-statistic)	Cointegration
LADVANC/LTRUE	-0.331146	-2.156829	
LADVANC/{LMSC}	0.630700	-2.404075	
LADVANC/{LSAMART}	0.421273	-2.388884	
{LSAMART}/LTRUE	-0.319897	-1.379933	
{LMSC}/{LSAMART}	0.563320	-2.520235	
{LMSC}/LTRUE	-0.476151	-2.405754	
{LPT}/{LSAMART}	0.222379	-2.381347	
{LPT}/LADVANC	0.284856	-2.155901	
{LPT}/{LMSC}	0.297883	-2.655508	*

Note that LADVANC, LTRUE, LMSC, LSAMART, LMSC and LPT are the log share price series where the log share price in parenthesis {-} sign represents inactive stock. Moreover, the residual series of each pair is tested for stationarity using augmented Dickey Fuller test (ADF). *, **, *** indicates the significant level at 10%, 5% and 1%, respectively.

Table 2.11: Engle and Granger output of identified pairs from cross sector (10 Years data)

Pairs	Beta Coefficient	ADF (t-statistic)	Cointegration
LADVANC/LBANPU	0.396588	-2.800844	*
LADVANC/LBEC	-0.940071	-2.443718	
LADVANC/LKBANK	0.749051	-2.706191	*
LADVANC/LLH	0.485135	-1.521430	
LADVANC/LLOXLEY	0.377801	-1.577689	
LADVANC/LPTTEP	0.539622	-2.880486	**
LADVANC/LSCB	0.757989	-2.349627	
LADVANC/LSCC	0.528764	-2.046520	
LBANPU/LBEC	-1.289359	-1.128720	
LBANPU/LKBANK	1.937042	-1.946207	
LBANPU/LLH	1.102990	-0.322586	
LBANPU/LLOXLEY	0.637301	-0.283190	
LBANPU/LSCB	1.922282	-2.675335	*
LBANPU/LSCC	1.231262	-0.149003	
LBANPU/LTRUE	-0.917618	-1.703353	
LBEC/LKBANK	-0.123009	-2.452733	
LBEC/LLH	-0.100678	-2.516800	
LBEC/LPTTEP	-0.094383	-2.435173	
LBEC/LSCB	-0.069280	-2.341277	
LBEC/LSCC	-0.121716	-2.589678	*
LBEC/LTRUE	0.059777	-2.089500	
LKABNK/LLH	0.413776	-1.292852	
LKABNK/LLOXLEY	0.412539	-1.550532	
LKABNK/LPTTEP	0.581111	-2.574806	*
LPTTEP/LSCB	1.327727	-2.835426	*

Note that the first column is the top two leading share price series from each sector. Moreover, the residual series of each cross sector pair is tested for stationarity using augmented Dickey Fuller test (ADF). *, **, *** indicates the significant level at 10%, 5% and 1%, respectively.

Additionally, table 2.11 presents the results of the Engle and Granger approach across different sectors. We examine 10 stocks, which are the 2 leading stocks from each industry category. The result indicates that 7 pairs from 39 potential pairs have a cointegrating relationship. However, there is only 1 pair matched in the Technology and Resource sectors (LADVANC & LPTTEP) that is significant at 5% and the rest are marginally significant at 10%.[17]

In summary, the results of the Engle and Granger approach indicate that 48 pairs from 5 sectors and 7 pairs from cross sectors out of the total of 238 potential pairs have a stationary long-run equilibrium relationship.

2.6.1.2 Error Correction Model

After we found cointegrated pairs, the next step was to estimate an ECM to measure the short term dynamic of the cointegrated variables i.e. whether they are influenced by the deviation from the long-run equilibrium. The summarized results of the error correction models are represented in table 2.12[18].

[17] See Appendix A2 for stock details.
[18] More result of Error correction and Granger causality of property and construction, services and technology sectors are available upon request.

Table 2.12: The summary result of Error Correction and Granger causality

Cointegrated pairs	Stock return	Speed of adjustment γ1	γ2	Granger causality
Resources sector				
LEGCO/LLANNA	DLEGCO	-0.0044		
	DLANNA		0.0103***	LEGCO→LLANNA
LBANPU/LEGCO	DBANPU	-0.0050***		LEGCO→LBANPU
	DEGCO		0.0010	
Financial sector				
LACL/LTMB	DACL	-0.0123***		LTMB→LACL
	DTMB		-0.0007	
LASP/LKK	DASP	0.0004		
	DKK		0.0055***	LASP→LKK
LBAY/LKBANK	DBAY	-0.0089**		LSCB→LBAY
	DKBANK		-0.0014	
LBAY/LSCB	DBAY	-0.0021		
	DSCB		0.0048*	LBAY→LSCB
LKBANK/LSCB	DKBANK	0.0018		
	DSCB		0.0122***	LKBANK→LSCB
LKK/LKTB	DKK	-0.0063***		LKTB→LKK
	DKTB		-0.0019	
LKK/LTMB	DKK	-0.0071***		LTMB→LKK
	DTMB		-0.0039**	LKK→LTMB
LSCB/LTMB	DSCB	-0.0030***		LTMB→LSCB
	DTMB		-0.0037**	LSCB→LTMB
{LAYUD}/LBBL	DAYUD	-0.0026		
	DBBL		0.0069*	LAYUD→LBBL
{LAYUD}/LSCB	DAYUD	-0.0020		
	DSCB		0.0057*	LAYUD→LSCB

Table 2.12: Continued				
Cointegrated pairs	**Stock return**	**Speed of adjustment $\gamma 1$**	**$\gamma 2$**	**Granger causality**
Service sector				
LBGH/LBH	DBGH	-0.0020		
	DBH		0.0103 ***	LBGH→LBH
LBGH/LROBINS	DBGH	-0.0001		
	DROBINS		0.0028 **	LBGH→LROBINS
LMAKRO/LROBINS	DMAKRO	-0.0085 ***		LROBINS→LMAKRO
	DROBINS		0.0055	
{LAHC}/{LBJC}	DAHC	-0.0019 **		LBJC→LAHC
	DBJC		0.0014 *	LAHC→LBJC

Note that the first column is the cointegrated log share price series while the stock return or the first difference of share price series (D) is in column 2. The inactive stock is in the parenthesis {-}. Moreover, $\gamma 1$ and $\gamma 2$ are the speed of adjustment. *, **, *** represents the significant level at 10%, 5% and 1%, respectively. → indicates the Granger causality flow from one stock to the other.

The first column represents the cointegrated pairs that we identified from the Engle and Granger approach while the first difference of stock or the stock return is in column two. The next column is the spread of adjustment coefficients and the last column is the direction of Granger causality.

As shown, at least one of the disequilibrium terms (γ_1 or γ_2) of all cointegrated pairs is significantly different from zero, which confirms the result of the EG cointegration test. Thus, a cointegration relationship exists and the short-run disequilibrium term will correct the system over the long term equilibrium value. The evidence exhibits 37 pairs with unidirectional long-run granger causality.

For instance, with stocks LEGCO and LLANNA from the Resource sector, the ECM result shows one way causality (LEGCO Granger causes LLANNA) as the adjustment coefficient of disequilibrium term (γ_2 = 0.0103) is significant and rejects the null hypothesis with a 5% confident interval. This finding indicates that the past value of

ΔLEGCO helps to predict the current or future price of LLANNA in the long-run. However, the null hypothesis of zero lagged coefficients of LEGCO cannot be rejected. This implies LEGCO Granger causes LLANNA in the long run rather than in the short run.

Moreover, we find 10 cointegrated pairs that have bidirectional long run Granger causality. In fact, the disequilibrium terms are significantly different from zero at 5% level. Therefore, the cointegrated pairs Granger cause each other but with different degree of response. For example, with stocks LKK and LTMB from the financial sector, both previous values of stocks contain information that can be useful to predict the future value of each other. In this scenario, DKK (γ_1 = 0.0071***) responds faster than DTMB (γ_2 = 0.0039**) to the previous period's disequilibrium as the coefficients are significant at 1% and 5%, respectively. Hence, we can conclude that LKK can respond faster than LTMB to reestablish the long-run equilibrium.

In addition, the size and sign of γ_1 and γ_2 are crucial as an indication of the mean reversion property toward long-run equilibrium. For this reason, we evaluate the cointegrated pairs and select most promising pairs to trade based on the correct sign and size of the adjustment coefficients. As a result, we select two cointegrated pairs that have the correct sign and speed of adjustment coefficients of approximately 0.01, which are LEGCO & LLANNA and LBGH & LBH. These two selected pairs are the fastest response to the previous period's deviation from the long run equilibrium. In addition, the inactive cointegrated pairs and cross sectors cointegrated pairs failed to meet our criterion as they are only marginally significant at 10%.

2.6.2 Profitability of Pairs Trading Strategies

In the first part, the pairs trading performance of 2 selected pairs (LEGCO & LLANNA and LBGH & LBH) are reported in simulation A, B, C and D, respectively. Moreover, in the second part, we select simulation A and B to compare the pairs trading performances of "correct sign" and "mix sign" cointegrated pairs.

2.6.2.1 Pair trading result in Simulation A (unlimited trading period with constant beta)

The pairs trading results of LEGCO & LLANNA (Resources sector) and LBGH & LBH (Services sector) are summarized respectively in table 2.13 and 2.14. The first column presents the trading bands of 1, 1.5 and 2 standard deviations. The second column contains Total Return (after transaction cost), Number of Trades, Return per Trade, Return per Year, Total Transaction Cost, Transaction Cost per Trade and Average Holding per Trade. Column 3, 4 and 5 report the result for strategy 1, 2 and 3, respectively.

The first selected pair from the Resource sector is presented in table 2.13, all pairs trading strategies tested on LEGCO & LLANNA yield positive return across all trading bands. The average returns across three strategies are increased and the numbers of trades are reduced as the trading bands are higher. For example, the average return on strategy 1 at 1, 1.5 and 2 SD bands are 9.26%, 24.19% and 30.63%, respectively. The findings also indicate the trading results of the three strategies at 1.5 and 2 SD bands are relatively similar. Also, on average, three strategies yield approximately 30% profit in the 2 SD band. Moreover, as expected, strategy 2 yields the highest total return and transaction cost because strategy 2 generates a large number of trades. For example in 2 SD bands, the average return, total return and total transaction cost are 30.63%, 183.77% and 5.81% for strategy 1, 30.87%, 802.63% and 24.39% for strategy 2 and 30.31%, 212.19% and 6.77% in strategy 3 respectively. Thus, pair traders will incur high investment costs in order to gain an “anomaly” return.

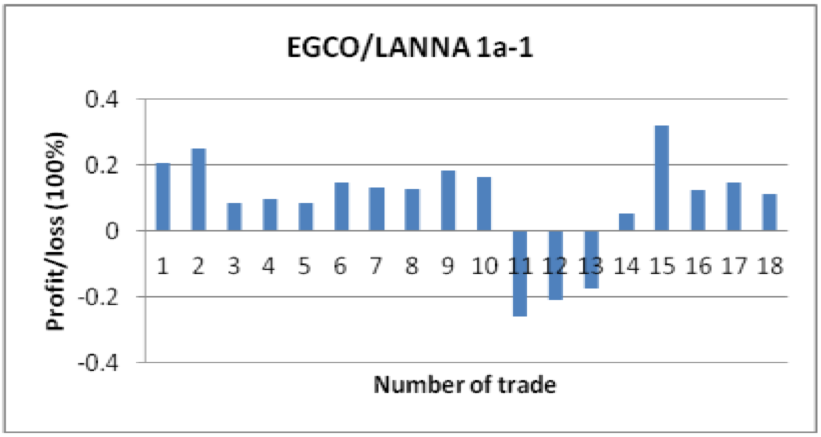
The illustration of profit and loss and accumulated graphs clearly show the profitability of pairs trading strategies. For example at the 1 SD band, the profit and lost pairs trading graph of strategy 1 with 1 SD band in simulation A (1a-1) and strategy 2 with 1 SD band in simulation A (2a-1) presented in figures 2.1. These show some negative returns due to the spread continuing to deviate thus prompting the stop loss trigger. Interestingly, our conservative strategy (3a-1) gives a positive return in every transaction. In addition, the accumulation of profit and loss graph in figures 2.2 also confirms that strategy 3 has outperformed the other 2 strategies in the sense that strategy 3 is able to give relative a similar average return at a lower risk. Strategy 3 at 1 SD band in simulation A (3a-1) in figure 2.2 shows that at the end of the trading period, the accumulated positive transactions are close to 200% profit for a 5-year trading period. Even though the accumulation of 1a-1 varies up and down due to negative transactions, the result of this strategy is a yield of about 150% at the end of the trading period.

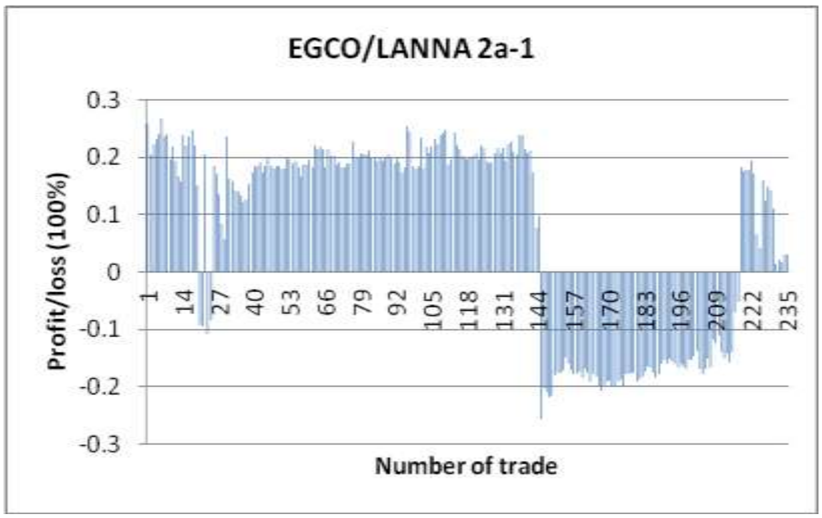
Table 2.13: The summary results of 3 pairs trading strategies with unlimited trading period and constant beta (Resource sector-LEGCO/LLANNA)

Trading Band	Strategy	1a	2a	3a
1	Total net return (100%)	1.5745	14.7552	1.9178
	No of trade	17	225	19
	R/Trade (100%)	0.0926	0.0656	0.1009
	R/Yr (100%)	0.3149	2.9510	0.3836
	Total Transaction cost (100%)	0.1248	2.0329	0.1257
	TC/Trade (100%)	0.0073	0.0090	0.0066
	Hold/Trade (days)	57	49	48
1.5	Total net return (100%)	1.9351	13.5183	2.5059
	No of trade	8	51	11
	R/Trade(100%)	0.2419	0.2651	0.2278
	R/Yr (100%)	0.3870	2.7037	0.5012
	Total Transaction cost (100%)	0.0768	0.4730	0.0962
	TC/Trade (100%)	0.0096	0.0093	0.0087
	Hold/Trade (days)	45	61	44
2	Total net return (100%)	1.8377	8.0263	2.1219
	No of trade	6	26	7
	R/Trade (100%)	0.3063	0.3087	0.3031
	R/Yr (100%)	0.3675	1.6053	0.4244
	Total Transaction cost (100%)	0.0581	0.2439	0.0677
	TC/Trade (100%)	0.0097	0.0094	0.0097
	Hold/Trade (days)	83	79	83

Note: 1a, 2a and 3a represent 3 strategies in simulation A. The table reports the percentage of total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. The trading band consists of 1, 1.5 and 2 standard deviations, respectively.

Figure 2.1 Profit and loss graphs of EGCO/LANNA (1 SD band in Simulation A)





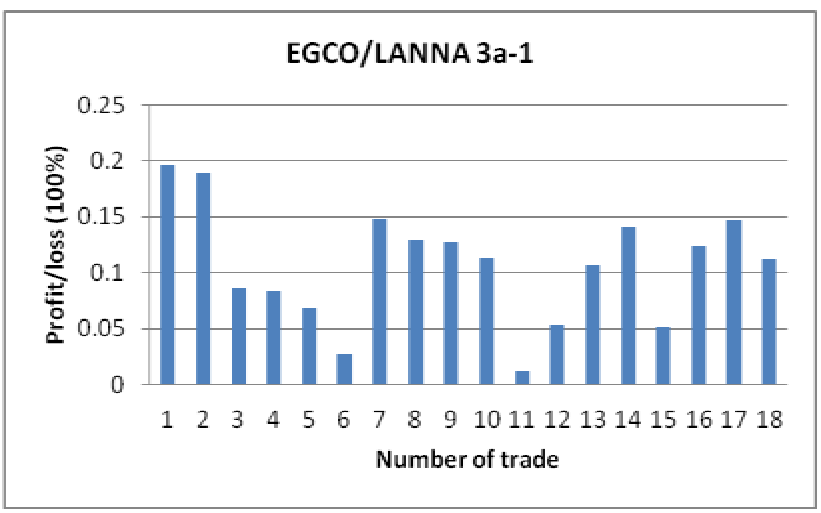
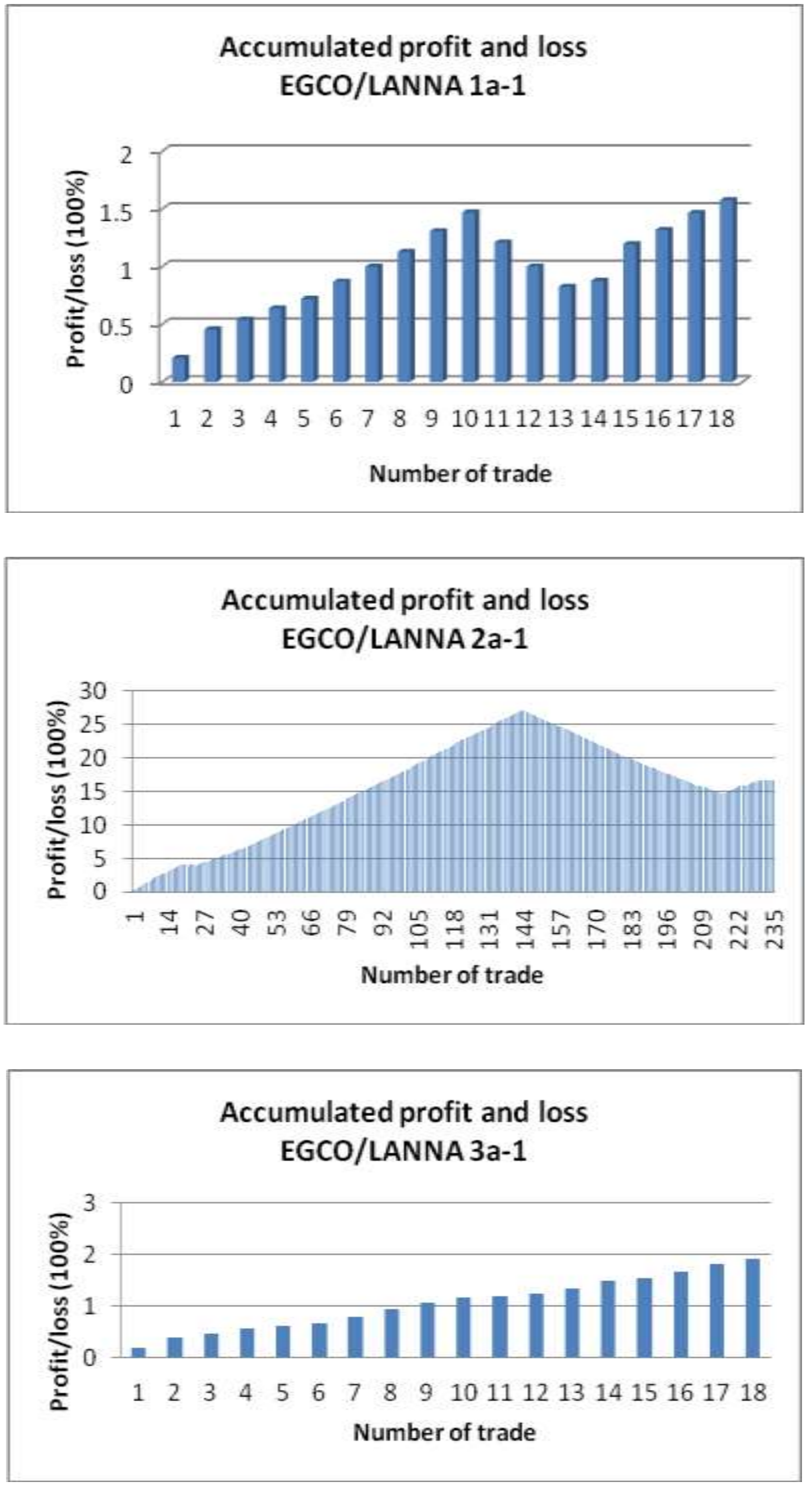


Figure 2.2 Accumulated profit and loss graphs of EGCO/LANNA (1 SD band in Simulation A)



The second selected pairs from the Services sector (LBGH & LBH) are presented in table 2.14. Pairs trading strategies yield a positive return at 1 SD band. The spread does not largely deviate beyond the first SD band, so there are no transactions occurring at the higher bands. In this particular pair, the average returns of strategy 1 and 3 are relatively close, which are 25.11% and 22.92%, respectively. However, the average return of strategy 2 is 46.13%, which is roughly twice as high as the other 2 strategies. In a 5-year trading period, the accumulated profit and loss transactions add up to 150.64% from strategy 1, 4705.10% from strategy 2 and 137.51% from strategy 3.

In summary, pairs trading without trading period constraints - and using a constant beta – appear to be profitable. All pairs trading strategies performed relatively well in the same trading bands but increased trading bands improve the average return. Moreover, a few transactions must be closed as they reach the stop loss signal in order to prevent massive losses, which drive away some profit from the strategy. At the end of the period, all strategies still provide accumulated positive returns.

Table 2.14: The summary results of 3 pairs trading strategies with unlimited trading period with constant beta (Services sector-LBGH/LBH)				
Trading band	**Strategy**	**1a**	**2a**	**3a**
1	Total net return (100%)	1.5064	47.0510	1.3751
	No of trade	6	102	6
	R/Trade (100%)	0.2511	0.4613	0.2292
	R/Yr (100%)	0.3013	9.4102	0.2750
	Total Transaction cost (100%)	0.0085	0.0935	0.0083
	TC/Trade (100%)	0.0014	0.0002	0.0014
	Hold/Trade (days)	214	196	196

Note that 1a, 2a and 3a represent 3 strategies in simulation A. The table reports total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. There are no transactions are reported at 1.5 and 2 SD bands as the spread does not extremely deviate beyond 1 SD band.

2.6.2.2 Pair trading result in Simulation B (unlimited trading period with updated beta)

The outcomes of 2 selected pairs performed in simulation B with unlimited trading period and employed an updated beta at the closing transaction are presented in tables 2.15 and 2.16. These tables are organized in the same format as described in simulation A.

In table 2.15, the average returns of LEGCO & LLANNA are slightly increased and some remain the same as the beta of this pair is constant over time. For example, at 1 SD band, the average returns of strategy 1 and 3 are slightly improved from the previous simulation 9.26% to 11.35% and from 10.09% to 11.81% respectively. Similar to simulation A, when the trading bands increase, we found higher average returns and fewer numbers of trade open positions as well as smaller transaction costs.

Moreover, updated beta improved the performance of pairs trading strategies for LBGH & LBH, which is presented in table 2.16. The average return of strategy 1 is improved by 115.96% (from 25.11% to 54.23%), strategy 2 is 98.46% (from 46.13% to 91.55%) and strategy 3 is 102.79% (from 22.92% to 46.46%) due to the beta of this pair increasing over time. Hence, simulation B results are better than those of simulation A.

In summary, strategy B shows an improvement of pairs trading strategies in the case of time varying updated beta over time. The results indicate that updated beta not only yields higher positive return but also lowers the loss. Our findings are compatible with the risk and return perspective where high risk yields high returns. Consequently, updated beta can be an alternative means for pair traders to maximize returns against a given level of risk.

Table 2.15: The summary results of 3 pairs trading strategies with unlimited trading period and updated beta (Resource sector-LEGCO/LLANNA)				
Trading Band	**Strategy**	**1b**	**2b**	**3b**
1	Total net return (100%)	1.9297	14.6679	2.2444
	No of trade	17	225	19
	R/Trade (100%)	0.1135	0.0652	0.1181
	R/Yr (100%)	0.3859	2.9336	0.4488
	Total Transaction cost (100%)	0.1254	2.0331	0.1263
	TC/Trade (100%)	0.0073	0.0093	0.0066
	Hold/Trade (days)	57	49	57
1.5	Total net return (100%)	1.9351	14.4129	2.5059
	No of trade	8	51	11
	R/Trade(100%)	0.2419	0.2826	0.2278
	R/Yr (100%)	0.3870	2.8825	0.5012
	Total Transaction cost (100%)	0.0768	0.4744	0.0962
	TC/Trade (100%)	0.0096	0.0093	0.0087
	Hold/Trade (days)	45	61	44
2	Total net return (100%)	1.8377	8.4392	2.1219
	No of trade	6	26	7
	R/Trade (100%)	0.3063	0.3246	0.3031
	R/Yr (100%)	0.3675	1.6878	0.4244
	Total Transaction cost (100%)	0.0581	0.2445	0.0678
	TC/Trade (100%)	0.0097	0.0094	0.0097
	Hold/Trade (days)	83	79	83
Note that 1b, 2b and 3b represent 3 strategies in simulation B. The table reports the percentage of total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. The trading band consists of 1, 1.5 and 2 standard deviations, respectively.				

Table 2.16: The summary results of 3 pairs trading strategies with unlimited trading period and updated beta (Services sector-LBGH/LBH)				
Trading band	**Strategy**	**1b**	**2b**	**3b**
1	Total net return (100%)	3.2540	93.3845	2.7876
	No of trade	6	102	6
	R/Trade (100%)	0.5423	0.9155	0.4646
	R/Yr (100%)	0.6508	18.6769	0.5575
	Total Transaction cost (100%)	0.0110	0.1580	0.0103
	TC/Trade (100%)	0.0018	0.0003	0.0017
	Hold/Trade (days)	214	196	196

Note that 1b, 2b and 3b represent 3 strategies in simulation B. The table reports total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. There are no transactions are reported at 1.5 and 2 SD bands as the spread does not extremely deviate beyond 1 SD band.

2.6.2.3 Pair Trading result in Simulation C (limited trading period with constant beta)

In this extreme case, we restrict the trading period to six months and employ constant beta. Hence, all transactions opened in the same 6-month period will use the same beta and close the trading positions at the end of the limited trading period. The summary results of 2 selected pairs are presented in table 2.17 and 2.18.

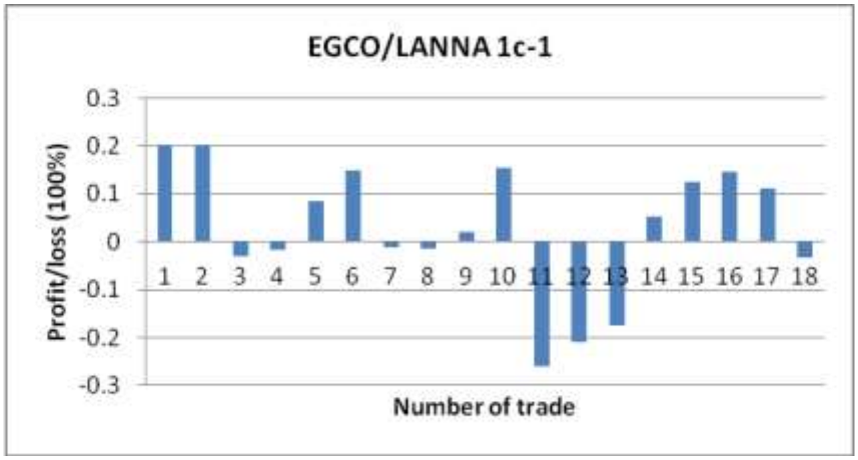
The result of LEGCO and LLANNA in table 2.17 shows positive returns across all strategies in various bands. In this simulation, the average return of strategy 2 is slightly better than the other 2 strategies in 1 SD band, but lower in the higher trading bands. Moreover, strategies 1 and 3 yield relatively similar outcomes in the 1.5 and 2 SD bands. For example, the average returns for strategy 1 and 3 at 1.5 SD are 23.69% and 22.78% and at 2 SD are 30.63% and 30.31% respectively. Whereas the average return of strategy 2 is about 19.54% and 25.64%, the total return over the 5-year trading period is the highest of all strategies due to a higher number of open trades. At the same time, strategy 2 becomes riskier because the strategy creates a lot of open signals, some of which are fault signals, thus making the strategy investment costly.

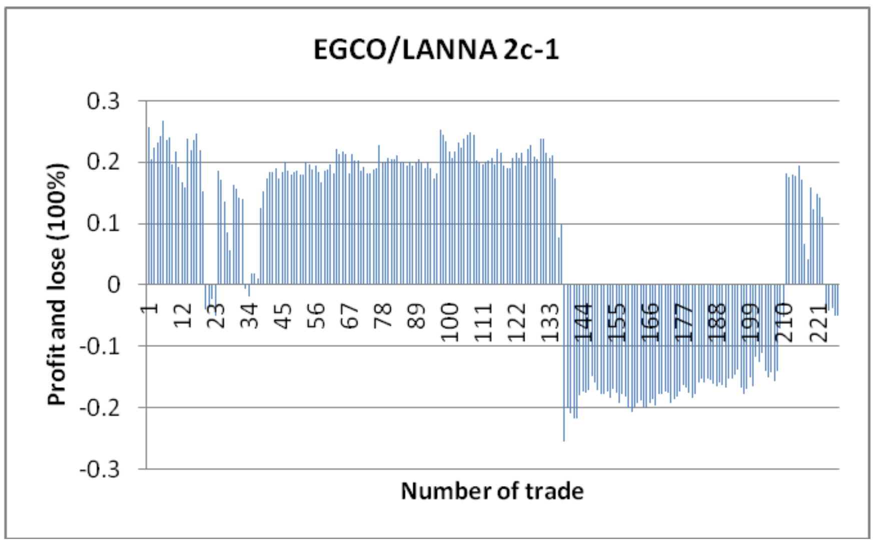
Table 2.17: The summary results of 3 pairs trading strategies with limited 6-month trading period with constant beta (Resource sector-LEGCO/LLANNA)

Trading Band	Strategy	1c	2c	3c
1	Total net return (100%)	0.4950	14.4293	0.6416
	No of trade	18	228	18
	R/Trade (100%)	0.0275	0.0633	0.0356
	R/Yr (100%)	0.0990	2.8859	0.1283
	Total Transaction cost (100%)	0.1614	2.0608	0.1145
	TC/Trade (100%)	0.0018	0.0018	0.0013
	Hold/Trade (days)	39	77	34
1.5	Total net return (100%)	2.3691	9.9665	2.5059
	No of trade	10	51	11
	R/Trade (100%)	0.2369	0.1954	0.2278
	R/Yr (100%)	0.4738	1.9933	0.5012
	Total Transaction cost (100%)	0.0953	0.4673	0.0962
	TC/Trade (100%)	0.0019	0.0018	0.0017
	Hold/Trade (days)	93	125	44
2	Total net return (100%)	1.8377	7.1798	2.1219
	No of trade	6	28	7
	R/Trade (100%)	0.3063	0.2564	0.3031
	R/Yr (100%)	0.3675	1.4350	0.4244
	Total Transaction cost (100%)	0.0581	0.2691	0.0677
	TC/Trade (100%)	0.0019	0.0019	0.0019
	Hold/Trade (days)	83	69	83

Note: 1c, 2c and 3c represent 3 strategies in simulation C. The table reports the percentage of total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. The trading band consists of 1, 1.5 and 2 standard deviations, respectively.

Figure 2.3 Profit and loss graphs of EGCO/LANNA (1 SD band in Simulation C)





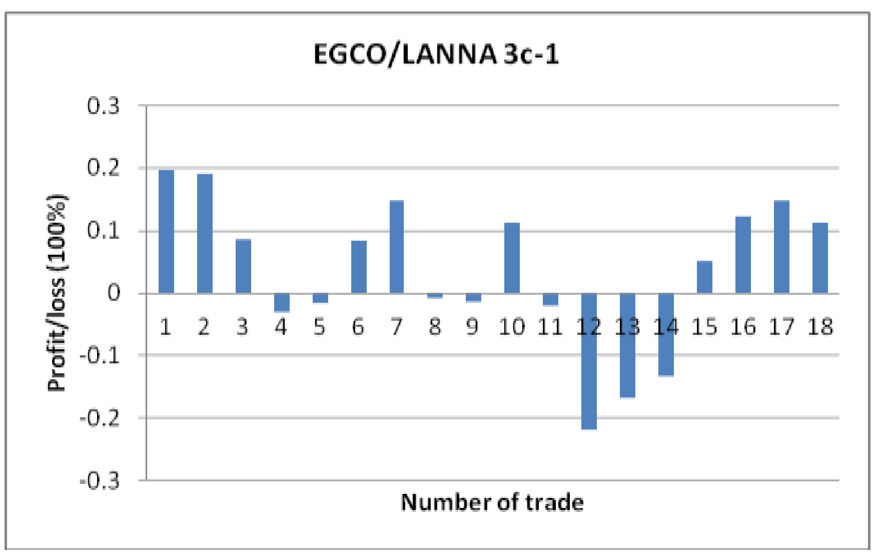


Figure 2.4 Profit and loss accumulated of EGCO/LANNA (1 SD band in Simulation C)

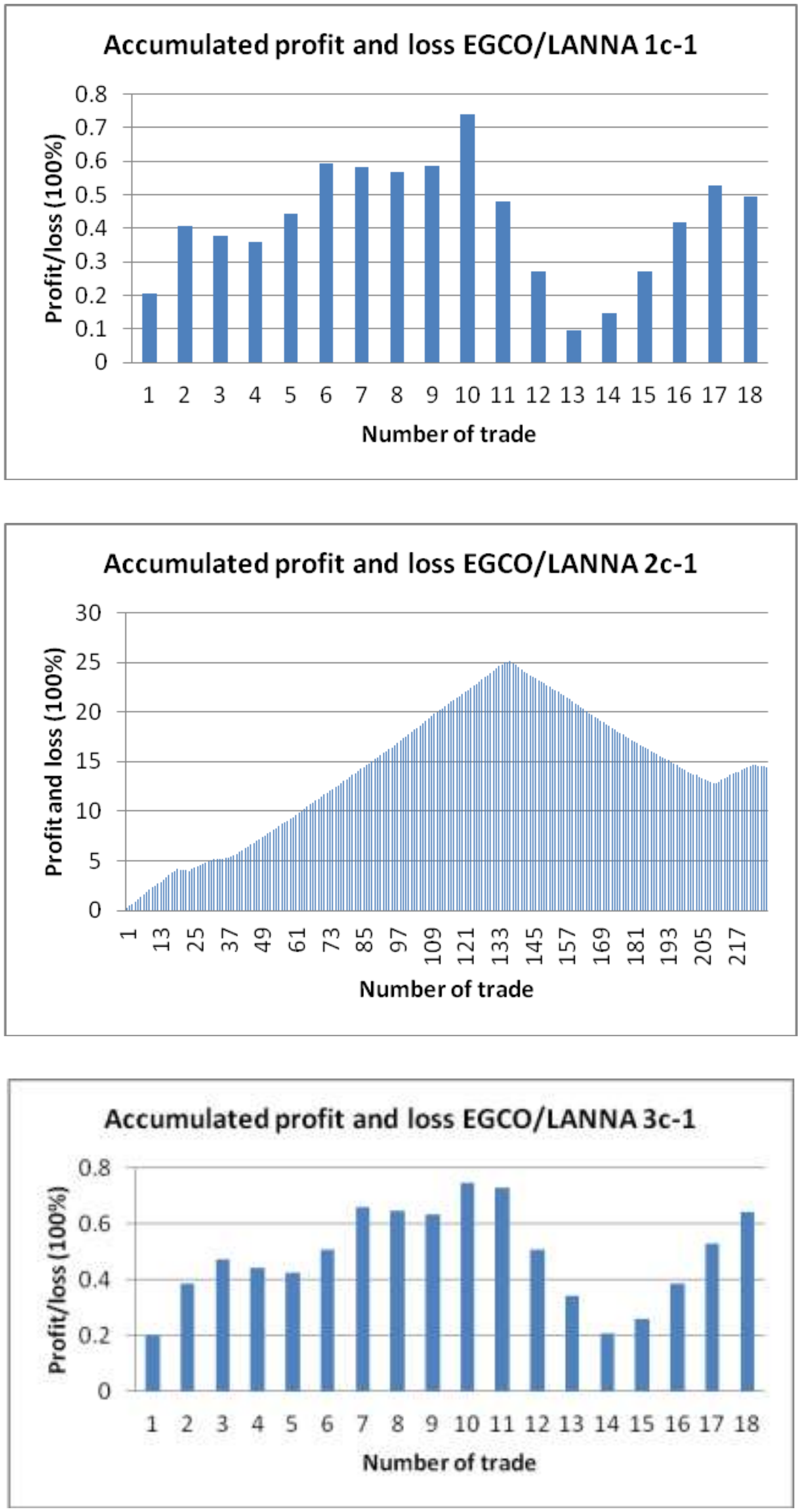


Figure 2.3 illustrates a profit and loss for EGCO/LANNA, 1c-1 (simulation C, strategy 1 with 1 standard deviation trading band). The graph indicates 8 negative transactions and 10 positive transactions, which means an approximately 55.56% chance of having a positive return. These 8 transactions have been closed due to reaching the stop loss trigger and end of period constraint. Moreover, there were 3 transactions during February 2008 to July 2008 that yielded a massive loss due to the spread showing a high deviation and reached the stop loss trigger at 2 SD. In figure 2.4, the accumulated graph of 1c-1 also clearly shows that the highest accumulated excess return is dramatically reduced from approximately 72% to 10% as the spread hits the stop loss trigger. At the end of the trading period, the excess return gradually accumulated to reach 49.5%. Similarly, the accumulated excess return for strategy 2c-1 is gradually increased to 2,500% and gradually declined to below 1,500% then rebounded to 1,442.93% at the end of trading period. In addition, the highest accumulated excess return of strategy 3c-1 is about 72% and the lowest is 20%. At the end of the period, the accumulated return of strategy 3 in Simulation C is 64.16%.

Although, the returns of this pairs are positive, pairs trading strategies give better results in simulation A where we do not limit the trading period. For example, the accumulated profit and loss transactions of all strategies at 1 SD band in simulation C are 49.50%, 1,442.93% and 64.16%, which are lower than simulation A (where the results of all strategies are 157.45%, 1,475.52% and 191.78%).

Moreover, the pairs trading results of LBGH & LBH in table 2.18 also yield positive returns across all strategies. However, the profit opportunities of the strategies are small when we limit the trading period. Compared to simulation A, the average returns at 1 SD band are reduced from 25.11% to 9.20%, 46.13% to 4.47% and 22.92% to 12.58% in strategy 1, 2 and 3 respectively.

Table 2.18: The summary results of 3 pairs trading strategies with limited 6-month trading period with constant beta(Services sector-LBGH/LBH)				
Trading band	**Strategy**	**1c**	**2c**	**3c**
1	Total net return (100%)	0.5518	4.5639	0.7550
	No of trade	6	102	6
	R/Trade (100%)	0.0920	0.0447	0.1258
	R/Yr (100%)	0.1104	0.9128	0.1510
	Total Transaction cost (100%)	0.01146	0.1603	0.0044
	TC/Trade (100%)	0.0004	0.0003	0.0001
	Hold/Trade (days)	69	59	72

Note: 1c, 2c and 3c represent 3 strategies in simulation C. The table reports total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. There are no transactions are reported at 1.5 and 2 SD bands as the spread does not extremely deviate beyond 1 SD band.

In summary, the big difference in the returns indicates that this "extreme" simulation is not as good as other simulations even though all strategies yield profit. The 6-month trading period constraint causes many of the transactions to close at the end of the period. We realized some positive returns due to the spread moving closer to equilibrium. Also, we found some negative returns when the open positions have to close at the end of the limited trading period with three possible events or scenarios.

Firstly, when the spread is widened, we face a small loss. Secondly, when the spread hits stop loss, we face a huge loss. Lastly, when the spread is narrower, we also face a small loss because the trade cannot make profit out of the small gap. Therefore, we cannot conclude that our pairs trading strategies have actually performed well in this simulation but rather a favorable spread moved in our direction as the majority of transactions were closed due to the trading period constraint.

2.6.2.4 Pairs Trading Result of Simulation D (limited trading period with updated beta)

In this simulation, the trading period is limited to 6 months with daily updated beta. Table 2.19 shows the result of LEGCO & LLANNA where an updated beta helped improves the profitability of pairs trading. The result indicates higher returns compared to simulation C. For example, at 2 SD level, the average returns of strategy 1, 2 and 3 have improved from 30.63% to 45.23%, 30.31% to 38.25% and 30.31% to 44.66%, respectively.

Table 2.19: The summary results of 3 pairs trading strategies with limited 6-month trading period with updated beta (Resource sector-LEGCO/LLANNA)				
Trade Band	**Strategy**	**1d**	**2d**	**3d**
1	Total net return (100%)	0.6378	20.8341	6.3242
	No of trade	18	228	18
	R/Trade (100%)	0.0354	0.0914	0.3513
	R/Yr (100%)	0.1275	4.1668	1.2648
	Total Transaction cost (100%)	0.1607	2.0367	0.1146
	TC/Trade (100%)	0.0018	0.0018	0.0013
	Hold/Trade (days)	39	77	34
1.5	Total net return (100%)	2.9019	13.3626	3.2477
	No of trade	10	51	11
	R/Trade (100%)	0.2902	0.2620	0.2952
	R/Yr (100%)	0.5804	2.6725	0.6495
	Total Transaction cost (100%)	0.0930	0.4636	0.0938
	TC/Trade (100%)	0.0018	0.0018	0.0017
	Hold/Trade (days)	94	125	44
2	Total net return (100%)	2.7141	10.7101	3.1267
	No of trade	6	28	7
	R/Trade (100%)	0.4523	0.3825	0.4466
	R/Yr (100%)	0.5428	2.1421	0.62533
	Total Transaction cost (100%)	0.0570	0.2593	0.0665
	TC/Trade (100%)	0.0019	0.0018	0.0019
	Hold/Trade (days)	83	69	83

Note: 1d, 2d and 3d represents 3 strategies in simulation D. The table reports total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. The trading band consists of 1, 1.5 and 2 standard deviations, respectively.

Table 2.20: The summary results of 3 pairs trading strategies with limited 6-month trading period with updated beta (Services sector-LBGH/LBH)				
Trading band	**Strategy**	**1d**	**2d**	**3d**
1	Total net return (100%)	1.1814	17.4948	1.2664
	No of trade	6	102	6
	R/Trade (100%)	0.1969	0.1715	0.2110
	R/Yr (100%)	0.2362	3.4989	0.2532
	Total Transaction cost (100%)	0.0101	0.0942	0.0032
	TC/Trade (100%)	0.0003	0.0001	0.0001
	Hold/Trade (days)	69	59	72

Note: 1d, 2d and 3d represents 3 strategies in simulation D. The table reports total net return, number of trade, average return per trade, average return per year, total transaction cost, average transaction cost per trade and average holding the buy/sell position per trade. There are no transactions are reported at 1.5 and 2 SD bands as the spread does not extremely deviate beyond 1 SD band.

In table 2.20, the average return of LBGH & LBH also confirms the better outcome of pairs trading strategies once beta is updated. In this pair, the average returns of strategy 1, 2 and 3 in simulation D are 19.69%, 17.15% and 21.10%, which are higher than the average results in simulation C.

In summary, the pairs trading strategies yield better average returns than simulation C for both selected pairs. Thus, traders can employ updated beta method to improve the profitability of the selected pairs over the shorter time horizon. However, the results indicate that pairs trading strategies perform best when we do not restrict the trading period.

Moreover, as mention in section 2.3.4.4, the implicit trading cost that the investor has to face when desire immediately trading the stock is the bid-ask spread. In the SET index, the tick size rule is imposed to control the minimum price change or the spread between the bid and ask prices[19]. The percentage bis-ask spread varies approximately from 1 to 2% per trade. Accounting for such spread, pair trading strategy still yields profitable results in this market. For example, simulation A with the lowest (1SD) band from table 2.13, the average returns from strategy 1 to 3 are 9.26%, 6.56% and 10.09%, while the average returns in the highest (2SD) band are approximately 30% for all strategies. These results indicate that the pair trading strategy can easily handle the bid-ask spread and still yield excess return. However, in the extreme trading simulation (such as simulation C), table 2.17, the average returns from strategy 1 to 3 (1SD band) are 2.75%, 6.33% and 3.56%, respectively. We still realize small positive returns after accounting for the bid-ask spread in the lowest trading band.

Overall, pairs trading outcomes from 4 different simulations confirm that pairs trading strategies are profitable in the Stock Exchange of Thailand. Our result is consistent with the previous results of Lin et al (2006) and Perlin (2007) who found that increasing the threshold value or trading bands will result in a lower number of trades and a higher average return. Moreover, the findings show that returns depend on the variation of beta over time. Firstly, when beta is consistent over a trading period ($\beta_o \approx \beta_c$), pairs trading strategies give approximately constant returns. Secondly, when beta is increased over time ($\beta_o < \beta_c$), the average returns are improved over simulation A. When trades are closed at the higher beta, the trading results are more positive and in some cases even produce smaller losses. Lastly, when beta is decreased over time ($\beta_o > \beta_c$), the findings show that an updated beta cannot improve the profitability of the strategies. In addition, our results are mixed. The findings show approximately 1.5 to 3 months for LEGCO & LLANNA but approximately 6 months for LBGH & LBH. Thus, we cannot conclude – unlike Gatev et al (1999) in the U.S market - that a pairs trading strategy is a long term investment strategy in Thailand. Do et al (2006) also point out that if the mean reversion of the pair is too strong, the profit opportunity of pairs trading might quickly disappear. This might not be the case in the Thai stock market because the highest speed of adjustment that we found in this study is approximately 1.03% in a day. Moreover, the

[19] Refer to table 2.4 for the tick size rules.

long-run spread takes at least 3 to 6 months to reverse. Therefore, there are plenty of opportunities for traders to take this profit.

2.6.2.5 “Correct sign” of adjustment coefficients

Pairs trading strategies tested on correct and incorrect signs of adjustment coefficient in descending order are presented in tables 2.21 and 2.22 respectively. Moreover, we select simulation A and B at the lowest band in order to study whether the size of correct and incorrect adjustment coefficients would affect the returns. At 1 SD level, the strategies would give minimum profit or loss that we might gain from the strategy.

The first, second and third columns represent the selected pairs, beta value from cointegration regression and the speed of adjustment coefficients estimated from the ECM. The fourth and fifth columns show the average returns from strategy 1, 2 and 3 at 1 SD band in simulation A and simulation B respectively.

In table 2.21, adjustment coefficients are ranked from 0.0103 to 0.0028. In particular, only 2 out of 23 pairs are higher than 0.01 while 21 pairs have lower ECM coefficient. The results indicate strategy 3A is the best as 12 out of 23 pairs yield positive returns while only 9 and 7 pairs yield positive return for strategy 1A and 2A respectively. Significantly, only 7, 5 and 10 pairs out of 21 low ECM coefficient pairs give positive returns for strategy 1A, 2A and 3A.

With an updated beta, strategy 3B indicates 16 pairs have improved (increased beta), 3 pairs have slightly reduced (decreased beta) and 4 pairs have remained the same (constant beta). Whereas, beta can improve only 4 pairs in 1B and 3 pairs in 2B, table 2.21 indicates the average holding period of strategy 1 and 2 is lower than 10 days. In other words, a large number of trading positions in these 2 strategies have to close due to reaching the stop loss trigger. Also, the low speed of adjustment pairs indicates a smaller number of open trades than the high speed of adjustment pairs, especially in strategy 2.

Table 2.21: Pairs trading result tested on "correct sign" pairs									
Pairs	**Beta**	**ECM**		**Simulation A (1 SD)**			**Simulation B (1 SD)**		
	Z= y-bx	γ1	γ2	1	2	3	1	2	3
EGCO/ LANNA	0.62	-0.0044	0.0103 ***	0.0926 [48] 17	0.0656 [57] 225	0.1009 [49] 19	0.1135	0.0652	0.1181
BGH/ BH	0.75	-0.0020	0.0103 ***	0.2511 [196] 6	0.4613 [196] 102	0.2292 [214] 6	0.5423	0.9155	0.4646
AMATA/ EMC	0.41	-0.0005	0.0093 ***	-0.0340 [4] 9	-0.0627 [4] 7	-0.0088 [16] 9	-0.0380	-0.0607	-0.0094
MAKRO/ ROBINS	0.42	-0.0085 ***	0.0055	-0.0219 [3] 38	-0.0075 [5] 49	-0.0023 [42] 37	-0.0218	-0.0365	0.0189
{AYUD}/ BBL	0.49	-0.0026	0.0069 *	-0.0017 [5] 36	-0.0463 [5] 51	0.0724 [103] 34	0.0033	-0.0353	0.1285
ERAWAN /ROBINS	0.91	-0.0069 ***	0.0014	0.0054 [5] 27	-0.0027 [7] 39	0.0135 [94] 27	0.0054	-0.0278	0.0566
SPALI/ {TSTH}	0.79	- 0.00005	0.0066 ***	0.0087 [5] 39	0.0113 [5] 60	-0.0273 [64] 36	0.0087	0.0113	-0.0290
LH/ STEC	0.66	-0.0041	0.0064 **	-0.0004 [3] 29	-0.0147 [3] 20	0.0239 [15] 31	-0.0004	-0.0147	0.0240
AMATA/ SCC	1.73	-0.0059 ***	0.0011	-0.0237 [4] 45	-0.0061 [4] 37	-0.0048 [24] 44	-0.0237	-0.0061	0.0046
{AYUD}/ SCB	0.45	-0.0020	0.0057 *	-0.0128 [9] 57	-0.0499 [9] 99	0.0058 [64] 56	-0.0095	-0.0436	0.0374
SCC/ {TSTH}	0.62	-0.0002	0.0057 ***	-0.0343 [2] 5	0.0400 [2] 5	0.0346 [44] 5	-0.0343	0.0400	0.0351
LPN/ SCC	1.65	-0.0056 ***	0.0009	-0.0297 [3] 9	-0.0240 [3] 10	0.6938 [90] 9	-0.0297	-0.0240	0.7676
BANPU/ EGCO	2.23	-0.005 ***	0.0010	-0.0025 [4] 38	-0.0050 [4] 43	0.0088 [33] 33	-0.0025	-0.0050	0.0071
BAY/ SCB	0.89	-0.0021	0.0048 *	-0.0080 [8] 36	-0.0124 [8] 63	-0.0134 [47] 36	-0.0080	-0.0124	0.0033
BGH/ {SPC}	2.29	-0.0046 **	0.0036 **	0.0030 [3] 25	-0.0245 [4] 15	-0.0849 [62] 27	-0.0139	-0.0576	0.0914
STEC/ {TSTH}	0.86	- 0.00097	0.0044 ***	0.02372 [3] 22	0.01991 [3] 17	-0.0203 [41] 24	0.0237	0.0199	-0.0177

Table 2.21: Continued

Pairs	Beta	ECM		Simulation A (1 SD)			Simulation B (1 SD)		
	Z= y-bx	γ1	γ2	1	2	3	1	2	3
ERAWAN /MAKRO	1.01	-0.0044 ***	0.00134	-0.0273 [3] 3	-0.0006 [4] 5	-0.0443 [14] 3	-	-	-
{BJC}/ ERAWAN	0.22	-0.0042 **	0.0038	-0.0101 [5] 19	-0.0105 [5] 30	-0.0156 [43] 19	-0.0101	-0.0105	0.0035
EMC/ {NPARK}	-1.1	-0.0033 **	-0.0039 ***	-0.2005 [2] 25	-0.0349 [2] 12	0.2841 [17] 24	-0.2001	-0.0341	0.2921
SCB/ TMB	-0.4	-0.0030 ***	-0.0037 **	-0.0348 [3] 10	-0.0507 [3] 8	-0.1040 [11] 10	-	-	-
LPN/ {TSTH}	0.91	-0.0006	0.0034 ***	0.0253 [2] 5	0.0606 [2] 3	0.0517 [10] 6	-	-	-
AMATA/ {TSTH}	1.56	-0.0012	0.0033 ***	0.0635 [3] 7	0.0623 [3] 6	0.0750 [12] 6	-	-	-
BGH/ ROBINS	1.92	-0.0001	0.0028 **	0.0129 [4] 21	-0.0080 [5] 31	-0.0004 [24] 26	0.0129	-0.0080	0.0008
Average return of low speed of adjustment (17 pairs)				-0.0193	-0.0139	0.0609	-0.0073	-0.0197	0.0832
Total average return (23 pairs)				0.0019	0.0313	0.0623	0.0149	0.0324	0.0859

Note: *, **, *** is the significant level at the 10%, 5% and 1%, respectively. Simulation A is unlimited trading period with constant beta while simulation B is unlimited trading period with undated beta. The numbers in simulation A are the average return, average holding period (in the parenthesis) and number of trades, which are the same for the case of simulation B. The average returns of a low speed of adjustment are 17 pairs, excluding 4 pairs that updated beta is not possible.

At the lowest SD band, the pairs trading strategies should generate many trading signals. Therefore, the lower numbers of trades from low speed adjustment pairs indicate that during our 5 years testing period, the long run spreads are least stationary when the spreads do not deviate around the mean. In addition, 9 cointegrated pairs between active and inactive stocks show 5 pairs from 1A, 5 pairs from 2A and 6 pairs from 3B are profitable. As a result, the total earning of 23 pairs in 5 years are 4.37% for 1A, 71.99% for 2A and 143.29% for 3A. After updating beta, the total profits are 34.45% for 1B, 74.52% for 2B and 197.57% for 3B. Therefore, pairs trading strategy 3 performed best in simulation B, which can capture the error correction mechanism even though our selected pairs have a very low speed of adjustment.

2.6.2.6 “Incorrect sign” of adjustment coefficients

Table 2.22 shows pairs trading results of mixed cointegration signs where 4 pairs show strong mean reversion property as adjustment coefficients are higher than 0.01 and 9 pairs have lower response rates toward long run equilibrium.

Table 2.22: Pairs trading result tested on "incorrect sign" pairs									
Pairs	**Beta**	**ECM**		**Simulation A (1 SD)**			**Simulation B (1 SD)**		
	Z= y-bx	γ1	γ2	1	2	3	1	2	3
LH/ SPALI	0.72	0.0031	0.0135 **	0.1021 [34] 35	0.2055 [36] 365	0.1561 [31] 35	0.1199	0.2271	0.1561
ACL/ TMB	0.53	-0.0123 ***	-0.0007	0.2139 [136] 26	-0.0056 [86] 267	0.1374 [349] 26	0.1550	-0.0109	0.1144
KBANK/ SCB	0.91	0.0018	0.01222 ***	0.1291 [103] 13	0.1697 [89] 82	0.1261 [105] 14	0.3046	0.3128	0.2908
BIGC/ ROBINS	0.67	-0.0085 ***	-0.0117 ***	-0.1615 [389] 16	-0.2403 [172] 365	-0.0515 [110] 16	0.0464	-0.0222	0.3389
BH/ {SPC}	2.87	-0.0090 ***	-0.0007	-0.0182 [7] 39	-0.0172 [7] 62	0.0144 [17] 23	-0.0182	-0.0172	0.0133
BAY/ KBANK	0.97	-0.0089 **	-0.0014	-0.0073 [3] 19	-0.0065 [3] 19	-0.0174 [63] 19	-0.0073	-0.0065	0.0372
KK/TMB	0.14	-0.0071 ***	-0.0039 **	-0.0103 [6] 45	-0.0159 [7] 96	-0.0031 [28] 46	-0.0110	-0.0165	-0.0055
LH/ {TSTH}	0.74	0.00008	0.0069 ***	-0.0045 [6] 25	-0.0213 [6] 38	0.0098 [86] 22	-0.0045	-0.0213	0.0119
ROBINS/ {SPC}	0.87	-0.0066 **	-0.0003	-0.0238 [24] 17	-0.063 [3] 11	-0.0354 [58] 22	0.0307	-0.063	0.0466
KK/KTB	0.29	-0.0063 ***	-0.0019	0.0150 [8] 59	0.0175 [9] 127	0.0048 [13] 60	0.0150	0.0175	0.0041
ASP/KK	0.97	0.0004	0.0055 ***	0.0093 [5] 16	0.0085 [5] 22	-0.0339 [80] 17	0.0093	0.0085	-0.0322
ITD/SCC	0.86	-0.0045 **	-0.0002	-0.0005 [4] 34	0.0047 [4] 40	0.0047 [28] 32	-0.0005	0.0047	0.019
Average return of low speed of adjustment (8 pairs)				-0.0050	-0.0116	-0.0070	0.0016	-0.0017	0.0118
Total average return (12 pairs)				0.0202	0.0004	0.0260	0.0532	0.0344	0.0800

Note: *, **, *** is the significant level at the 10%, 5% and 1%, respectively. Simulation A is unlimited trading period with constant beta while simulation B is unlimited trading period with undated beta. The numbers in simulation A are the average return, average holding period (in the parenthesis) and number of trades, which are the same for the case of simulation B. The average returns of low speed of adjustment are 8 pairs (the error correct term is smaller than 0.01).

Similar to the correct signs results, strategy 3 indicates the highest number of pairs that yield positive returns, which are 7 out of 12 pairs. 4 of them are low mean reversion pairs. Consequently, 5 pairs give positive returns in 1A and 2A. Moreover, updated beta can improve the returns of 7 pairs in 3B but cannot improve over the low ECM adjustment pairs in 1B and 2B. Similar to "correct sign" and low speed of adjustment pairs, the long run spreads are least stationary. Therefore, the long run spreads do not deviate about the mean. As a result, the total trading of all 12 pairs for strategy 1, 2 and 3 are 24.33%, 5.2% and 31.2% in simulation A. Once beta is updated, the returns improved to 63.94%, 41.3% and 99.46% in simulation B. The finding of incorrect sign cointegrated pairs also confirms that strategy 3B is the best pairs trading strategy in this analysis.

In general, "correct sign" and the size of speed of adjustments do matter for the profitability of pairs trading strategy in this empirical study. As low speed of adjustment coefficients indicates least stationary of the cointegrated pairs, strategy 3 seems to be the best strategy to employ. As a result, the average returns are -1.93% for strategy 1A (-0.73% for 1B), -1.39% for strategy 2A (-1.97% for 2B) and 6.09% for strategy 3A (8.32% for 3B) in "correct sign" with low speed of adjustment pairs. In contrast, the average returns of "incorrect sign" with low speed of adjustment pairs are -0.5% for strategy 1A (0.16% for 1B), -1.16% for strategy 2A (-0.17% for 2B) and -0.70% for strategy 3A (1.18% for 3B). Therefore, pairs trading strategy 3 can capture the error correction mechanism of "correct sign" even though the spread is least stationary. Moreover, we found some negative and positive returns from "incorrect sign" of low speed of adjustment pairs, which are not statistically significant. Thus, "incorrect sign" pairs should not be employed for pairs trading as the long run spreads do not represent a mean reversion mechanism.

2.7 Conclusion

In this study, we have investigated the profitability of pairs trading in the Stock Exchange of Thailand. A cointegration approach has been used to determine the stationary long run relationship between Thai stocks listed in SET100. The test considered the 10-year daily closing share price of five industries from January 1999 to

December 2008. Three trading strategies were tested in four different simulations with 1 SD, 1.5 SD and 2 SD trading boundaries.

This empirical study has used the Engle and Granger's cointegration approach to detect the long run cointegration relationship in Resources, Financial, Property & Construction and Services sectors and has indicated that the long-run relationship is stationary and meaningful. Nevertheless, there was no indication of cointegration in the Technology sector, except for one pair of inactive stocks that was marginally significant at 10%. Moreover, we have also attempted to match the stocks that do not belong to the same industry categories and the results were marginally significant in which the cointegration result was not attractive enough to be selected for our trading simulation.

Moreover, the outcome of the error correction model indicates the speeds of adjustment coefficients are significantly different from zero. The sizes of the speed of adjustment criterion quantify 6 cointegrated pairs that have a strong mean reversion property in which the short term deviation will quickly respond to the long-run equilibrium. However, 2 out of 6 pairs are selected as these had a correct sign for cointegration regression as suggested by Alexander (2008).

In addition, our empirical findings show that the pairs trading strategy is profitable. Firstly, our empirical findings confirm that pairs trading is a neutral strategy in which different strategies give a similar average return although some pairs of stocks do not have a zero beta. However, Alexander and Dimitriu (2002) suggest that market neutrality in pairs trading strategy does not require beta to be zero to immunize it against systematic risk. The interdependencies within the cointegrated stocks will ensure that the spread will converge to an equilibrium relationship over a period of time (Schmidt, 2008). Moreover, strategy 3 is a conservative strategy but can perform in a relatively similar manner to the other two strategies. Hence, strategy 3 is favorable in dealing with lower risk and yields relatively similar returns to the riskier strategies. Moreover, the political instability and volatility of the stock market have no effect on the performance of pairs trading strategy in which - consistent with Alexander (1999)'s empirical study - pairs trading strategy is a market neutral strategy; therefore, the fluctuation of the stock market cannot affect the anomaly return from the strategy.

Secondly, altering the trading boundaries has a positive relationship with average excess returns and a negative relationship with number of open trades and transaction costs. The higher trading bands, the greater excess return, the fewer number of open trades, thus the lower transaction cost.

Moreover, the different simulations show remarkable results. All simulations yield positive returns for our selected cointegrated pairs. As expected, pairs trading strategies perform best in simulation B, followed by A, D and C. Simulation B gives higher excess returns than A as an updated beta can improve the trading results. Once the trading period is limited to 6 months, simulation C is less attractive even though an updated beta can improve the result in simulation D. As many transactions have to close due to reaching the end of the trading period, we cannot conclude that the strategy actually performs well with a trading period constraint or whether the spread moved in a favorable direction by chance. Thus, simulation C and D are not recommended.

In addition, our findings of both "correct" and "incorrect sign" especially low speed of adjustments pairs indicated that cointegration sign and size of speed of adjustment do matter for the profitability of the pairs trading strategy. As a result, strategy 3 seems to be the best pairs trading strategy that can capture the error correction mechanism in least stationary long run equilibrium pairs. Although "incorrect sign" of low speed of adjustment pairs give some positive returns, the results are not statistically significant when the long-run equilibrium of "incorrect sign" pairs does not have an error correction mechanism. Moreover, strategy 3 is able to capture the error correction mechanism of inactive pairs and all inactive pairs appear to be in the low speed of adjustment category in which a pairs trading strategy can give positive returns as long as inactive pairs have the correct sign.

In summary, our empirical study shows that the pairs trading strategy is profitable in the Stock Exchange of Thailand. A pairs trading is a medium term investment tool, which takes at least 3-6 months for the short term deviation to reverse back to its long run equilibrium in the case of high correction adjustment pairs. Therefore, without trading period constraints, pairs trading strategies can perform well in broad category sectors. Significantly, updated beta simulation can be an alternative method to maximize return against a given risk when beta is increased over time and the trading period constrained. Pairs trading strategy is a market neutral strategy where we can bet on the deviation of the spread that will converge back to the long run equilibrium no matter whether the market is bull or bear. Once cointegrated pairs have the “correct sign” that represents an error correction mechanism, traders can benefit from a positive return even though cointegrated pairs have a low adjustment speed towards equilibrium.

CHAPTER III

FORECASTING AND TRADING PERFORMANCE OF ERROR CORRECTION MODEL: EVIDENCE FROM STOCK EXCHANGE OF THAILAND

3.1 Introduction

Error correction models (ECM) have been used in various fields of research for both modeling and forecasting. The ECM received more attention due to the contributions of Granger (1986) and Engle and Granger (1987), which showed that cointegrated time series have an error correction representation. The intuition behind the error correction mechanism is that short term disequilibrium will correct itself in the long run. Hence, ECM should yield better forecasts in the short run and, undoubtedly, better forecasts in the long run; however, this result contradicts the principle of market efficiency. Granger (1986) suggests that a pair of cointegrated stocks reflects an inefficient market on the basis that two stocks have a common trend, which is tied together in the long run. This implies the predictability of the price change in which the past value of one stock can help to predict the current or future price of another stock.

In the efficient market, the share price series should incorporate all available information (Fama, 1970). Hence, none of the market players can beat the market in the sense of predictability and profitability that would yield excessive returns. The literatures have employed the cointegration approach to test for market efficiency. The findings support Granger's (1986) implication that efficient markets cannot be cointegrated. In foreign exchange rate markets, Hakkio and Rush (1989) and Baillie and Bollerslev (1989) found that forward and spot rates are cointegrated, which indicate inefficiency. Moreover, Kasa (1992) employed quarterly data of stock markets from the period of 1974 to 1990. The author discovered one co-movement that affected the stock markets, of the United States, Canada, Japan, the United Kingdom and Germany.

In this study, we employ a standard ECM to forecast individual share prices from Thailand Stock Exchange Market. The previous literatures employed cointegration approaches and found evidence of predictability and an improvement of forecasting accuracy in the long horizon. In the bivariate cointegration approach, the first empirical study was done by Engle and Yoo (1987); they conducted small simulation to compare the forecasting performance of Engle and Granger (EG) 2 steps approach relative to unrestricted vector autoregressive (UVAR). The empirical findings showed that the short term forecast is dominated by UVAR while EG 2-step approach produced more accurate forecast in the long run. The results also confirmed the notation of authors that employing Bayesian stochastic prior restriction would give poorer forecasting performance. The authors also pointed out that the increased forecast accuracy would approach infinity for long-term forecast horizons. In addition, LeSage (1990) conducted larger experiments to test the predictability of ECM and VAR models. The results confirmed the previous findings that ECM is the best predictor in cointegrated industries. He also found inferior forecasting performance of the BVAR relative to ECM; thus, the results supported the findings of Engle and Yoo. Moreover, a number of studies have tested the predictability of model based on cointegrating relationship between two variables such as Shoesmith (1992) and Amisano and Serati (1999). Their empirical studies also contributed to the same findings in which can be concluded that the error correction mechanism can help to improve the forecast accuracy in the long run. Furthermore, the empirical studies such as Shoesmith (1995a), Lin and Tsay (1996), Tong (2001) and McCrae, Lin, Pavlik and Gulati (2002) have conducted forecasting experiments using multivariate Johansen's cointegration technique. The forecasting results also showed that the cointegrating relationship can indeed help to improve the forecast accuracy, especially in the longer forecast horizons.

The objective of our empirical study is to investigate i) the forecasting performance of the simple ECM on cointegrated share price series; ii) the trading simulation based on obtained prediction; iii) the informational efficiency of Thailand stock exchange market.

The remainder of this chapter is organized as follow. Section 3.2 discusses the empirical findings on the forecasting accuracy of cointegrated models in bivariate and multivariate frameworks. Section 3.3 describes the ECM and benchmark models that will be compared in this study. The forecasting procedures are also presented in this section. In section 3.4, the various forecast evaluation to measure the forecast accuracy are discussed. Moreover, the forecasting performance and trading simulation are reported in section 3.5 and 3.6, respectively. Section 3.7 contains the conclusion of this study.

3.2 Literature review

The previous literatures have showed the forecasting power of the cointegration models in various samples including macroeconomic variables, interest rates, exchange rates and equity prices. Engle and Granger two steps approach is widely implemented in bivariate setting while Johansen's cointegration approach is employed in multivariate framework.

3.2.1 Bivariate forecasting model

The first application is the study of Engle and Yoo (1987), which contributed to study the forecasting ability of cointegration model in a bivariate framework. The authors conducted a small simulation to compare Engle and Granger two steps approach to unrestricted vector autoregressive in level (UVAR) on cointegrated systems. The 20-step forecast performance of Engle and Yoo (1987) is evaluated on mean square error (MSE). The empirical findings showed that the short term forecast is dominated by UVAR while EG two steps approach produces accurate forecast in the long run. The authors also pointed out that the increased forecast accuracy would approach infinity in the long forecast horizons.

The second application is the empirical study of LeSage (1990), which conducted larger experiments to test Granger (1986) and Engle and Yoo (1987) forecasting ability of ECM and VAR models. Additionally, LeSage (1990) attempted to test the Engle and Yoo's (1987) argument that employing Bayesian stochastic prior restriction would give poorer forecasting performance. Thus, LeSage (1990) employed 4 forecasting models, which are ECM, Bayesian error correction model (BECM), vector autoregressive (VAR) and Bayesian vector autoregressive (BVAR). The monthly Ohio labor data for 50 industries are used. The estimation period is from 1977 to 1982 while the forecasting exercise is performed in the period from 1983 to 1985. The mean absolute percentage forecast error (MAPE) is used to evaluate the 12-step forecasting performance in this study. The empirical outcomes of LeSage (1990) firstly indicated that the ECM is the best long-term forecaster in cointegrated industries. Secondly, BVAR outperformed the other forecasting models in the possibly of cointegration industries. This result suggested that the variables were not truly cointegrated in this analysis. Finally, in non cointegrated industries, the forecasting performances were mixed. Moreover, the findings of LeSage (1990) also supported the Engle and Yoo (1987)'s argument.

Moreover, the study of Shoesmith (1992) also supported the previous findings that error correction model is superior to unrestricted VAR and BVAR in the longer forecast horizon. In his study, the tests of cointegration and causality are employed to capture the interrelatedness of state, regional and U.S employment. The results indicated that the cointegration relationship is not often found in the U.S as the evidence showed that the presence of cointegration among the states and regions are rarely seen. In contrast, the causality test based on final prediction error showed that there is a causality flow from U.S employment to state and regional employment. Therefore, this finding implied that the changes in the U.S economic activities also have an effect to the changes in the state and regional activities. Shoesmith (1992) also investigated the forecasting ability of error correction model using regional data. The main interest of the author was the forecasting specification for non cointegrated series in the short forecasting horizon. In general, the empirical study of Shoesmith suggested that forecasting accuracy of unrestricted VAR can be improved following the simple implication. The cointegration and causality tests are applied to each pair; 1) an error correction specification should be used if the series are cointegrated; 2) a VAR in stationary specification should be used if the series are not cointegrated but there is a presence of causality; 3) the series should be estimated in stationary form if neither of the series are cointegrated and no causality flow between the series.

Additionally, Amisano and Serati (1999) further tested the forecasting performance of BECM but added the informative prior on loading coefficients. The BECM was evaluated against BVAR, which is based on RMSE and Thiel's coefficient. The results showed that BECM with informative prior yielded smaller forecasting errors at all 20 step-ahead, which is superior to BECM without informative prior and BVAR. However, BECM without informative prior is the second best forecaster for the longer forecast horizons. Amisano and Serati (1999) also pointed out that with informative prior; BECM can improve the short run forecasts, but it not significantly different relative to the competing models. This could be due to the combination of no informative prior on factor loading and of informative prior on the lagged difference variables give too much emphasize to the long run. However, in a theoretical view, the great improvement of long run forecast is a distinct mechanism of error correction terms.

3.2.2 Multivariate forecasting model

Shoesmith (1995a) also attempted to examine the forecasting performance of error correction mechanism in a multivariate framework. In this study, the author used Johansen's multivariate model to estimate the cointegration relationship. The finding showed that the Johansen's cointegration model can improve the forecasting accuracy in the longer horizons. Moreover, Shoesmith (1995b) further compared the forecasting performances between the ECM and VAR model with and without Litterman's (1980) Bayesian restriction. The Johansen's (1988) cointegration technique is applied to Litterman's six-variable system. The results showed that the BECM outperformed all the benchmark models over both short and long forecasting horizons. The benchmark models include VAR in levels, BVAR in levels, BVAR in difference and unrestricted BECM. Moreover, Shoesmith pointed out that including inappropriate error correction term could result in a substantial reduction in the long term forecast accuracy, as the result of the superior forecasting performance of the BECM model relative to the unrestricted BECM model. Additionally, the superior forecasting performance of the ECM and BECM models over the VAR and BVAR in levels indicated that the error correction is the best approach in capturing short and long run dynamics in multivariate cointegration (Shoesmith, 1995b).

Moreover, the empirical study of Lin and Tsay (1996) also used Johansen's cointegration test in capturing the long-run relationship in the system of variables. The main aim of this paper was to test whether the cointegration relationship can improve the accuracy of the forecasts, especially in the long forecast horizons. In particular, the forecasting model with correct unit-root specification should outperform the model with incorrect unit-root specification or stationary specification. In their research, financial and macroeconomic data are utilized, including monthly exchange rates and bond yields of five major economic (namely Canada, France, Germany, Japan and the UK), monthly interest rates in Taiwan and the U.S, industrial production indexes of five major economies and export and import between the U.S and five major economies. Johansen's test is applied to detect the presence of unit-roots. The authors also conducted forecasting simulation in which one- to 60-steps ahead of VAR models with different number of unit-roots are determined. The main findings of Lin and Tsay are summarized in the following;

- The results indicated the failure of unit-root constraints in the case of monthly interest rate for the U.S. The authors argued that the potential reason of this failure could be due to the series been stationary with the unit-root close to the unit circle. In theory, the long term forecast of a stationary process should be the same with the average of the time-series. Also, the available information at forecast origin is used to predict in the long-term in which this information might not be informative. Thus, the forecasting model could perform poorly in the longer horizon if the series is stationary.
- One result indicated the convergence and good forecasting performance of the model with no presence of unit root in the long horizon. This implied that the series might be stationary. On the other hand, Johansen's cointegration tests detected 5 unit roots in the system. Therefore, the authors concluded that these 5 unit roots might be close to the unit circle.
- In analyzing five exchange rates, the cointegration test failed to detect any unit root; thus indicating that the exchange rates system is not cointegrated. In contrast, the forecasting model with 4 unit roots produced relatively good forecasts. Thus, the result suggested that the series might have a cointegrating vector.

In general, the empirical study suggested that specifying the correct number of unit roots is crucial, which provided better forecasting power in the long term prediction. As a result, and as expected, the forecasting performance of correct specification is superior to the incorrect one. Moreover, the finding also pointed out that the conventional cointegration tests have a low power in rejecting the unit root hypothesis as the unit root is close to unity. However, in the empirical simulation, the separation of the unit root from near unit root is indicated in the obtained long-term forecasts.

Additionally, Tong (2001) conducted multiple steps ahead forecasting experiment (10, 20, 30, 60 and 90 days ahead) using Johansen's (1988) model for 7 major currencies. These are the British pound, Deutsche mark, Japanese yen, Canadian dollar, French franc, Italian lira and Swiss franc from 1975 to 1995. The forecasting accuracy is evaluated in term of the root mean squared errors (RMSE) and the mean absolute prediction errors (MAPE). The main contribution of this research is that the exchange rate mechanism system (EMS) played an important role in governing the cointegrating relationship in the seven-currency system. The evidence showed that when the EMS is relatively stable, the cointegrating relationship is highly significant (this includes fractionally cointegrated). In contrast, when the EMS is volatile, the cointegrating relationship is not exhibited. As Tong pointed out that those EMS currencies are not completely independent assets as required by Granger (1986), the cointegrating relationship found among this group of currencies cannot be seen as evidence of market inefficiency. Moreover, Tong found some evidence that cointegrating relationship provide better forecasting ability. These results are summarized in the following subsamples.

- In the first subsample period from 1975 to 1979 where the EMS was not formally established, the currencies were found to be not cointegrated. In fact, VECM outperformed the random walk model in the longer horizons of 30 and 90 days ahead.
- In the second period from 1979 to 1984 where the EMS was volatile, the currencies were found to be fractionally cointegrated. The forecasting results indicated that the seven-currency VECM provided better forecasting accuracy than the RW model for the British pound, Canadian dollar, French franc and Italian lira. But the forecasting result of EMS VECM appeared to be the best forecaster as the model can beat the RW alternative at all horizons.

- In the third period from 1985 to 1989 where the EMS was relatively stable, the currencies were found to be cointegrated. The two VECM models were superior to the RW model in most cases (excluding the Deutsche mark and Swiss franc) in which the forecasting models lose their forecasting ability to the RW model in the longer horizon. In addition, the EMS VECM appeared to be the best forecasting model. This result pointed out that the forecasting gain can be obtained by utilizing the cointegrating relationship of the EMS currencies. Moreover, the forecasting performance obtained from this subsample also indicated better result than the previous subsample where the EMS was more volatile and fractionally cointegrated. The inferior forecasting performance of the previous subsample could be due to the fractional cointegration in which the disequilibrium term took longer time to move back to the long-run equilibrium. Thus, this finding suggested that the speed of adjustment is crucial, as it might alter the forecasting accuracy of the model.
- In the fourth period from 1990 to 1994 where the EMS were volatile, the currencies were fractionally cointegrated. The superior forecasting performance could be realized in the longer forecasting horizons in this sample, except for the British pound and Italian lira. In 1992, these two currencies were heavily attacked, which lead them to leave the exchange rate mechanism system.

In general, the empirical findings of Tong (2001) supported the previous literatures in multivariate framework. The cointegrating relationship can help to improve the forecasting accuracy. The results also showed that the forecasting performances of cointegrated series are better than the forecasting performances of fractional cointegrated series. As the non-stationary series are fractionally cointegrated, the disequilibrium takes a longer time to reverse back to the long run equilibrium. Therefore, the finding of fractional cointegration also implies the low speed of adjustment of the error correction model.

The recent study of McCrae, Lin, Pavlik and Gulati (2002) has investigated the forecasting performance of multivariate cointegration model in Asian exchange rate markets. The authors attempted to compare the forecasting performance from a Box-

Jenkins univariate model that incorporates integration (the autoregressive-integrated moving-average model, ARIMA) to a multivariate Johansen model that incorporates integration and cointegration (ECM). The daily actual exchange rates are employed from January 1985 to February 1997. These included the Japanese yen, Thai baht, Singapore dollar, Malaysian ringgit and the Philippine peso. Based on RMSE criterion, the results showed that the ARIMA model can outperform the ECM in the short forecast horizons (one to five days) for 4 out of 5 currencies, except Singapore dollar. On the other hand, the ECM dominated the ARIMA model in the medium forecast horizons (6 to 40 days), except Thai baht. As a result, the ECM appears to be the best forecaster for Singapore dollar while ARIMA model is the best forecaster for Thai baht at all forecast horizons. Moreover, the ARIMA model outperformed the ECM from 1 to 9 steps ahead; then, the ARIMA model is outperformed by the ECM from 9 steps onward for Japanese yen and Malaysian ringgit. Hence, this finding indicated that the ARIMA model is relatively better to forecast in the short horizon while the ECM is more accurate in the long horizon. McCrae et al (2002) also suggested that the ECM could perform well in the short forecasting horizon in the case when ARIMA model contains a lower order of moving average components. In addition, the prediction errors of ECM relative to the ARIMA also increase in the diminishing rate as the forecast horizon rises. This result reflected the property of error correction mechanism that incorporates the long run adjustment in the ECM while the ARIMA does not have (McCrae et al, 2002). Therefore, the empirical findings of McCrae et al (2002) also confirmed the previous literatures that favor the use of the ECM as the forecasting model.

Moreover, Mastern, Banerjee and Marcellino (2009) tested the forecasting accuracy of the factor-augmented error correction model (FECM), which was proposed by Benerjee and Marcellino (2009). The authors conducted a Monte Carlo experiment and used various empirical applications to proof that FECM can be implemented as an alternative forecasting tool. The authors incorporated a common non-stationary factor (f) into 3 models. The common factor is extracted from a large information set, which is available for forecasting purpose. The first model is a standard ECM, which involves two variables, y and x where x is a proxy for a common factor, f. The second model is the factor-augmented vector autoregressive model (FAVAR) where the change in y is explained by its own lags and by lags of the change in f. The third model is the FECM, which is nested by FAVAR in the sense that the additional lagged of error correction term is obtained from the regression between y and f. The forecasting performances of these 3 models are evaluated in term of the mean squared forecast error (MSE). The Monte Carlo simulation showed the evidence favoring the use of the FECM over the FAVAR in term of forecast accuracy. The result also suggested that the magnitude of error correction mechanism matters in forecasting performance. However, the standard ECM can be the competitive candidate if the error correction term and the common factor are not significant and the sample study is not sufficiently large enough. In addition, the authors pointed out that the problem of employing the FECM is related to the computation of the informative factor, which requires a large dimension of data. Otherwise, the factor is non-informative and therefore useless for forecasting purposes. Moreover, the authors also conducted 4 empirical experiments using real and nominal macroeconomic variables, monetary variables, interest rates and exchange rates. The experiment is conducted in bivariate and small multivariate frameworks, with and without cointegration and common factors. The authors concluded that the FECM is the best forecaster in this analysis. The FECM produced more accurate forecasts, which underpin the usefulness of error correction mechanism and common factors.

In summary, the previous literatures indicated the similar findings in both bivariate and multivariate frameworks. The presence of cointegration can help to improve the forecasting accuracy, especially in the longer forecasting horizons. The speed of adjustment of disequilibrium term is also crucial for forecasting purposes.

3.3 Empirical framework

3.3.1 Forecasting with an Error Correction Model

Engle and Granger (1987) propose a simple approach to identify cointegrated bivariate series. By definition of cointegration, two share price series are required to be non-stationary, or $I(1)$ process (integrated of order one) and a linear combination of them stationary, or $I(0)$ process. The first step of the Engle and Granger two steps approach is to use ordinary least square (OLS) regression to estimate a pair of log share price series.

$$y_t = \beta_0 + \beta_1 x_t + e_t \tag{3.1}$$

In a situation where β_0 is a constant, β_1 is cointegration coefficient and e_t is a white-noise series with zero mean and constant variance. The next step is to check the stationary of obtained residual series on the basis of augmented Dickey Fuller test (ADF)[20].

$$\hat{z}_t = y_t - \beta_0 - \beta_1 x_t \tag{3.2}$$

In another situation where $\hat{z}_t$ represents disequilibrium term if {zt} is *I*(0), the share price series y and x are said to be cointegrated. Therefore, the long run equilibrium of this pair of stocks is tied together in which the tendency of deviation of this pair will move back toward a particular point in time. Moreover, the Granger Representation theorem shows that cointegration relationship has an error correction mechanism. That is:

$$\Delta x_t = \alpha_1 + \gamma_1 z_{t-1} + \varepsilon_{1t} \tag{3.3}$$

$$\Delta y_t = \alpha_2 + \gamma_2 z_{t-1} + \varepsilon_{2t} \tag{3.4}$$

where z_{t-1} represents the deviation of disequilibrium term at time t-1, obtain from equation (3.2). α_1 and α_2 represent the constants, γ_1 and γ_2 represent the speed of adjustment coefficients and Δ denotes the first difference.

In addition, Alexander (2008) suggested an appropriate sign for disequilibrium adjustment (γ_1 and γ_2) in order to capture error correction mechanism. The short term disequilibrium has to be corrected to the long run equilibrium in the way that both prices of x and y are adjusted. Recall the residual series from equation (3.2), the table below shows how Alexander (2008) defined error correction mechanism.

[20] There are several unit root tests that can be applied. However, in this study, we employed ADF test as Engle and Granger (1987) suggested. Moreover, Akaike information criterion (AIC) is used to determine the appropriate lags for our cointegration model.

Table 3.1: Alexander (2008) error correction signs

Cointegration coefficient	EC adjustment coefficients		Disequilibrium variable (z_t)
Assume $\beta_1 > 0$	$\gamma_1 < 0$	$\gamma_2 > 0$	➢ If z_t is positive, x will decrease and y will increase in which both variables are reducing z_t. ➢ If z_t is negative, x will increase and y will decrease in which both variables are increasing z_t.
Assume $\beta_1 < 0$	$\gamma_1 < 0$	$\gamma_2 < 0$	➢ If z_t is positive, both x and y will decrease in which both affect z_t to decrease. ➢ If z_t is negative, both x and y will increase in which both affect z_t to decrease.

Note that β_1 represents a cointegration slope obtained from a level regression. In addition, γ_1 and γ_2 are the speed of adjustment coefficients while z_t is the error correction term or the estimate residual series.

Moreover, once share price series x_t and y_t are counteracted then, Granger causality flow must exist at least in one direction in the cointegrated system. Thus, if y Granger causes x, the past value of y must be capable of helping to forecast the value of x better than the past value of x alone (Alexander, 2008).

The optimal one-step-ahead forecast at forecast origin t is

$$\hat{x}_{t+1} = x_t + \alpha_1 + \gamma_1 z_t + \varepsilon_{1t} \tag{3.5}$$

$$\hat{y}_{t+1} = y_t + \alpha_2 + \gamma_2 z_t + \varepsilon_{2t} \tag{3.6}$$

The optimal h-step-ahead forecast at forecast origin t is

$$\hat{x}_{t+h} = x_{t+h-1} + \alpha_1 + \gamma_1 z_{t+h-1} + \varepsilon_{1t+h} \tag{3.7}$$

$$\hat{y}_{t+h} = y_{t+h-1} + \alpha_2 + \gamma_2 z_{t+h-1} + \varepsilon_{2t+h} \tag{3.8}$$

Based on full sample cointegration results from chapter 2, firstly, we classified cointegrated pairs into “correct sign” and “mix sign” according to Alexander (2008) implication. Secondly, 2 forecasting experiments are conducted.

i) Specified ECM.

In this experiment, we include both one and two-way Granger causalities. In the case of one-way directional Granger causality, for instance, the EC term in equation (3.7) is significantly different from zero while the equation (3.8) is not. We forecast 20 step-ahead of stock x and model stock y as a random walk (excluding the disequilibrium term). Moreover, in the case of two-way directional Granger causalities, we model both equations (3.7) and (3.8) as the ECM.

ii) Misspecified ECM.

In this experiment, we ignore the insignificance of EC term where the cointegrated pairs have one-way directional Granger causality. For instance, we forecast stock x for 20 step-ahead and also model stock y as the ECM including insignificant EC term.

3.3.2 Forecasting with Random walk and Random walk with drift model as benchmarks

The first benchmark model is a random walk in which the best forecast of the price tomorrow is the price today. Assuming zero constant, thus, the optimal h-step-ahead forecast at forecast origin t is

$$\hat{x}_{t+h} = x_{t+h-1} \tag{3.9}$$

$$\hat{y}_{t+h} = y_{t+h-1} \tag{3.10}$$

In the second benchmark model, we allow for nonzero drift term. The random walk with drift model is estimated using AR (1) process. Therefore, $\alpha \neq 0$ and the optimal h-step-ahead forecast at forecast origin t is

$$\hat{x}_{t+h} = \alpha_1 + \rho_1 x_{t+h-1} \tag{3.11}$$

$$\hat{y}_{t+h} = \alpha_2 + \rho_2 y_{t+h-1} \tag{3.12}$$

3.3.3 Forecasting evaluation

3.3.3.1 Point Forecast

The common forecast accuracy measures how well the forecast model fits with the actual price. The forecast errors are defined as follow:

$$\text{Mean square error (MSE)} = \left(1/n\right) \sum_{i=1}^{n} e_{t+h,i}^2$$

$$\text{Mean absolute error (MAE)} = \left(1/n\right) \sum_{i=1}^{n} |e_{t+h,i}^2|$$

$$\text{Root mean square error (RMSE)} = \sqrt{MSE}$$

If *e* is the forecast error which is the differential between the actual price and estimated price at forecast origin, $e_{t+h} = x_{t+h} - \hat{x}_{t+h}$, h is the forecast horizon and n is the post-sample, which is 472 in our case. The smallest MSE, MAE or RMSE indicate the best forecast as the predicted price is closely approximated to the actual price.

3.3.3.2 Relative predication error

Moreover, to compare which of the competing models performed better in term of a closer estimate to the real price, the relative measures are determined. Consider M1 as the benchmark models (in our case random walk and random walk with drift) and M2 as the ECM,

The relative MSE ratio = MSE(M1) / MSE(M2)

The relative MAE ratio = MAE(M1) / MAE(M2)

The relative RMSE ratio = RMSE(M1) / RMSE(M2)

If the relative ratio > 1, the proposed model (M2) is better forecast than the benchmark model (M1). On the other hand, M1 outperforms M2 if the relative ratio < 1.

3.3.3.3 Winning percentage

As a MSE is an average of the whole sample, which gives an overview of the forecasting performance for each horizon. However, the averages smooth out the significant forecast accuracy of the model. Therefore, we calculate the "winning percentage" of the proposed model (M2) wins over the benchmark model (M1). The MSE of M2 is compared to the MSE of M1 at every forecasting point.

3.3.3.4 Theil's inequality

The next forecast evaluation method that we employ in this study is the Theil's inequality statistic, which measures how well the forecasting model predicts against the naïve model, in our case, the RW and RWD. The Theil's U statistic is calculated as:

$$U(h) = \frac{\sqrt{\Sigma(y_{t,i} - \hat{y}_{t,i})^2}}{\sqrt{\Sigma(y_{t,i})^2} + \sqrt{\Sigma(\hat{y}_{t,i})^2}} \tag{3.14}$$

The Theil statistic yields the value between 0 and 1. If the Theil statistic is closer to zero (one), this indicates that the forecasting accuracy of the proposed model is greater (lesser) than the benchmark model. Thus, the best forecasting model in terms of accuracy will indicate the lowest U statistic. Moreover, the Theil statistic is reported in terms of relative ratio. Similar to the relative prediction ratio in 3.3.3.2, the relative ratio of U is U of M1 divided by U of M2. If the ratio is greater than 1, meaning that M2 has outperformed M1. Conversely, M2 is outperformed by M1 if the ratio is less than 1.

3.3.3.5 Equal Forecast Accuracy

Besides the point forecast errors comparison, in this section, we evaluate the forecast errors whether the difference between the MSE of 2 competing models is significantly different from zero. This implies that the predictability of forecasting models is not identical. Thus, Clark and West (2007) test is employed to test for equal forecast accuracy.

The RW model (M1) can be seen as a restricted model and the ECM (M2) can be seen as a less parsimonious model, which nests RW. If the parameter in M2 is equal to zero, M2 reduces to M1. However, if an additional parameter in M2 is not significant improving the forecasting accuracy, the model would generate forecasting noise. Thus, Clark and West (2007) suggest that the MSE should be adjusted for such noise.

Clark-West adjustment (adj) is the sample average of forecast prices at time t from M1 and M2, which are $\hat{y}_{1t,t+h}$ and $\hat{y}_{2t,t+h}$, respectively.

$$adj = (n^{-1})\sum_{t=1}^{n}(\hat{y}_{1t,t+h} - \hat{y}_{2t,t+h})^2$$

where n represents the number of prediction, which is 472 time in our case. The mean square prediction errors of M1 and M2 are denoted by τ_1 and τ_2, respectively.

$$\tau_1 = (n^{-1})\sum_{t=1}^{n}(y_{t+h} - \hat{y}_{1t,t+h})^2$$

$$\tau_2 = (n^{-1})\sum_{t=1}^{n}(y_{t+h} - \hat{y}_{2t,t+h})^2$$

Hence, the adjusted MSE of M2 is simply computed as $\tau_2 - adj$.

$$\tau_{2-adj} = (n^{-1})\sum_{t=1}^{n}(y_{t+h} - \hat{y}_{2t,t+h})^2 - \left[(n^{-1})\sum_{t=1}^{n}(\hat{y}_{1t,t+h} - \hat{y}_{2t,t+h})^2\right]$$

The null hypothesis is that M1 has the same prediction error relative to M2. This implies the forecasting accuracy of M1 and M2 are equal. On the other hand, the alternative hypothesis is that M2 has a smaller MSE than M1.

The difference between the MSE of M1 and adjusted MSE of M2 ($\tau_1 - \tau_2 + adj$) equates on a constant. Then, t-statistic is calculated to measure the equal forecast accuracy. If the difference is significantly positive, the null hypothesis is rejected. In other words, the statistic is greater than 1.645 or 1.282 for one-tailed test at 5% and 10% level, respectively.

In summary, the forecasting performance is defined on how well the forecasting model fits, which measures in term of forecast errors. However, since the forecasting accuracy cannot guarantee the profitability of the forecasting model in practice, in the next sub-section, we will examine how well our forecasting model predicts the next turning point, which will facilitate the trader to make trading decisions.

3.3.3.6 Direction of change forecast

Swanson and White (1997) pointed out that the direction of change is a useful method for market analysts to forecast the next turning point or the future price movement. Regardless of the magnitude of change, we examine how well the forecasting models can follow the actual price. The confusion matrix is used to determine this aspect, consider the 2 x 2 contingency table below:

	Actual up	Actual down
Predicted up	a_{11}	a_{12}
Predicted down	a_{21}	a_{22}

(3.15)

The columns in 3.15 correspond to the actual movement up or down while the rows correspond to the predicted moves up or down. Hence, the diagonal cells (a_{11} and a_{22}) correspond to the correct directional prediction. In contrast, the off-diagonal cells (a_{12} and a_{21}) correspond to the incorrect directional prediction. The performance of forecasting model is determined in term of confusion rate (CR) as follow:

$$CR = \frac{(a_{12} + a_{21})}{(a_{11} + a_{12} + a_{21} + a_{22})} \tag{3.16}$$

The least confusion rate indicates that the forecasting model has a high probability to forecast the future price movement correctly. Moreover, we compare the CR in term of relative ratio in order to clearly show the forecasting performance of our model against the benchmarks.

3.3.3.7 Forecast encompassing

Finally, the forecast encompassing approach is used to evaluate whether either models can encompass the other. Fair and Shiller (1989, 1990) proposed the encompassing test to compare forecast information of different models through the following regression:

$$x_{t+h,i} - x_{t,i} = \beta_0 + \beta_1 \left(\hat{x}^{(1)}_{t+h,i} - x_{t,i}\right) + \beta_2 \left(\hat{x}^{(2)}_{t+h,i} - x_{t,i}\right) + v_{t+h,i}, \quad i = 1, \dots, n \qquad (3.17)$$

In a situation where $\hat{x}^{(1)}_{t+h}$ *and* $\hat{x}^{(2)}_{t+h}$ denote the h-step-ahead forecast of x_t from the estimation of error correction model and random walk with drift, respectively. Hence, the ECM encompasses the RWD when (β_0, β_1, β_2) = (0, 1, 0). Conversely, the RWD encompasses the ECM when (β_0, β_1, β_2) = (0, 0, 1). In another case, the parameters can be any value, which indicate that neither model encompasses the other and both models contained information useful for h-step-ahead forecasting of x_t.

3.4 Data

The data employed in this study is a daily share price series from the stock exchange of Thailand (SET) running from January 1999 to December 2008. The sample period that we select includes periods of recession, boom and stability. Hence, it is noteworthy to examine how our forecasting model reacts with a volatile emerging market.

Share price series has to be listed for at least 10 years and actively trade in SET100. The parameters of Engle and Granger 2 steps approach is estimated using 8 years from January 1999 to December 2006 (1,962 days). Then, the forecasting and trading simulations are assessed from January 2007 to December 2008 (472 days). For each interaction, the model is re-estimated recursively in order to update the estimated parameters before forecasting 20 step-ahead. The recursive estimation uses all data up to the window width in which the window is enlarging one day ahead. Our 20 steps forecasting procedures are carried out for 472 replications with the first forecast starting at the beginning of January 2007.

3.5 Empirical results

In this section, the forecasting performances are evaluated by several forecast accuracy tests including point forecast errors, Clark and West (2007)'s equal forecast accuracy, Swanson and White (1997)'s direction of change and Fair and Shiller (1989)'s forecast encompassing. The relative forecasting accuracy of ECM to benchmarks are presented in two groups based on "correct sign" and "mix sign". We attempt to examine the Alexander's criterion, i.e. whether the disequilibrium signs matter in this analysis. In addition, the average prediction errors of all samples under specified and misspecified conditions are reported to give an overview of the forecasting performance.

3.5.1 Cointegration result

In chapter 2, the Engle and Granger 2-steps approach and ECM have been applied to the share price series from 5 different sectors, which are Resource, Financial, Property & Construction, Services and Technology sectors. The full-sample period estimation indicates cointegration relationship in 4 sectors, except for the Technology sector.

In table 3.2 and 3.3, we report the cointegration estimations of "correct sign" and "mix sign" pairs, respectively[21]. Column 1 and 2 contain the cointegrated pairs and ADF statistics. In column 3, 4 and 5, the first difference of stocks and the speed of adjustment coefficients (γ_1 and γ_2) are presented. In table 3.2, the ADF statistics are significant at 1%, 5% and 10% level, which indicate that 13 pairs are found to be cointegrated based on the Engle and Granger's approach[22]. Moreover, the speed of adjustment by ECM is significantly different from zero. Specifically, the result shows that 12 pairs have one-way directional causality while the EGCO and LANNA pair has two-way Granger causality. This implies that EGCO Granger causes LANNA with the faster speed of adjustment (γ_2= 0.0103, significant at 1%). At the same time, LANNA also Granger causes EGCO with slower speed of adjustment (γ_1= -0.0044, significant at 10%).

[21] We select some results to report in this table, more results are available upon request.
[22] The lag selection is determined by Akaike information criterion.

Moreover, in table 3.3, we select 9 pairs that represent the "mix sign" group. The Engle and Granger cointegration result shows that all these pairs are significantly cointegrated. The ADF test significantly rejects the presence of unit root on the residual series for all cases at 1%, 5% and 10% level. The finding also shows significant nonzero error correction term. This result indicates 2 out of 9 pairs that exhibit two-way directional causality. However, the only difference between the "correct sign" and "mix sign" group seems to be the sign of the error correction term. In particular, we obtain the same signs of γ_1 and γ_2 in the "mix sign" group, which contradicts to the Alexander's criterion. Thus, this might prevent the disequilibrium to move back in the long run. In other words, stock x and stock y cannot adjust in respect to the deviation of disequilibrium (z_t)[23].

[23] See table 3.1 for Alexander's error correction sign.

Table 3.2: Cointegration estimation of full sample (Correct sign)

Cointegrated pairs	ADF		Speed of adjustment	
			γ_1	γ_2
LEGCO/LLANNA	-3.3878 **	DEGCO	-0.0044 * (0.0024)	
		DLANNA		0.01031 *** (0.0038)
LAMATA/LEMC	-3.1278 **	DAMATA	-0.0005 (0.00093)	
		DEMC		0.0093 *** (0.00266)
LMAKRO/LROBINS	-3.7639 ***	DMAKRO	-0.0085 *** (0.0026)	
		DROBINS		0.0055 (0.0036)
LERAWAN/LROBINS	-3.3745 **	DERAWAN	-0.0069 *** (0.0022)	
		DROBINS		0.0014 (0.0023)
LAMATA/LSCC	-3.2499 **	DAMATA	-0.0059 *** (0.0021)	
		DSCC		0.0011 (0.0011)
LLPN/LSCC	-2.8913 **	DLPN	-0.0056 *** (0.0019)	
		DSCC		0.0009 (0.0009)
LBANPU/LEGCO	-2.7258 *	DBANPU	-0.0050 *** (0.0014)	
		DEGCO		0.0009 (0.0009)
LBAY/LSCB	-2.8164 *	DBAY	-0.0021 (0.0026)	
		DSCB		0.0048 * (0.0025)

Table 3.2: Continued

Cointegrated pairs	ADF		Speed of adjustment	
			γ_1	γ_2
LBGH/LROBINS	-2.5753 *	DBGH	-0.0001	
			(0.0009)	
		DROBINS		0.0028 **
				(0.0011)

Note that EGCO, LANNA, BANPU, AMATA, EMC, MAKRO, ROBINS, ERAWAN, LPN, SCC, BAY, SCB and BGH are the name of stocks in SET100 where "L" represents logarithm form and "D" represents the first difference. Augmented Dickey Fuller test (ADF) is reported in statistic testing the stationarity of the residual series obtained from EG approach. γ_1 and γ_2 are the speed of adjustment and standard errors are also reported in parenthesis. ***, **, * denote the level of significant at 1%, 5% and 10%, respectively.

Table 3.3: Cointegration estimation of full sample (Mix sign)

Cointegrated pairs	ADF		Speed of adjustment	
			γ_1	γ_2
LLH/LSPALI	-2.9175 **	DLH	0.0031 (0.0029)	
		DSPALI		0.0135 ** (0.0040)
LACL/LTMB	-3.6029 ***	DACL	-0.0123 *** (0.0038)	
		DTMB		-0.0007 (0.0027)
LKBANK/LSCB	-4.3446 ***	DKBANK	0.0018 (0.0033)	
		DSCB		0.0122 *** (0.0037)
LBIGC/LROBINS	-4.6650 ***	DBIGC	-0.0085 *** (0.0024)	
		DROBINS		-0.0117 *** (0.0039)
LBAY/LKBANK	-2.8559 *	DBAY	-0.0089 ** (0.0035)	
		DKBANK		-0.0014 (0.0029)
LKK/LTMB	-2.6640 *	DKK	-0.0071 *** (0.0019)	
		DTMB		-0.0039 ** (0.0018)
LKK/LKTB	-2.7494 *	DKK	-0.0063 *** (0.0019)	
		DKTB		-0.0019 (0.0017)
LASP/LKK	-3.4238 **	DASP	0.0004 (0.0019)	
		DKK		0.0055 *** (0.0018)

Table 3.3: Continued

Cointegrated pairs	ADF		Speed of adjustment	
			γ_1	γ_2
LITD/LSCC	-2.9128 **	DITD	-0.0045 **	
			(0.0017)	
		DSCC		-0.0002
				(0.0010)

Note that LH, SPALI, ACL, TMB, KBANK, LSCB, BIGC, ROBINS, BAY, KK, TMB, KTB, ASP, ITD and SCC are the name of stocks in SET100 where “L” represents logarithm form and “D” represents the first difference. Augmented Dickey Fuller test (ADF) is reported in statistic testing the stationarity of the residual series obtained from EG approach. γ_1 and γ_2 are the speed of adjustment and standard errors are also reported in parenthesis. ***, **, * denote the level of significant at 1%, 5% and 10%, respectively.

3.5.2 Forecasting performance of "correct sign"

In the "correct sign" group, 10 out of 13 pairs yield superior predictions than the benchmark models based on several forecast evaluations, which indicate that the ECM is more accurate in predicting future prices. In this section, we aim to present the best and the worst scenarios to show clearly how good and bad we can get from this "correct sign" group. Therefore, we select 2 cointegrated pairs that have the highest and the lowest magnitude of disequilibrium adjustment to demonstrate how the forecasting models perform.

Table 3.4 and 3.5 contain the forecasting results in the "correct sign". The ECM is compared against RW and RWD models for h = 1, 3, 5, 10, 15 and 20 steps ahead. In table 3.4, the MSE, MAE, RMSE, Theil's coefficient (U) and confusion rate (CR) are shown in terms of ratio, which is relative to RW and RWD. Moreover, the Fair and Shiller test (FS) is shown in terms of p-value where FS1 represents a test of ECM and FS2 represents a test of RWD. The frequency percentages of ECM winning over RW and RWD (WIN) based on each single point MSE comparison is also reported. In addition, Clark and West equal forecast accuracy is reported in table 3.5. In the first column, we report some selected forecast horizon, which is similar to table 3.4. The MSE of RW model (τ1), MSE of ECM (τ2), Clark and West adjustment term (adj), adjusted MSE of ECM (τ2-adj), the different between MSE of RW and adjusted MSE of ECM (τ1- τ2+adj) and t-statistic are also reported in columns 2 to 7, respectively.

Table 3.4: Forecasting performance relative to benchmarks (correct ECM sign)												
	ECM relative to RW						**ECM relative to RWD**					
h	1	3	5	10	15	20	1	3	5	10	15	20
γ = 0.0103 ***	LEGCO/**LLANNA**											
MSE	1.01	1.01	1.02	1.05	1.07	1.09	1.01	1.01	1.02	1.06	1.09	1.11
MAE	0.99	0.99	1.01	1.02	1.03	1.03	0.99	1.00	1.01	1.02	1.04	1.06
RMSE	1.00	1.00	1.01	1.03	1.04	1.05	1.00	1.00	1.01	1.03	1.04	1.06
WIN	0.41	0.49	0.50	0.56	0.59	0.58	0.46	0.51	0.53	0.60	0.68	0.65
U	1.00	1.00	1.01	1.03	1.04	1.05	1.00	1.00	1.01	1.03	1.04	1.05
CR	1.78	1.05	1.00	1.00	0.96	1.00	1.78	1.05	1.00	1.02	0.98	1.01
FS1	-	-	-	-	-	-	0.50	0.56	0.23	0.05	0.00	0.00
FS2	-	-	-	-	-	-	0.22	0.24	0.05	0.00	0.00	0.00
γ = 0.0028 **	LBGH/**LROBINS**											
MSE	1.00	0.92	0.93	0.92	0.91	0.90	1.00	0.92	0.93	0.94	0.95	0.95
MAE	0.97	0.94	0.95	0.95	0.96	0.96	0.99	0.95	0.97	0.98	0.98	0.99
RMSE	1.00	0.96	0.96	0.95	0.96	0.95	1.00	0.96	0.97	0.97	0.98	0.98
WIN	0.35	0.31	0.38	0.38	0.38	0.40	0.45	0.37	0.42	0.43	0.44	0.46
U	1.00	0.96	0.96	0.96	0.96	0.95	1.00	0.96	0.97	0.97	0.98	0.98
CR	1.19	0.99	0.99	0.94	0.92	0.96	1.19	0.99	0.99	0.95	0.96	0.97
FS1	-	-	-	-	-	-	0.02	0.00	0.00	0.24	0.37	0.38
FS2	-	-	-	-	-	-	0.05	0.00	0.00	0.58	0.46	0.37

Note that MSE, MAE, RMSE, Theil's coefficient (U) and confusion rate (CR), the results are reported in ratios (the forecast performance of ECM relative to the forecast performance of benchmarks). Moreover, WIN represents the frequency percentage of ECM win the benchmarks in term of MSE comparison at single point forecasts. Fair and Shiller test (FS) is reported in term of p-value where FS1 represents a test of ECM and FS2 represents a test of random walk with drift. γ indicates the speed of adjustment of ECM term with *** and ** signs indicating significant at 1% and 5%, respectively.

Table 3.5: Clark and West Test for equal forecast accuracy (Correct sign)

h	τ_1	τ_2	adj	τ_2-adj	$\tau_1 - \tau_2$ + adj	t-stat (SD)
LEGCO/**LLANNA**						
1	0.001052	1.12E-03	3.89E-06	0.001118	-6.55E-05	-4.63
						(0.00001)
3	0.003303	0.003291	1.14E-05	0.003279	2.39E-05	1.38
					*	(0.00002)
5	0.006029	0.005916	2.85E-05	0.005888	14.1E-05	4.15
					**	(0.00003)
10	0.012047	0.01145	10.5E-05	0.011345	70.2E-05	7.44
					**	(0.00009)
15	0.020111	0.018717	22.4E-05	0.018493	161.8E-05	8.52
					**	(0.00019)
20	0.02852	0.026083	38.2E-05	0.025701	281.9E-05	9.22
					**	(0.000306)
LBGH/**LROBIN**						
1	0.000967	0.001047	1.43E-05	0.001033	-6.61E-05	-3.79
						(0.000017)
3	0.003618	0.003925	3.51E-05	0.00389	-0.00027	-2.52
						(0.000108)
5	0.00559	0.005965	6.44E-05	0.005901	-0.00031	-2.73
						(0.000114)
10	0.006024	0.006535	20.5E-05	0.006329	-0.0003	-2.61
						(0.00012)
15	0.010614	0.011574	44.3E-05	0.011131	-0.00052	-2.37
						(0.000218)
20	0.013804	0.015413	77.6E-05	0.014637	-0.00083	-2.70
						(0.000308)

Note that τ_1 is the MSE of the parsimonious model (Random walk), τ_2 is the MSE of an alternative model (Error correction model), adj is the Clark-West adjustment term, which is the difference between forecast of 2 models. Moreover, τ_2-adj is the MSE of ECM after account for adjustment. ** and * denote T-stat significant at 5% and 10% level according to Clark and McCracken (2005), respectively. Standard deviation (SD) is reported in the parenthesis

3.5.2.1 First case: High speed of adjustment

In the first case (table 3.4), we have selected a cointegrated pair of LEGCO and LLANNA, which represents the highest speed of disequilibrium adjustment (γ_2 = 0.0103). This selected pair has two-way directional causality. The speed of adjustment γ_1 is marginally significant at 10% while γ_2 is strongly significant at 1%. This implies that the Granger causality flow from LEGCO to LLANNA is more substantial than from LLANNA to LEGCO. Hence, the past value of LEGCO is useful in predicting the future price of LLANNA.

The findings indicate that the ECM can forecast the price of log LANNA better than both benchmarks, which are RW and RWD models. Based on point forecast evaluation, the ratios of MSE, MAE and RMSE show some percentage gains for ECM against RW and RWD. For example, at 1 step-ahead, the relative ratio of MSE for ECM against RW and RWD is about 1% while the respective ratios against both benchmarks are 9% and 11% at 20 step-ahead. As the horizon rises, the relative ratio also increases. This implies that the ECM can beat the benchmark models, especially in the longer forecast horizons. Moreover, the WIN percentage tell the same story; showing that the ECM has a lower chance of winning over the benchmarks in the short run but a higher chance in the long run. For instance, the ECM has 58% chance of winning over the RW and 65% chance of winning over the RWD at 20 step-ahead while only 41% and 46% chance of winning the respective benchmarks at 1 step-ahead. The relative ratio of Theil coefficient also favors the ECM.

In addition, the forecast evaluation based on the direction of change shows that the ECM is more likely to be less “confused” in the short forecast horizon. In fact, the CR ratio for ECM relative to RW and RWD is approximately 78%, which is the highest gain at 1 step-ahead. However, once the forecast horizon rises, our forecasting model and benchmarks have the equivalent chances to predict the next turning point correctly. This also implies that the ECM is more accurate in forecasting the future price movement at 1 step-ahead. Additionally, based on the forecast encompassing, the result is inconclusive. The Fair and Shiller encompassing test shows that both the ECM and RWD are statistically significant at 10, 15 and 20 step-ahead. This outcome indicates that both models contain some information that helps in forecasting in the long run but the result is inconclusive in term of the forecasting model encompassing one another.

In term of equal forecast accuracy, the outcome of Clark and West test in table 3.5 confirms that the ECM is superior to the RW model. The result shows that the ECM has smaller MSE than the RW model from 3 to 20 step-ahead. After accounting for Clark and West adjustment (adj), the adjusted MSE of ECM is even smaller. As a result, the difference between MSE of RW and adjusted MSE of ECM ($\tau1$- $\tau2$+adj) is positive and large enough to reject the null hypothesis of equal prediction accuracy. The t-statistic is significant at 10% (at 3 step-ahead) and 5% (at 5, 10, 15 and 20 step-ahead), which indicates that the ECM has an advantage over RW model. This also implies that after accounting for estimation noise associated with additional parameters in the ECM, the past value of disequilibrium term and LEGCO have additional predictive value for LLANNA, in particular the longer forecast horizon.

3.5.2.2 Second case: Low speed of adjustment

In the second case, LBGH and LROBINS pair represents the lowest magnitude of disequilibrium adjustment (γ_2 = 0.0028) in this "correct sign" analysis. LBGH and LROBINS pair has one-way directional causality, which is significant at 5% confident interval. Thus, LBGH Granger causes LROBINS.

In contrast to 3.5.2.1, the forecasting performance of LBGH and LROBINS pair shows some evidence that the ECM cannot beat the RW and RWD models. Firstly, the relative ratio of MSE, MAE and RMSE shows the loss for the ECM over both benchmarks. For example, at 1-step ahead, the relative ratios of MSE against the RW and RWD show neutral result. This indicates the forecasting performances of all 3 models are identical. However, at 20-step ahead, the ECM cannot predict as well as the benchmark models, where we realize the loss of 10% and 5% against RW and RWD, respectively. The winning percentage of the ECM over benchmarks also yields lower than a 50% chance of winning. Moreover, Theil's coefficient confirms that the ECM cannot beat the benchmark models.

In addition, the confusion rate ratio gives the best result at 1 step-ahead. The relative CR ratios against RW and RWD show 19% gain for ECM, meaning that at 1 step-ahead, the ECM is more accurate in predicting the future price movement. In contrast to the high speed adjustment pair, the Fair and Shiller encompassing test is statistically significant at 1, 3 and 5 step-ahead. The findings indicate that the ECM and RWD contain information that help to forecast the price of LROBINS in the short forecast horizons. Neither model is encompassing each other.

Moreover, the null hypothesis of equal forecast accuracy cannot be rejected in the case of LBGH and LROBINS pair. The findings indicate that the MSE of ECM is larger than the MSE of RW model even accounting for Clark-West adjustment. We observe negative value for the difference (τ_1- τ_2+adj) where τ_1 is less than adjusted $\tau_{2.}$ This implies that the additional parameters in the ECM do not contain any useful information for forecasting the price of LROBINS. Therefore, in the low speed of adjustment pair, the ECM is outperformed by benchmark models where the error correction component cannot improve the predictability in the long run.

In summary, the forecasting performance of the "correct sign" group shows evidence of a better prediction of the ECM against the RW and RWD in the case of high speed adjustment. This result reveals that the magnitude of adjustment might alter the predictability of our forecasting model as the low speed adjustment might take a longer time to move back to the long run equilibrium. As expected, the ECM yields better predictability for the higher strength of adjustment and inferior forecasting performance for the lower strength of adjustment.

3.5.3 Forecasting performance of "mix sign"

In the "mix sign" group, we obtained 9 cointegrated pairs that the disequilibrium adjustment contradicts the "Alexander's implication". The findings indicate that the ECM does not predict as good as RW and RWD models. However, we find that only 3 out of 9 cointegrated pairs can beat the benchmarks in some forecast horizons. In this section, the highest and the lowest speed of adjustment pairs are selected to demonstrate the forecasting performance of this group. Thus, table 3.6 and 3.7 contain the forecasting performance of the “mix sign” group in which the results are presented similarly as in table 3.4 and 3.5, respectively.

3.5.3.1 First case: High speed of adjustment

In the first case of high magnitude of disequilibrium adjustment, LLH and LSPALI pair is selected. The speed of adjustment (γ_2 = 0.0135) is significant at 5%, which indicates one-way directional flow from LLH to LSPALI. The forecasting evaluation in table 3.6 indicates that the ECM cannot predict the price of LSPALI as good as RW and RWD models. Based on point forecast evaluation, the relative ratios of prediction errors yield the value less than one, which indicate that the ECM cannot beat both benchmarks. For example, at 20 step-ahead, the loss of relative MSE of ECM against RW and RWD are 22% and 15%, respectively. However, at 1 step-ahead, we realize 1% loss for ECM relative to RW and no gain and loss for ECM relative to RWD. Theil’s coefficients also tell the same story that the forecasting performance of ECM is poorer as the forecast horizon rise. This finding indicates that the error correction mechanism seems not improving the predictability in the longer horizons. Moreover, WIN yields lower than 50% at all 20 step-ahead. This finding suggests that the ECM has a lower chance to win over the benchmark models.

However, based on the direction of change, we find that the ECM is a least “confused forecaster” at 1 step-ahead as the CR ratio is as high as 142% against both benchmarks. The CR ratio also shows the value greater than one at all 20 step-ahead. This finding indicates that the ECM outperforms the benchmark models in term of forecasting the price movement. In addition, the Fair and Shiller encompassing test indicates that the ECM encompass RWD from 3 to 20 step-ahead.

Table 3.6: Forecasting performance of ECM relative to benchmarks (Mix ECM sign)												
	ECM relative to RW						**ECM relative to RWD**					
h	1	3	5	10	15	20	1	3	5	10	15	20
γ = 0.0135 **					LLH/**LSPALI**							
MSE	0.99	0.97	0.93	0.88	0.82	0.78	1.00	0.99	0.96	0.93	0.88	0.85
MAE	0.96	0.96	0.93	0.85	0.82	0.80	0.97	0.98	0.95	0.88	0.86	0.85
RMSE	1.00	0.99	0.99	0.94	0.91	0.88	1.00	1.00	0.98	0.96	0.94	0.92
WIN	0.44	0.45	0.44	0.40	0.41	0.41	0.47	0.47	0.47	0.45	0.47	0.47
U	0.99	0.98	0.96	0.93	0.90	0.86	1.00	0.99	0.97	0.95	0.92	0.89
CR	2.42	1.20	1.02	1.10	0.17	1.19	2.42	1.20	1.02	1.09	1.20	1.24
FS1	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00	0.00
FS2	-	-	-	-	-	-	0.00	0.20	0.24	0.32	0.38	0.60
γ = -0.0045 **					**LITD**/LSCC							
MSE	0.99	0.99	0.99	1.00	1.01	1.02	0.99	0.99	0.99	0.99	1.01	1.02
MAE	0.99	0.99	0.99	1.00	1.02	1.03	0.99	0.99	0.99	1.00	1.02	1.03
RMSE	0.99	0.99	0.99	1.00	1.01	1.01	0.99	0.99	0.99	0.99	1.01	1.01
WIN	0.46	0.46	0.50	0.51	0.51	0.54	0.47	0.46	0.49	0.28	0.28	0.28
U	1.00	0.99	1.00	1.00	1.01	1.01	1.00	0.99	0.99	1.00	1.01	1.01
CR	1.61	0.99	1.00	0.99	1.04	0.99	1.61	1.00	1.00	0.98	1.05	0.98
FS1	-	-	-	-	-	-	0.40	0.66	0.77	0.47	0.10	0.03
FS2	-	-	-	-	-	-	0.73	0.90	0.86	0.10	0.00	0.00

Note that MSE, MAE, RMSE, Theil's coefficient (U) and confusion rate (CR), the results are reported in ratios (the forecast performance of ECM relative to the forecast performance of benchmarks). Moreover, WIN represents the frequency percentage of ECM win the benchmarks in term of MSE comparison at single point forecasts. Fair and Shiller test (FS) is reported in term of p-value where FS1 represents a test of ECM and FS2 represents a test of random walk with drift. γ indicates the speed of adjustment of ECM term with *** and ** signs indicating significant at 1% and 5%, respectively.

Table 3.7: Clark and West Test for equal forecast accuracy (Mix sign)

h	τ_1	τ_2	adj	τ_2-adj	τ_1 - τ_2 + adj	t-stat (SD)
LLH/**LSPALI**						
1	0.000388	0.000327	4.18E-05	0.000285	0.000103	5.66
					**	(0.00002)
3	0.0014	0.001445	0.0002	0.001245	0.000155	2.48
					**	(0.00006)
5	0.002368	0.00252	0.000519	0.002001	0.000366	2.77
					**	(0.00013)
10	0.005339	0.006128	0.001827	0.004301	0.001038	3.15
					**	(0.00033)
15	0.008831	0.011008	0.003805	0.007203	0.001628	3.22
					**	(0.00051)
20	0.012338	0.0164	0.006358	0.010043	0.002295	3.09
					**	(0.00074)
LITD/**LSCC**						
1	0.001578	0.001551	4.60E-06	0.001546	3.22E-05	2.90
					**	(0.000011)
3	0.005201	0.005273	2.06E-05	0.005253	-5.20E-05	-1.57
						(0.000033)
5	0.009383	0.009469	5.15E-05	0.009418	-3.48E-05	-0.55
						(0.000062)
10	0.018906	0.018871	0.000201	0.018671	0.000236	1.40
					*	(0.000168)
15	0.029711	0.02932	0.000446	0.028873	0.000837	2.72
					**	(0.000308)
20	0.038209	0.037589	0.000784	0.036804	0.001404	3.33
					**	(0.000421)

Note that τ_1 is the MSE of the parsimonious model (Random walk), τ_2 is the MSE of an alternative model (Error correction model), adj is the Clark-West adjustment term, which is the difference between forecast of 2 models. Moreover, τ_2-adj is the MSE of ECM after account for adjustment. ** and * denote T-stat significant at 5% and 10% level according to Clark and McCracken (2005), respectively. Standard deviation (SD) is reported in the parenthesis.

In table 3.7, the null hypothesis of equal forecast accuracy is rejected for all 20 step-ahead after Clark-West adjustment. Before being adjusted for noise, the MSE of ECM is larger than the MSE of RW, which supports the previous forecast evaluation that the ECM cannot beat the benchmarks alternatives. However, after accounting for Clark and West adjustment, the adjusted MSE (τ_{2}-adj) is smaller than the standard MSE (τ_2). Hence, τ_1- τ_2+adj is positively significant in this analysis. The findings point out that τ_2 is inflated by useless additional parameter in the ECM. Therefore, the ECM cannot forecast the price of LSPALI as well as the benchmark models, and the error correction term does not improve the predictability in the long run.

3.5.3.2 Second case: Low speed of adjustment

For the low magnitude of adjustment, LITD and LSCC pair is selected, which has Granger causality flow from LSCC to LITD. The forecasting performance of LITD and LSCC pair with the low speed of adjustment (γ_1 = -0.0045) shows a similar result to 3.5.3.1. However, in this pair, the forecast performance shows a little improvement on forecast accuracy at the longer horizon. Based on point forecast evaluation, we gain approximately 2% at 20 step-ahead for the ECM relative to RW and RWD while we lose about 1% at 1 step-ahead. Moreover, WIN gives more than 50%, which indicates that the ECM has a higher chance to win over the RW from 10 to 20 step-ahead in term of smaller MSE. However, we obtained the diverse direction for a winning percentage when compared to RWD model. This result yields lower than 50% chance that the ECM wins over RWD. The U ratio also shows the gain for ECM relative to benchmarks at the longer forecast horizons. In particular, the ECM gains 1% over both benchmarks from 15 to 20 step-ahead.

Furthermore, based on the direction of change, confusion rate ratio gives similar outcome. At 1-step ahead, the CR ratio is 61%, which indicates that ECM is the least “confused” model. In addition to forecast evaluation based on the Fair and Shiller encompassing test, the finding is inconclusive. P-value of FS1 for ECM is larger than 0.05, except for 20 step-ahead and FS2 for RWD is significant at 15 and 20 step-ahead. Additionally, the findings of Clark and West equal forecast accuracy significantly reject the null hypothesis at 1, 10, 15 and 20 step-ahead.

In summary, the results of "mix sign" cointegrated pairs are less attractive than the "correct sign" pairs comparing to the benchmarks. Importantly, there are 10 out of 13 cointegrated pairs from "correct sign" group that can outperform the competing models. Whereas, only 3 out of 9 cointegrated pairs from "mix sign" group can beat the benchmarks in some horizons. The results of table 3.6 and 3.7 are mixed. Although, we found cointegration relationship in "mix sign" pairs based on ADF basis, in fact, the ECM is not superior to benchmarks. This poor forecasting performance of "mix sign" group might, possibly, be due to error correction term with an inappropriate sign that does not converse to the long run equilibrium.

3.5.4 Forecasting error of specified VS misspecified ECM

In this section, we aim to compare the prediction errors of ECM against RW and RWD on both "correct sign" and "mix sign" groups. The average prediction errors obtained from specified ECM is summarized in table 3.8 and misspecified ECM where we ignore insignificant disequilibrium is reviewed in table 3.9. The forecasting performances are evaluated in terms of average MSE of all cointegrated pairs at each forecasting horizon. Based on Alexander's disequilibrium sign, we have 13 cointegrated pairs in "correct sign" and 9 pairs in "mix sign".

3.5.4.1 Specified ECM

Table 3.8 contains the average MSE of specified ECM, RW and RWD, which is divided into A (correct sign) and B (mix sign). The superscript "^{L}" is assigned to the lowest average of forecasting errors for each horizon.

In table 3.8A, the ECM can outperform RW from 9 to 20 step-ahead. The average MSE of specified ECM is slightly larger than MSE of RW from 1 to 8 forecasting horizons. As the forecasting horizon rises, the ECM gives a smaller MSE than RW from 9 to 20 forecasting horizons. At 1 step ahead, MSE of the ECM is approximately 0.00001 larger than MSE of RW, which is almost indifferent. Whereas, MSE of the ECM is smaller than RW by 0.00014 at 20 step-ahead. The results indicate that the specified ECM has a superior forecast performance relative to RW in the longer forecast horizons while the forecasting performance of ECM and RW are almost the same in the short forecast horizon.

Moreover, the ECM can outperform RWD at all 20 forecast horizons. The gap between the MSE of ECM and RWD is ranged from 0.00001 to 0.00137. In the first 5 step-ahead, the predictability of RWD shows competitive result comparing to ECM. However, the RWD becomes inaccurate as the forecasting horizon rises, which implies that the RWD is not suitable for long term forecasting.

In addition, the specified ECM of the "mix sign" group in table 3.8B indicates that the specified ECM cannot outperform both benchmarks at any forecasting horizon. The RW model seems to be the best forecaster in this analysis as the result yields the lowest MSE at all forecasting horizons. Also, RWD is the second best forecaster in this analysis. The spread between MSE of ECM against RW and RWD is wider than 3.8A. In this case, it varies from 0.00001 to 0.000194 comparing to RW and from 0.00001 to 0.000164 comparing to RWD. Therefore, the inferior forecasting result of ECM could be due to the mix disequilibrium sign.

Table 3.8 – The average of MSE Forecast Errors (Specified ECM)			
Forecast Horizon	**ECM**	**RW**	**RWD**
A: Average MSE for the 13 Cointegrated Pairs with Correct sign			
1	0.00116	0.00115^{L}	0.00116
2	0.00243^{L}	0.00243^{L}	0.00244
3	0.00384	0.00380^{L}	0.00383
4	0.00522	0.00517^{L}	0.00522
5	0.00654	0.00648^{L}	0.00656
6	0.00778	0.00773^{L}	0.00784
7	0.00889	0.00885^{L}	0.00900
8	0.01007	0.01005^{L}	0.01024
9	0.01133^{L}	0.01133^{L}	0.01157
10	0.01267^{L}	0.01269	0.01300
11	0.01416^{L}	0.01420	0.01457
12	0.01562^{L}	0.01568	0.01611
13	0.01720^{L}	0.01727	0.01778
14	0.01878^{L}	0.01887	0.01946
15	0.02047^{L}	0.02057	0.02125
16	0.02213^{L}	0.02224	0.02302
17	0.02378^{L}	0.02392	0.02480
18	0.02544^{L}	0.02559	0.02658
19	0.02708^{L}	0.02722	0.02833
20	0.02869^{L}	0.02883	0.03006
B: Average MSE for the 9 Cointegrated Pairs with Mix sign			
1	0.00084	0.00083^{L}	0.00083^{L}
2	0.00179	0.00176^{L}	0.00176^{L}
3	0.00285	0.00274^{L}	0.00275
4	0.00387	0.00370^{L}	0.00371
5	0.00489	0.00465^{L}	0.00467
6	0.00577	0.00547^{L}	0.00550
7	0.00651	0.00617^{L}	0.00620
8	0.00731	0.00689^{L}	0.00693
9	0.00805	0.00758^{L}	0.00763
10	0.00894	0.00838^{L}	0.00844
11	0.01002	0.00934^{L}	0.00942
12	0.01116	0.01036^{L}	0.01046
13	0.01243	0.01151^{L}	0.01163
14	0.01377	0.01272^{L}	0.01286
15	0.01522	0.01402^{L}	0.01429
16	0.01651	0.01519^{L}	0.01537
17	0.01774	0.01628^{L}	0.01650
18	0.01900	0.01739^{L}	0.01764
19	0.02025	0.01847^{L}	0.01875
20	0.02144	0.01950^{L}	0.01980

Note that the forecasting performance of error correction model (ECM), random walk model (RW) and random walk with drift model (RWD) are reported. ^{L} indicates the lowest average mean square prediction error (MSE) for each of 20 step-ahead.

3.5.4.2 Misspecified ECM

In this sub-section, average MSEs of misspecified ECM are calculated where insignificant disequilibrium terms are included. In table 3.9, the average prediction errors of "correct sign" and "mix sign" are shown in 3.9A and 3.9B, respectively. In table 3.9A, the averages MSE indicate that the ECM cannot beat the RW at all 20 forecasting horizons. The spread between MSE of the ECM and RW varies from 0.00004 to 0.00068. However, the ECM can beat RWD from 7 to 20 forecasting horizons and the spread varies from 0.00003 to 0.00055. Similar to 3.8B, the results in table 3.9B show that the misspecified ECM cannot outperform any of the two benchmarks for the "mix sign" group. In particular, the RW model is the best forecaster while the RWD model is the second best forecasting model in this case.

In summary, the difference between the average MSE conducted by misspecified and specified ECM is substantial, which alters the predictability of the model against the benchmark models. For instance, at 20 step-ahead, the MSE of specified ECM and misspecified ECM is 0.02869 and 0.02951, respectively. By including insignificant EC term, the forecast accuracy can be reduced by 2.85% in the "correct sign" group. Similar to the previous literature, LeSage (1990) and Mastern, Banerjee and Marcellino (2009) pointed out that the error correction term plays an important role in which the significant EC term is responsible for the long run forecasting improvement. By including insignificant EC term, this only creates forecasting noise, which makes a larger gap between the forecast and the actual price. Our findings also confine the results of the previous literatures such as Engle and Yoo (1987), LeSage (1990) and Lin & Tsay (1996) that the ECM can outperform the benchmark models at the longer forecast horizons. In our study, the specified ECM with the correct sign wins over RW at 9 to 20 step-ahead forecasts. Moreover, in the "mix sign" group, only 3 out of 9 pairs produce marginal improvement to forecast the stock price. This result suggests that the ECM should not apply to cointegrated pairs with the mix sign of disequilibrium term.

Table 3.9- The average of MSE Forecast Errors (Misspecified ECM)

Forecast Horizon	ECM	RW	RWD
A: Average MSE for the 13 Cointegrated Pairs with Correct sign			
1	0.00119	0.00115^{L}	0.00116
2	0.00248	0.00243^{L}	0.00244
3	0.00390	0.00380^{L}	0.00383
4	0.00529	0.00517^{L}	0.00522
5	0.00662	0.00648^{L}	0.00656
6	0.00786	0.00773^{L}	0.00784
7	0.00894	0.00885^{L}	0.00900
8	0.01011	0.01005^{L}	0.01024
9	0.01137	0.01133^{L}	0.01157
10	0.01274	0.01269^{L}	0.01300
11	0.01427	0.01420^{L}	0.01457
12	0.01581	0.01568^{L}	0.01611
13	0.01745	0.01727^{L}	0.01778
14	0.01908	0.01887^{L}	0.01946
15	0.02084	0.02057^{L}	0.02125
16	0.02258	0.02224^{L}	0.02302
17	0.02433	0.02392^{L}	0.02480
18	0.02606	0.02559^{L}	0.02658
19	0.02780	0.02722^{L}	0.02833
20	0.02951	0.02883^{L}	0.03006
B: Average MSE for the 9 Cointegrated Pairs with Mix sign			
1	0.00093	0.00083^{L}	0.00083^{L}
2	0.00197	0.00176^{L}	0.00176^{L}
3	0.00310	0.00274^{L}	0.00275
4	0.00424	0.00370^{L}	0.00371
5	0.00534	0.00465^{L}	0.00467
6	0.00634	0.00547^{L}	0.00550
7	0.00718	0.00617^{L}	0.00620
8	0.00809	0.00689^{L}	0.00693
9	0.00890	0.00758^{L}	0.00763
10	0.00983	0.00838^{L}	0.00844
11	0.01091	0.00934^{L}	0.00942
12	0.01203	0.01036^{L}	0.01046
13	0.01330	0.01151^{L}	0.01163
14	0.01461	0.01272^{L}	0.01286
15	0.01603	0.01402^{L}	0.01429
16	0.01724	0.01519^{L}	0.01537
17	0.01841	0.01628^{L}	0.01650
18	0.01965	0.01739^{L}	0.01764
19	0.02087	0.01847^{L}	0.01875
20	0.02202	0.01950^{L}	0.01980

Note that the forecasting performance of error correction model (ECM), random walk model (RW) and random walk with drift model (RWD) are reported. ^{L} indicates the lowest average mean square prediction error (MSE) for each of 20 step-ahead.

3.6 Trading simulation and results

The motivation of this study is not only to explore the predictability of error correction model in the Stock Exchange of Thailand, but also to develop profitable trading strategies that can be implemented, based on our forecasting results. The trading simulation is conducted to ensure that the forecasting model is not only predictable in statistical terms but also practically profitable. In this section, we apply 3 trading strategies that involve the average forecast of 20 steps ahead and the direction of predicted change in making buy or sell consideration.

3.6.1 Trading simulation

Our trading simulation covers a period from January 2007 to December 2008, which is the same as the forecasting period. The forecasting model predicts 472 times of 20 step-ahead forecasts. We perform the trading strategies within 20 days period. As we trade on every predicted price, the transaction cost might be a crucial factor that alters the profitability of the trading strategy. Hence, a round trip (buy and sell) transaction cost (0.1605%) is employed[24]. In addition, we form 3 trading strategies to test on our forecasting model, which will be described below.

Strategy 1: Average forecasts

Buying undervalued or selling overvalued stock is what active investors are looking for. We attempt to identify whether the actual price is under or overvalued, thus, an appropriate trading action can be performed profitably based on a forecasting scenario. In this strategy, we compare the actual price to the average of 20 step forecasts in which we assume that the stock is undervalued (overvalued) when the actual price is below (above) the average of predicted prices.

$$Buy: \; y_t < \frac{\Sigma \hat{y}_{t+1} + \hat{y}_{t+2} + \cdots + \hat{y}_{t+20}}{20}$$

$$Sell: \; y_t > \frac{\Sigma \hat{y}_{t+1} + \hat{y}_{t+2} + \cdots + \hat{y}_{t+20}}{20}$$

[24] 0.1605 % transaction cost based on internet trading based of Kim Eng Thailand.

Therefore, we buy (sell) one unit of the stock when the actual price today is lower (higher) than the average of predicted prices for the next 20 step ahead with an expectation that the stock price will be increased (decreased). Moreover, all trading positions are closed in the next 20 days.

Strategy 2: Direction of predicted change

In this strategy, we attempt to utilize our forecasting results based on the forecast of the next turning point. Regarding to the forecasting results, the ECM is best performed at 1 step ahead in terms of correctly predicting the future price movement. Hence, the trading position is opened based on the direction signal, which is described below.

$$Buy: \; y_t < \hat{y}_{t+1} = up$$

$$Sell: \; y_t > \hat{y}_{t+1} = down$$

If the actual price today is lower (higher) than the predicted price of tomorrow, a buying (selling) signal is indicated. Hence, we enter the trading position based on these direction signals. Similar to strategy 1, the trading strategy trades every day during 2 years trading period. However, each trading position will be closed if the direction of the predicted price has changed to an opposite sign otherwise at 20 step-ahead.

Strategy 3: Average forecasts and direction of predicted price

In addition, we combine these 2 strategies together in order to filter out fault trading signal.

$$Buy: \; y_t < \frac{\sum \hat{y}_{t+1} + \hat{y}_{t+2} + \cdots + \hat{y}_{t+20}}{20} \; and \text{ up" signal}$$

$$Sell: \; y_t > \frac{\sum \hat{y}_{t+1} + \hat{y}_{t+2} + \cdots + \hat{y}_{t+20}}{20} \; and \text{ "down" signal}$$

In this trading strategy, buy (sell) position is opened when these 2 conditions are met. Firstly, the actual price is lower (higher) than the average of all 20 step predicted prices. Secondly, the actual price is lower (higher) than the forecast price at 1 step-ahead, which implies "up" ("down") direction signal. Moreover, each trading position is closed in the following 20 days.

3.6.2 Trading results

The trading result based on the ECM forecast detailed above is reported in table 3.10. To conserve space, we only present results for 4 selected cointegrated pairs from the "correct sign" group that have different magnitude of disequilibrium; they will be used to illustrate the trading strategy performances. The first column presents 3 trading strategies and the name of the selected pairs, which are LEGCO & LLANNA (γ = 0.0103), LAMATA & LSCC (γ = -0.0059), LBANPU & LEGCO (γ = -0.0050) and LBGH & LROBINS (γ = 0.0028). Column 2, 3 and 4 contain the total return, monthly return and average return that has already accounted for transaction cost. The last column is the number of trading positions performed in this simulation. The trading performance shows the positive returns for LEGCO & LLANNA, LAMATA & LSCC and LBANPU & LEGCO.

3.6.2.1 High speed of adjustment pair

Firstly, LEGCO and LLANNA pair is selected to demonstrate the trading performance in the case of high speed adjustment. The trading simulation based on the prediction of ECM yields profitable result even after accounting for the transaction cost. Specifically, strategy 1 gives an average return of 2.26%, monthly return of 44.31% and 2-year accumulated return of 1,065.45%. Moreover, strategy 2 shows lower returns than strategy 1. The average return, monthly return and the total return of strategy 2 are 1.98%, 38.91% and 933.84%, respectively. Moreover, an attempt to reduce the transaction cost, the strategy 3 incorporates strategy 1 and 2 together; thus, the number of trading signals is lower. As a result, strategy 3 yields the average return of 2.52%, monthly return of 40.25% and the total return of 965.95%. Additionally, the numbers of open trading positions are reduced from 472 to 384 that are lower by 18.6%. The trading results show that strategy 3 is superior to other strategies as the evidence of the highest average return with a fewer number of trading positions.

Table 3.10: Trading strategy return based on ECM forecast

Trading strategy	Total return (2 years)	Monthly return (÷24 months)	Average return (÷ n)	Number of trades (n)
LEGCO/**LLANNA** (γ = 0.0103)				
Strategy 1	10.6545	0.4439	0.0226	472
Strategy 2	9.3384	0.3891	0.0198	472
Strategy 3	9.6595	0.4025	0.0252	384
LAMATA/LSCC (γ = -0.0059)				
Strategy 1	8.3993	0.3499	0.0178	472
Strategy 2	2.8526	0.1189	0.0061	472
Strategy 3	4.4804	0.1867	0.0127	353
LBANPU/LEGCO (γ = -0.0050)				
Strategy 1	4.4651	0.1860	0.0095	472
Strategy 2	1.9269	0.0803	0.0041	472
Strategy 3	2.8741	0.1198	0.0079	363
LBGH/**LROBINS** (γ = 0.0028)				
Strategy 1	-4.4750	-0.1865	-0.0095	472
Strategy 2	-4.2173	-0.1757	-0.0089	472
Strategy 3	-3.7632	-0.1568	-0.0095	397

Note that the returns of the 3 strategies are reported in percentage for the total return of 2-year trading period, monthly return and average return. LLANNA, LEGCO, LBGH, LROBIBS, LBANPU, LAMATA and LSCC are the log price of individual stock listed in Stock Exchange of Thailand and the stock that we perform trading strategies are in bold text. γ represents the speed of adjustment of error correction term.

3.6.2.2 Median speed of adjustment pair

The second and third pairs with the speed of adjustment in the median rank also present positive returns for 3 trading strategies. Ignoring the negative sign of EC term, LAMATA & LSCC pair (γ = -0.0059) has higher speed of adjustment than LBANPU & LEGCO pair (γ = -0.0050). Thus, as expected, the higher adjustment pair yields better trading returns in this analysis. Similar to the previous pair, the total return of strategy 1 presents the highest returns in this study. In addition, the average return of these 2 pairs indicate that strategy 1 (1.78% for LAMATA & LSCC and 0.95% for LBANPU&LEGCO) is the best trading strategy and strategy 3 is the second best (1.27% for LAMATA & LSCC and 0.79% for LBANPU & LEGCO) as the strategy gives a higher average return with a fewer number of trades against strategy 2 (0.61% for LAMATA & LSCC and 0.41% for LBANPU & LEGCO).

3.6.2.3 Low speed of adjustment pair

In the low speed of adjustment pair, LBGH & LROBINS (γ = 0.0028) shows negative returns. Based on the total returns, strategy 1 has the highest loss of -447.50%, followed by strategy 2 with the loss of -421.43% and strategy 3 with the loss of -376.32%. Moreover, the average return per trade indicates that strategy 2 has the smallest loss amongst other strategies (strategy 2 is -0.89% and strategy 1 and 3 are -0.95%).

In summary, the trading simulations of selected cointegrated pairs with various magnitude of disequilibrium adjustment give evidence of positive returns. In fact, we observed the highest profit from the highest adjustment and some loss from the lowest speed of adjustment. Our trading performances convey the same story as the forecasting results which we found unpredictable and unprofitable for very low speed of adjustment pairs. However, the majority of cases were profitable and predictable, which can be seen as the evidence of market inefficient in Stock Exchange of Thailand.

3.7 Conclusion

In this chapter, we conducted forecasting and trading simulation on daily share price series from the Stock Exchange of Thailand. The forecasting simulation is performed to explore the predictability of error correction model on cointegrated pairs in which we classified into “correct sign” and “mix sign” cointegration based on Alexander’s (1998) criterion. In addition, simple trading strategies are employed to test whether we could exploit any positive returns from this prediction.

Theoretically, if cointegrated series deviate from the equilibrium in the short run, the disequilibrium can be corrected in the following time period until the equilibrium is restored. The error correction component can improve the predictive capability in the long run. In this chapter, we found that the error correction model was the best forecaster when the model had “correct sign” of the speed adjustment coefficients as suggested by Alexander (2008). Thus, the error correction model outperformed both the random walk model from 9 to 20 step-ahead and the random walk with drift alternative at all 20 forecasting horizons. Consequently, in the short forecasting horizons, the ECM slightly underperformed the RW. The direction of change also indicated that the ECM was the least “confused” model in predicting the future price movement at 1 step-ahead.

A somewhat surprising finding was that the ECM produced bad forecasting result for the “mix sign” group, although we found that the “mix sign” pairs are cointegrated and statistically significant. The inference can be made under the “mix sign” cointegration that the share price series might not be truly cointegrated. As a result, the majority of prediction failures (6 out of 9 cases) of the ECM indicated poor forecasts compared to the benchmark models.

Additionally, the substantial forecasting errors could be realized if misspecified ECM is considered. Similar to the previous literatures, our findings confirmed that the strength of error correction adjustment is crucial in a forecasting aspect. We realized better forecasting results for higher magnitude of disequilibrium adjustment and indeed, outperformed the RW and RWD forecasters if the strength of adjustment is efficiently large.

Moreover, trading simulation yielded positive returns at all 3 trading strategies but the returns are altered by the magnitude of a disequilibrium adjustment. Similar to forecasting performance, trading strategies could not yield positive returns if cointegrated pairs had a low magnitude of adjustment.

As the results, forecasting simulation confirmed that the ECM is superior to benchmark models in terms of forecast accuracy in the longer horizons. However, the true cointegration of variables seems to be robust to consider before implementing the ECM. Otherwise, the ECM would be useless for forecasting purpose where error correction mechanism is not exhibited. If the unit root tests (in our case ADF) failed to detect the unit root, the error correction sign suggested by Alexander (2008) could be an alternative criterion to consider in this aspect as it might be helpful in detecting non-cointegration variables. Moreover, the predictability and profitability based on the ECM forecasting can be interpreted as evidence that the Stock Exchange of Thailand is a weak-form efficient market.

CHAPTER IV

TESTING THE FORWARD RATE UNBIASED HYPOTHESIS IN ASIAN EXCHANGE RATES USING CONVENTIONAL REGRESSIONS AND LOGISTIC SMOOTH TRANSITION REGRESSION

4.1 Introduction

In an efficient market, the information should be fully reflected in the price of the forward exchange rate, and it should be impossible for the foreign exchange participants to earn excessive returns on speculation. Thus, the efficient market hypothesis (EMH) implies that the forward exchange rate is an unbiased predictor of the corresponding spot exchange rate. This is also known as the forward rate unbiased hypothesis (FRUH), which has attracted a considerable amount of interest in testing whether the forward exchange rate is indeed an unbiased predictor of the future spot exchange rate under the assumptions of risk neutrality and rational expectation in an efficient foreign exchange market.

The hypothesis is popularly tested by the conventional regression of the rate of appreciation of the spot exchange rate on the lagged forward premium. The FRUH holds if the estimation gives zero constant, unity slope coefficient and serially uncorrelated residuals. While some studies have supported this hypothesis, a large number of studies have widely found the negative slope coefficient for the floating currencies, which violated the condition of the FRUH. This phenomenon is also known as the forward bias puzzle. Engle (1996b) conducted the survey to assess the validity of the unbiased hypothesis. He concluded that the models are unsuccessful in explaining the magnitude of the risk premium as they routinely reject the forward rate unbiased hypothesis. Moreover, in one of the most influential studies attempted to explain the forward bias puzzle, Fama (1984a) advocated that the rejection of FRUH could be due to the time-varying risk premium in which the speculators require higher excess return to compensate higher risk. Hence, the forward exchange rate is not a rational predictor of the corresponding spot rate (Bonga-Bonga, 2009). Other possible explanations of this rejection include irrational expectation (Froot and Frankel, 1989; Froot and Thaler, 1990), learning or peso problem (Lewis, 1989; Sachsida, Ellery and Teixeria, 2001), central bank interventions (McCallum, 1994; Ferreira, 2004) and econometric specification (Baillie and Bollerslev, 2000; and Maynard and Phillips, 2001). Given the unsuccessful explanation of the forward premium anomaly in a linear framework, some literatures have attempted to explain the existing anomaly employing nonlinear study (Sarno, Valente and Leon, 2004; Ballie and Kilic, 2006; Amri, 2008).

However, the justification for employing non-linear model are addressed through the empirical studies on the presence of transaction cost (see, Dumas, 1992; Sercu and Wu, 2000), the intervention of monetary authority (Mark and Moh, 2007) and the existence of limits to speculation hypothesis (Lyons, 2001). More specifically, Dumas (1992) developed a one good, two countries model in spatially separated markets with proportional transaction costs. He found that the speed of adjustment reverts nonlinearly toward the equilibrium and also depends on the extent of the deviation from purchasing power parity (Ballie and Killic, 2006). Moreover, Sercu and Wu (2000) showed that the transaction cost causes a bias in the forward premium regression (Ballie and Killic, 2006). The presence of transaction cost creates a band of inaction where traders will not engage in the market until the deviation is sufficiently large enough to offset these costs (McMillan, 2004). Furthermore, Mark and Moh (2007) investigated a continue-time model of UIP based on the idea that unanticipated central bank interventions might cause forward bias puzzle. Their empirical findings showed that the forward bias intensifies during periods in which the central banks are intervening (Mark and Moh, 2007). A more recent empirical study of Castro (2008) also indicated an increased usage of nonlinear models as the central banks appear to have asymmetric preference. This implied that the central banks tend to respond differently to the economic situations (i.e. bull or bear). In general, the relationship between spot and forward exchange rates is nonlinear due to a variable speed of adjustment toward the long run equilibrium (Taylor and Peel, 2000). This might occur because the investors would rather participate in large deviations than small deviations. The same reasoning applied to limits to speculation hypothesis of Lyons (2001) that investors will only participate in a specific trading strategy if the strategy yields a Sharpe ratio at least equal to an alternative trading strategy (Sarno, Valente and Leon, 2004). This implication creates a band of inaction where the small bias is not attractive to attract the capital. Thus, the forward bias does not imply profit opportunity and will persist until the forward bias becomes sufficiently large enough to attract capital.

In this study, we aim to test the forward rate unbiased hypothesis in Asian exchange rate markets under linear and nonlinear frameworks, utilizing monthly spot and forward exchange rates from 1997 to 2011, using 11 currencies. Our selected sample includes developed and developing economies. As previous findings of Frankel and Poowanala (2010) revealed that the forward bias in the emergent market was less severe than the industrialized market, our sample offers an opportunity to explore in this aspect. Thus, we also aim to investigate whether the small bias can be exploited.

Moreover, we expect that the forward bias in emerging currencies will persist longer than the major currencies. The persistence of this forward bias might indicate asymmetric behavior. Therefore, a smooth transition model is employed to capture this nonlinear adjustment behavior of the spot and forward exchange rates. This model allows the transition from one regime to another occurs smoothly and the transition variable being the forward premium can asymmetrically adjust. The goal of employing a logistic smooth transition model is to better understand the dynamics of the exchange rates. Firstly, the linear conventional Fama regression, the linear error correction model and the nonlinear logistic smooth transition model are used to estimate the spot and forward relationship. Secondly, Wald statistic is used to test whether the estimate slope coefficient is significantly different from the true theoretical value of one. Moreover, to ensure the robustness of the models, we also consider Q statistics of Ljung-box (1978) tests on residual and square residuals, no remaining nonlinearity test and parameter constancy test. Finally, we conduct some forecasting simulation to assess whether the future spot exchange rate is unpredictable under the assumption that the forward market is efficiently unbiased.

The remainder of this chapter is structured as follows. Section 4.2 provides the literature review on theoretical background and the previous studies on the forward rate unbiased hypothesis in both linear and nonlinear frameworks. The empirical models employed in this study are explained in section 4.3. In section 4.4, we discuss the data while section 4.5 reports the estimation results. Section 4.6 investigates the forecasting simulation and reports the forecasting performance. The conclusion is summarized in section 4.7.

4.2 Literature review

4.2.1 Uncover Interest Parity

In an efficient market, the foreign exchange market participants are efficient in exploiting information embedded in the forward exchange rate to predict the future spot rate, and it is impossible to earn excessive returns. This also implies that the forward rate is the unbiased predictor of the future exchange rate.

Empirically, the earliest literatures have employed a regression in level specification to test for the unbiased hypothesis. The level regression of the logarithm of the future spot exchange rate, s_{t+1}, on the logarithm of the current forward exchange rate, f_t.

$$s_{t+1} = a + bf_t + \varepsilon_{t+1} \tag{4.1}$$

The evidence supports the FRUH that the slope coefficient (*b*) is unity and constant (*a*) is zero (Cornell, 1977; Levich, 1979 and Frankel, 1980). Granger and Newbold (1974) pointed out that the tests on non stationary exchange rates in level specification could result in spurious regression (Messe and Singleton, 1982 and Meese, 1989). However, this is not true if these 2 non-stationary series are co-integrated. Specifically, if s_{t+1} and f_t from equation (4.1) are co-integrated with co-integrating vector (1, -1), the residual series (ε_{t+1}) is stationary or follows an *I*(0) process. OLS estimator will be super consistent for the true *b* equal to unity. However, the test is not efficient and yields the slope coefficient deviate from the true theoretical value of one in the finite samples (Zivot, 1998).

Moreover, the foreign market efficiency or FRUH is derived from the basis parity condition, which is the uncovered interest parity (UIP) and cover interest parity (CIP).

In the theory of UIP, the expected future rate of appreciation (depreciation) is equal to the interest rate differential, which is shown in equation (4.2).

$$E_t(\Delta s_{t+1}) = \left(i_{t,1} - i^*_{t,1}\right) \tag{4.2}$$

where $\Delta s_{t+1} = s_{t+1} - s_t$, $E_t(.)$ is the market expectation based on the information available at time *t*, $i_{t,1}$ and $i^*_{t,1}$ are the nominal interest rates available at 1 periods to maturity on domestic and foreign securities, respectively. Moreover, the theory of UIP states that the expected return or rate of appreciation on a currency equals the interest rate differential, or equivalently the forward premium (Sarno, Valente and Leon, 2004). Thus, testing UIP in the form of equation (4.2) is equivalent to testing CIP in terms of the relationship between spot and forward exchange rates under the assumption that foreign exchange market participants are rational and risk neutral. The CIP is $f^1_t - s_t = i_{t,1} - i^*_{t,1}$, where f^1_t is the logarithm of the 1-period forward rate. Hence, the popular method of testing UIP is in the form of the expected return or the rate of appreciation of spot rate equals the lagged forward premium (discount):

$$s_{t+1} - s_t = a + b(f_t - s_t) + e_{t+1} \tag{4.3}$$

The UIP or FRUH is tested based on the joint hypothesis b = 1 and a = 0 and e_{t+1} is serially uncorrelated. This difference specification became popular and widely used by a number of researchers (e.g. Fama, 1984a; Froot & Thaler, 1990; Baillie & Bollerslev, 2000; Bansal & Dahlquist, 2000 and Frankel & Poonawala, 2010). Following the previous literatures, we call equation (4.3) as the Fama regression.

Additionally, the Fama regression requires the forward discount to be stationary or *I*(0) process in order to balance the equation. Hence, s_t and f_t should be cointegrated with cointegrating vector of (1, -1). In contrast, Baillie (1989) argued that the Fama regression in difference specification is misspecified. He suggested that the vector auto regression needs to add error correction terms or lags of the forward discount.

In the co- integration framework, some previous literatures have found that the spot and forward exchange rates are cointegrated and the FRUH is rejected. Baillie and

Bollerslev (1989) were among the pioneers who employed the Engle and Granger two-step cointegration approach. The authors attempted to explain the information efficiency in the foreign exchange markets, which are GBP, DEM, FFR, ITL, CHF, JPY and CAD during March 1980 to January 1985. The finding of six stochastic trends implied that the weak form efficiency in the exchange rate market is violated. Moreover, the intercept and slope coefficients were respectively close to zero and one but not enough to make the FRUH hold. Moreover, Barnhart and Szakmary (1991) tested the FRUH using seemingly unrelated regression (SUR) on level, difference and error correction specifications. The results showed that the monthly spot and forward exchange rates from the U.K., Germany, Japan and Canada are co- integrated within the sample period 1974 and 1988. In general, the authors concluded that the error correction specification is superior to level and difference specifications in testing FRUH based on the distribution properties of the models even though the FRUH is rejected. Moreover, the possible cause of rejection is due to unstable estimated coefficients as the estimated slope coefficients became increasingly negative through time. This result indicates the anomaly. In addition, the authors also attempted to explain this anomaly by considering two methods. However, neither modeling the exchange rates as a function of central bank intervention nor modeling the excess returns to a world stock index give the validate explanation for the negative beta.

On the contrary, Crowder (1994) disputed that the existence of cointegrating vector in a system of exchange rates does not necessarily imply inefficiency. Alternatively, the author suggested that the stationary linear combination of cointegrated exchange rates may proxy for stationary and time varying forward risk premium. Crowder (1994) employed vector error correction model (VECM) on 3 major currencies, which are GBP, DEM and CAD from January 1974 to December 1991. The results exhibited two cointegrating vectors in a system of 3 exchange rates, which implied a stationary long run relationship governing their co-movement. Moreover, he used Augmented Dickey Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests to validate his null hypothesis that the error correction term is a proxy for the risk premium. As a result, the forward premium was found to be non-stationary, which indicated that the error correction property is not compatible to be the proxy for the risk premium.

Therefore, he concluded that the stationary linear combinations of exchange rate markets that have the cointegrating relation are indeed interpreted as evidence of inefficiency. Kan and Andreosso-O'Callaghan (2007) applied Johansen cointegration approach in the Asian Pacific region. Ten Asian Pacific currencies are tested for the market efficiency after the 1997 Asian crisis. The data covered the period 31 December 1996 to 15 May 2003. The results suggested some evidence of co-movement between spot and forward exchange rates. In the multivariate case, they found more than one cointegrating vector in this system. Hence, the findings suggested that the foreign exchange markets of the Asian Pacific region were inefficient. Moreover, the FRUH is rejected based on the Wald statistic. This result indicated the violation of the market efficiency in Asian Pacific currencies. In contrast to Crowder (1994), Kan and Andreosso-O'Callaghan (2007) found the forward premium was stationary based on ADF and PP unit root tests.

In contrast, some previous literature provided evidence of accepting the FRUH in the co-integration framework. Naka and Whitney (1995) examined the efficiency of 7 major currencies from January 1974 to April 1991 using three regressions in level, difference and ECM specifications. The ECM specification included the lagged of error correction term derived from the level regression of current spot rate on the previous period of forward rate. The findings suggested some evidence that both level and error correction specifications yielded the similar results in which the FRUH cannot be rejected. Whereas the difference specification rejected the FRUH, as the slope coefficients were found to be inconsistent over time. Moreover, Villanueva (2007) applied Gregory and Hansen (1996) cointegration methods that allow for endogenous breaks in intercept, slope and time trend, and Bai (1997)'s multiple breaks method. The monthly spot rate and 1-month forward rates of DM, JPY and GBP from January 1975 to March 2005 are analyzed. As a result, the cointegration with breaks regression yielded stationary co-integrating residuals and unitary slopes across regimes. Moreover, the forward premium regression estimated for subsamples identified by cointegration regression with breaks found short run unbiasedness in some regimes. Therefore, the FRUH held in both short-run and long-run when allowed for structural breaks. Villanueva (2007) highlighted that the forward premium being stationary or non-stationary might not be due to lack of co-integration in spot and forward exchange rates but caused by the structural breaks.

In summary, the empirical findings reported common results, which rejected UIP, FRUH and EMH regardless of choice of currencies and sample period. In fact, the forward bias puzzle is the widespread empirical finding that the estimate slope coefficient is not statistically different from zero and mostly close to negative unity. Froot and Thaler (1990) reported the average estimated beta across 75 published studies is -0.88. This implies that in bias forward exchange market, the traders can expect that the more the forward rate is at a premium (discount), the less prediction of the domestic currency to depreciate (appreciate). Similarly, under the theory of UIP, the more domestic interest rates exceed foreign interest rates, the more the tendency for the domestic currency to appreciate over the holding period and vice versa (Sarno, Valente and Leon, 2005).

4.2.2 The forward bias puzzle

A large number of empirical studies have been conducted to test whether the forward exchange rate is an unbiased predictor of the future spot exchange rate under the assumptions of risk neutrality and rational expectation in an efficient foreign exchange market. As mention before, the widespread findings indicated the rejection of the null hypothesis in which the beta coefficient is significantly less than unity and mostly negative. This failure is referred in the forward exchange rate literature as the forward bias puzzle. If the foreign exchange rate market is efficient, it should not be possible to generate anomaly returns through arbitrage in the forward market. Hence, the common finding of the forward bias also indicates that the foreign exchange market is inefficient. A number of reasons for the forward bias puzzle have been identified, which can be classified into 5 main groups. These include time-varying risk premium, irrational expectation, learning or peso problem, central bank interventions and econometric specification (Engle, 1996b; Bai and Mollickb, 2010).

4.2.2.1 Time-Varying Risk Premium

The first attempt to explain the forward bias puzzle is the time-varying risk premium.

Researchers assumed that investors are not risk-neutral; thus, risk-averse investors demand a risk premium as a compensation for holding foreign assets that are perceived to be riskier than domestic assets. In other words, investors require the future spot exchange rate to be lower than the forward exchange rate. The existence of a time-varying risk premium in the foreign exchange market has been accepted in the literatures that induce the deviation of forward rate from the future spot rate. Fama (1984a) first attempted to solve the forward bias puzzle. The author found a negative correlation between forward risk premium and expected future spot rate. The author also argued that the inconsistency of the forward discount is due to missing variable representing the risk premium. Moreover, Hodrick and Srivastava (1984) found conditional expectation of risk premium is a nonlinear function of the forward premium and the presence of heteroscedasticity in forecast errors. Additionally, Domowitz and Hakkio (1985) employed capital asset pricing model (CAPM) and autoregressive conditional heteroscedasticity (ARCH) to capture a time-varying risk premium. They found no correlation between a time-varying risk premium and the forward discount bias, which gave little favor to the existence of a time-varying risk premium. Moreover, Baillie and Bollerslev (2000) examined the German mark relative to US dollar based on a fractionally integrated GARCH in mean model. The findings suggested that small sample sizes and persistent autocorrelation of the forward premium are underlying the forward premium puzzle. Additionally, Roll and Yan (2000) suggested that the forward discount bias arises due to the spot rate, the forward rate and forward premium have no stationary time series.

4.2.2.2 Irrational Expectations

The second interpretation to explain the forward discount bias is due to irrational expectations by foreign exchange market participants. The rational expectation assumption does not hold if the traders can forecast and outperform the market on average based on the same information available at the time including past values that are expected to form the expectations. This indicated that the expectation errors in spot exchange rate and the forward discount are correlated. The researchers such as Froot and Frankel (1989) and Froot and Thaler (1990) have conducted the survey-based to measure the expectations regarding to forward discount bias in the foreign exchange market. For example, Froot and Frankel (1989) employed uncovered interest parity (UIP) regression based on the rational expectations. The result indicated that the variation of the forward discount is related to the expected depreciation, rather than a time varying risk premium.

4.2.2.3 Learning or Peso Problem

The next interpretation to account for the forward bias puzzle is learning or peso problem. A peso problem is the situation when a small probability of an event can cause a large effect in the foreign exchange market (Krasker, 1980). In other words, the investors have heterogeneous expectations toward the major policy shift that will occur in the prolonged period, which cause the depreciation or forward discount bias (Lewis, 1989; Evans and Lewis, 1995). Lewis (1989) suggested that the expectation error could be due to the investors rationally learn about the true market or learn about a new depreciation period that used to form expectations. Later, Evans and Lewis (1995) examined UIP regression and pointed out that the deviation from the UIP condition could be due to the peso problem occur in the prolonged period in which the expectation of future spot exchange rate is different from the forward exchange rate. Moreover, Sachsida, Ellery and Teixeria (2001) tested the significance of interception of spot and forward exchange rates in Brazil from 1984 to 1998. The researchers found the estimation of interception terms were highly significant during the period of 1994 to 1998, which indicated the possibility of the peso problem occurring in this period. In addition, Carvalho, Sachsida, Loureiro and Moreira (2004) investigated the foreign exchange rates in Argentina, Brazil, Chile and Mexico. They found the presence of peso problem in Brazil before floating regime period as the test yielded smaller intercept term during the flexible regime period of 1999 to 2001.

4.2.2.4 Central Bank intervention

Some researchers believe that the central bank intervention can be one of the main reasons causing the forward discount bias. Buying and selling foreign currency is a directly effective tool for the central bank to influence exchange rates. However, this policy intervention creates unanticipated changes in the prolonged period, which results in the deviation of forward market. McCallum (1994) studied the effect of interest rate as the monetary authorities' policy to foreign exchange rate movements. The author highlighted that the estimation of slope coefficient was possibly lower than unity as the policy intervention leaded to the joint determination of the expected depreciation and the interest rate differential. Even though the UIP condition held, McCallum (1994) still found negative slope. Extending McCallum's study, Chinn and Meredith (2004) and Ferreira (2004) also advocated that monetary policy actions induced bias in exchange rate markets. For example, Ferreira (2004) analyzed the forward discount bias in emerging countries by including inflation and output gap movement into McCallum (1994) study. Their results suggested that the forward bias occurred due to monetary policy actions. Moreover, Cavoli and Rajan (2006) tested the persistent deviation from the UIP condition during the pre financial crisis in 1997. The result indicated that the deviation from the UIP condition is marginally effected by large capital inflows to 5 East Asian countries. Hence, the authors concluded that the deviation of UIP condition which persisted during the pre-crisis period could be explained by the intervention of central banks.

4.2.2.5 Econometric Specification

Another stand of literature, such as Baillie and Bollersleve (2000) and Maynard and Phillips (2001) has identified econometric misspecification as the cause of forward discount bias. For example, Baillie and Bollerslev (2000) drew attention to factors such as small sample bias and high persistence in forward discount that possibly caused the deviation from the UIP condition. Baillie and Bollerslev (2000) found that the slope estimation is widely dispersed over different small sub-periods, which pointed out that the slope slowly converged to the true value of one. Hence, their findings could be seen as evidence of a statistical artifact, which induced the forward discount bias. Moreover, Maynard and Phillips (2001) estimated a stationary dependent variable on a near-unit root independent variable by OLS estimator. They found that the regression of stationary dependent variable on nonstationary fractionally integrated independent variable generated nonstandard limit distribution with long left tails (Choi and Zivot, 2007). This implied that the nonstandard limit distribution may induce slope coefficient to converge to zero in which explained the forward discount bias (Choi and Zivot, 2007). In addition, considering the structural breaks, Sakoulis and Zivot (2005) found that the forward discount is not persistent. Similarly, Choi and Zivot (2007) provided additional support that the forward discount bias is due to the statistical properties of the data. They found that the persistence in the forward discount is reduced when they estimated the long memory properties of the monthly forward discount series with structural breaks in mean.

In summary, the existence of literatures attempting to explain why the tests reject the FRUH and the UIP remains a highly controversial topic. As none of the studies regarding time-varying risk premium, irrational expectation, peso-problem and learning, central bank intervention and econometric specification has fully delivered validation for the forward discount puzzle.

4.2.3 Emerging markets

Recent studies such as Flood and Rose (2002), Jeon and Seo (2003), Frankel and Poonawala (2010) and Bai and Mollickb (2010) have addressed the presence of forward discount bias in emerging economies. Overall, the forward discount biases in emerging countries seem to be less severe than the developed countries, as reported by Frankel and Poonawala (2010).

Firstly, Flood and Rose (2002) examined 13 developed and 10 developing currencies using uncovered interest parity. The daily data of interest and foreign exchange rates were collected during the 1990s. Their findings showed that the interest differential bias in the crisis countries was smaller than the non-crisis countries regardless of developed or developing countries. Flood and Rose (2002) concluded that the UIP worked better during crisis periods as they found that the FRUH held during the crisis period while it was rejected in other periods.

Secondly, Jeon and Seo (2003) investigated the effect of the Asian financial crisis on foreign exchange market efficiency during January 1996 to February 2001. Daily spot exchange rates and 3, 6 and 9-month forward rates of Thailand, Indonesia, Malaysia and

South Korea were analyzed within and cross country exchange rates using the fully modified least square estimator and threshold co-integration. The authors divided their study into pre-crisis period, first post-crisis period and second post-crisis period. The cross-country efficiency analysis indicated no evidence of cointegration relationship in the system of 4 exchange rates in the full sample but not in the first post-crisis. This implied that the foreign exchange markets were generally efficient but inefficient during the 1997-98 Asian financial crisis. Moreover, the within country analysis showed no cointegration relationship between spot and forward exchange rates for Thailand and South Korea during the first sub-period of post-crisis. The FRUH also cannot be rejected in both THB and KRW, thus supporting the efficient market hypothesis. The slope coefficient was greater than 1 for the pre-crisis period while it was less than unity for the first post-crisis period and not different from the unity for the second post-crisis period. The results suggested that the efficiency of these two currencies was disturbed after the outbreak of the 1997-98 financial crisis where the foreign exchange markets were volatile during the first post-crisis period.

Thirdly, Frankel and Poonawala (2010) studied the forward exchange rate markets for 35 currencies, which consisted of 21 developed economies and 14 emerging economies. Monthly spot rates and 1-month forward rates from December 1996 to April 2004 were examined using the conventional OLS regression of difference specification, seemingly unrelated regression (SUR) and pooling regression. The slope coefficients for industrialized economies were significantly less than zero whereas the coefficients for emerging currencies were seldom significantly less than zero and often positive. Therefore, the results indicated that the forward discount was less biased for emerging currencies than the major currencies. The researchers also suggested that the stronger bias of major currencies might not be due to the forward risk premium.

Finally, Bai and Mollickb (2010) studied how two financial crises (the 1997 Asian currency crisis and the 2000 Turkish financial crisis) affected the forward discount bias in 14 emerging countries, which consisted of 8 Asian countries and 6 non-Asian countries. Monthly spot rate and one-month forward rates were collected from December 1996 to December 2007, which covered the two financial crises. Bai and

Mollickb (2010) employed error correction model to test for the FRUH. The authors tested for structural breaks in the different specifications as the financial crisis may cause structural breaks in which the regression might suffer from parameter instability. The authors employed several methods to test for the structure change. These include Hansen's (1992) unknown stability test, Andrews-Quandt (1993) one-time structural break test and Bai and Perron (1998, 2003) multiple structural break tests. The results indicated that 10 out of 14 countries rejected the FRUH. However, once taking into account for structural breaks, the FRUH holds during the crisis period for 7 out of 10 countries. Besides the FRUH holding during the financial crisis, the sign of slope coefficients for crisis countries, which were Indonesia, Malaysia, Thailand and Turkey, changed from negative to unity while the sign was unchanged for the non-crisis countries. Therefore, Bai and Mollickb (2010) concluded that the structural breaks associated with the financial crisis have more dominant effect on the forward discount bias than other structural breaks associated with government intervention or exogenous shocks.

4.2.4 Nonlinearity in the spot and forward relationship

The previous research analyzing the spot and forward relationship generally uses linear conventional approach. However, failure of uncover interest parity empirically might indicate that the spot and forward relationship might be characterized by nonlinearity. Several authors argue that the nonlinear relationship might be due to the presence of transaction cost (see, Dumas, 1992; Sercu and Wu, 2000), central bank intervention (see, Mark and Moh, 2007) and limits to speculation (Lyons, 2001; Sarno, Valente and Leon, 2004; and Ballie and Kilic, 2006).

The empirical study of Lyons (2001) examined the deviation of UIP in the currency market. The monthly data covers from January 1980 to December 1998 (including Deutsche Mark, Japanese Yen, UK Pound, Swiss Franc, French Franc and Canadian Dollar). The author proposed the "limits to speculation hypothesis" based on the idea that the financial institutions will only be interested in participated a currency trading strategy if the strategy yields a Sharpe ratio at least equal to an alternative investment strategy (Sarno, Valente and Leon, 2004). Thus, this implication creates a band of inaction where the forward bias is too small to attract capital. This bias will persist until it becomes large enough to generate a Shape ratio that better than an alternative investment strategy. Thus, a Sharpe ratio is used as a key factor to indicate the attractiveness of the investment strategy. Lyons (2001) reported the average Sharpe ratio for buy-and-hold equity strategy of 0.4[25]. If a Sharpe ratio is smaller than 0.4, this implies that an alternative strategy is riskier and not attractive to invest (Sarno, Valente and Leon, 2004). The uncover interest parity hypothesis is tested whether a = 0, b = 1 and zero Sharpe ratio. A Sharpe ratio becomes nonzero when the slope coefficient deviates from unity. Lyons pointed out that a band of inaction occurs when the variation of slope coefficient is between -1 and 3. This finding showed that the forward bias and a Sharpe ratio are too small to attract speculative capital within this band. Hence, the financial institutions would have no incentive to take up the currency strategy since a buy-and-hold equity strategy would yield a higher return per unit of risk (Sarno, Valente and Leon, 2004). This finding also indicated that the equilibrium adjustment between the spot and forward relationship is not symmetric or linear and can be seen as evidence of nonlinear and asymmetric adjustment in the foreign exchange market (Baille and Kilic, 2006).

Moreover, Sarno, Valente and Leon (2004) tested the limits to speculation hypothesis of Lyons (2001) by employing exponential smooth transition regression (ESTR) with the excess return as the transition variable[26]. Spot and forward exchange rates at 1- and 3-month maturity are examined including the Japanese yen, the UK sterling, the German mark, the Euro and the Swiss franc from January 1985 to December 2002. These 5 major currencies are relative to US dollar. The authors found strong evidence of nonlinearity in spot and forward relationship. In particular, the authors found small Sharpe ratio associated to small forward bias, which violated the UIP condition. The finding suggested that even though the persistent forward bias is statistically significant,

[25] The Sharpe ratio is defined as $\frac{E[R_s] - R_f}{\sigma_s}$, where $E[R_s]$ is the expected return on the strategy, R_f is the risk free interest rate and the different between expected return and risk free interest rate is divided by the standard deviation of the return to the strategy (σ_s).

[26] In Sarno, Valente and Leon (2004), the transition variable has been standardized by dividing it by the sample variance of the transition variable as recommended by Granger and Terasvirta (1993) and Terasvirta (1994, 1998). Hence, the excess return became Sharpe ratio.

it is too small and not profitable. In contrast, when a Sharpe ratio is substantially large, the financial institutions would take up the profit opportunities. This action induces the spot and forward relationship to rapidly revert toward the UIP condition. Moreover, the finding also indicated that the UIP does not hold all the time, which is due to the investor ignored to exploit the uneconomically small forward bias. The result implied that on average, the exchange rates have been close to the UIP equilibrium. Thus, the authors concluded that the prior literatures have rejected the UIP in a linear framework is statistically rather than economically. It also cannot be concluded that neither the UIP does not hold at all nor the market is inefficient (Sarno et al, 2004).

In addition, the empirical study of Baillie and Kilic (2006) also employed nonlinear smooth transition model to test the UIP condition in spot and forward market. In contrast to Sarno et al (2004), Baillie and Kilic (2006) used logistic function with risk adjusted forward premium as the transition variable. The monthly spot and forward exchange rates are collected from December 1978 to December 1998. These included Belgian Franc, Canadian Dollar, Dutch Guilder, French Franc, German Mark, Italian Lira, Japanese Yen, Swiss Franc and UK pound. Similar to the previous literature, the authors found nonlinearity relationship in the spot and forward market. The main finding of Baillie and Kilic (2006) was that the large forward premium tends to occur in the upper regime where the UIP condition is more likely to hold while the forward discount (small and/or negative value) appears in the lower regime where the anomaly is more likely to occur. In particular, the result showed negative estimated β_1 and large and positive estimated β_2. The authors also advocated that the transaction costs and the presence of limits to speculation could induce the forward premium anomaly.

Similarly, Amri (2008) applied nonlinear least square to estimate logistic smooth transition model with the risk adjusted forward premium as the transition variable[27]. The weekly spot rate and forward exchange rates at 3-month and 6-month maturities are analyzed. The data included Sterling pound from the period 1982 to 2007, Swedish crown, Euro and Canadian dollar from the period 1990 to 2007 and the Swiss franc for

[27] Risk adjusted forward premium is the forward premium is divided by its standard deviation.

the period 1972 to 2007. The results confirmed the previous findings and showed the existence of nonlinear relationship capturing the spot and forward exchange rates.

Furthermore, the recent empirical study of Bonga-Bonga (2009) has been investigated nonlinearity in the emergent currencies. Bonga-Bonga (2009) tested the forward rate unbiased hypothesis between monthly Rand-US dollar spot and forward exchange rates in linear and nonlinear frameworks covering the period from January 1994 to August 2008. The period from January 1994 to November 2006 is used for estimation while the period from December 2006 to August 2008 is used for out-of-sample forecast. Based on linear estimation, the FRUH is rejected as the estimated slope is significantly different from unity and nonzero constant. Moreover, the cumulative sum of the recursive residual (CUSUM) test also indicated that the constant and slope estimated by the linear regression are not stable. This finding indicated that the relationship between the spot and forward rates is indeed nonlinear. In addition, Bonga-Bonga used logistic smooth transition regression (conducted in level) with the lagged forward premium as the transition variable. As a result, the author found nonlinearity relationship in this market. In contrast to the empirical finding of Baillie and Kilic (2006), Bonga-Bonga (2009) found that the FRUH cannot be rejected in the lower regime as the transition variable moves toward zero. In particular, the estimated slope of forward rate is 1.00345 with the transition function is zero. This result indicated that the FRUH held for negative forward premium in Rand currency. The out-of-sample forecast also confirmed that the LSTR is appropriated to use in this currency. As a result, the LSTR outperformed the linear OLS regression and the random walk model in one-month-ahead.

4.3 Empirical framework

Linear and nonlinear models are used to investigate the relationship between spot and forward exchange rates. In the linear framework, we apply two conventional regressions, which are estimated in a difference specification and error correction specification. Firstly, the conventional regression in difference specification or Fama regression is to equate the spot return (Δs_{t+1}) on the lagged forward discount $(f_t - s_t)$ or forward premium (the forward discount is obtained when the spread $(f_t < s_t)$ is negative while the forward premium when the spread $(f_t > s_t)$ is positive). Moreover, the second approach is based on the error correction model, which equates the spot return on the lagged disequilibrium term. In addition, our data sample covers key financial events, which are the 1997-98 Asian financial crisis and the subprime crisis, in which these events could have caused a structural break in our time series. Thus, the linear conventional regressions might suffer from parameter instability (Bai and Mollickb, 2010). Hence, we attempt to estimate the linear regression in smaller subsamples, which are divided according to the financial events. Furthermore, in nonlinear framework, we apply smooth transition regressions to examine whether the relationship is better explained by nonlinear model.

4.3.1 Conventional Regression

Firstly, the order of integration of spot and forward rate is determined using 3 different unit root tests: (i) Augmented Dickey Fuller (ADF), (ii) Phillip-Perron (PP) unit root test of the null hypothesis of nonstationary, (iii) Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test of the null hypothesis of stationarity.

Secondly, we employ 2 conventional regressions for Asian spot and forward exchange rates. The forward discount bias is tested as:

i) Difference specification

$$s_{t+1} - s_t = a + b(f_t - s_t) + e_{t+1} \tag{4.4}$$

The change in the spot rate $(s_{t+1} - s_t)$ is widely found stationary in the literature and e_{t+1} follows the white noise process, which is also stationary. Therefore, the forward discount must also be stationary in order to meet the time series property. Thus, we apply ADF, PP and KPSS unit root tests to detect the unit root in forward discount series. Based on Wald statistic, the forward rate unbiased hypothesis cannot be rejected under the restriction $a = 0 \text{ and } b = 1$.

ii) Error correction specification

The error correction specification is presented as follows:

$$s_{t+1} - s_t = a + b(f_t - \beta s_t)\left\{\sum_{i=1}^{k-1} \delta_{st}\Delta s_{t-i+1} + \sum_{i=1}^{k-1} \delta_{ft}\Delta f_{t+i-1}\right\} + u_{t+1} \tag{4.5}$$

where k is the number of lags. Equation (4.5) collapses to the original difference regression if k = 1 and β = 1. The change in the spot rate is regressed on the lag stationary residual $[\varepsilon_{t+1} or\ (f_t - \beta s_t)]$ series obtained from level specification ($s_{t+1} = a + bf_t + \varepsilon_{t+1}$) and the lags of the change in spot and forward exchange rates. We select the optimal lags based on Akaike information criterion. Similarly, the FRUH cannot be rejected if $a = 0\ and\ b = 1$, based on Wald statistics.

4.3.2 Logistic Smooth Transition Regression

One of the causes of the forward biased anomaly could be due to the fact of using linear approximation when the data exhibits nonlinearity (Alper, Ardic and Fendoglu, 2007). Moreover, the presence of transaction cost and monetary intervention create a band of inaction. Also, the limits to speculation hypothesis by Lyons (2001) suggest a band of inaction where the investor has been on hold until the forward bias becomes large enough to generate a Sharpe ratio that better than an alternative investment strategy. This finding is confirmed by previous empirical studies of Sarno, Valente and Leon (2004) and Ballie and Kilic (2006), who employed smooth transition regression on major currencies. Therefore, we employ logistic smooth transition model to capture nonlinearity and overcome the possibility of structural break in Asian currencies.

The logistic smooth transition regression (LSTR) is

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_{t,1} - s_t)][1 - F(z_t;\gamma,c)] + [\alpha_2 + \beta_2(f_{t,1} - s_t)]F(z_t;\gamma,c) + u_{t+1} \tag{4.6}$$

where u_{t+1} is a zero mean, stationary disturbance term, $F(z_t;\gamma,c)$ is the transition function, which determines the degree of reversion of the deviations from UIP. The logistic function is written as follow

$$F(z_t;\gamma,c) = \left(1 + exp(-\gamma(z_t - c))\right)^{-1} \text{, with } \gamma > 0, \tag{4.7}$$

where z_t is the transition variable, which is the lagged forward premium $(f_{t,1} - s_t)$ in this context, c is a location parameter or threshold variable and γ is a transition parameter governing the speed of adjustment to UIP, which is restricted to be greater than zero. As z_t increases, the logistic function changes monotonically from 0 to 1. When $\gamma = 0$, $F(z_t;\gamma,c) = 0.5$ for all transition variable, the LSTR model reduces to a linear dynamic model with parameters $\alpha = \alpha_1 + 0.5\alpha_2$, and $\beta = \beta_1 + 0.5\beta_2$. While the LSTR model becomes a threshold model when $\gamma \to \infty$. The lower the absolute values of γ, the slower the speed of transition between the two extreme regimes. The logistic function in (4.7) is bonded to be 0 and 1, which corresponds to the two extreme values and this can be summarized in the table below[28].

Regimes	**Transition function $F(z_t;\gamma,c)$**	**Transition variable (z_t)**	**UIP condition**
Upper	➔ 1	∞	Hold
Inner	= 0.5	c	Transition regime between 2 extreme regimes
Lower	➔ 0	$-\infty$	Reject

Similar to the linear framework, the Wald test is used to test the FRUH in each regime. Thus, the FRUH cannot be rejected if α = 0 and β = 1. As shown in the table above, the empirical finding of Baillie and Kilic (2006) suggests that the UIP (and FRUH) is more likely to hold in the upper regime where the transition function is approaching one while

[28] This table shows the empirical finding of Baillie and Kilic (2006) using logistic smooth transition model to test the UIP condition in major currencies.

the transition variable is approaching infinity. On the other hand, the UIP is more likely to reject as the transition function and transition variable is approaching zero and negative infinity, respectively. Therefore, the forward bias anomaly tends to occur in the lower regime. In this study, we estimate the LSTR model by using maximum likelihood estimation (MLE)[29].

4.4 Data

The forward rate unbiased hypothesis has been investigated extensively in major currencies such as British pound, Canadian dollar, German mark, French franc, Italian lira and Japanese yen using linear and nonlinear models. However, limited numbers of studies have studied in Asian currencies, especially the emerging economies. Therefore, it is our aim to examine the FRUH in Asian countries. Also, we aim to examine whether the forward bias of emerging Asian country is less pronounced than the advanced country as Frankel and Poonawala (2010) previously found.

The monthly spot exchange rates and corresponding one-month forward exchange rate for 11 Asian currencies (including both emerging and advanced countries) are obtained from DataStream. The utilized currencies are Chinese yuan (CYN), Hong Kong dollar (HKD), Indian rupee (INR), Indonesian rupiah (IDR), Japanese yen (JPY), South Korean won (KRW), Malaysian ringgit (MYR), Philippines peso (PHP), Singapore dollar (SGD), Taiwanese new dollar (TWN) and Thai baht (THB). The currencies are transformed into logarithm form relative to U.S dollar. The summary statistics of 11 Asian currencies are reported in table 4.1. The summary statistics show that, on average, the spot exchange rate is approximately close to the associated forward exchange rate. Moreover, JPY, KRW, MYR, PHP, SGD and THB have the standard deviation in the range of 0.1 while HKD, CNY, INR and TWN appear to have the smallest standard deviation. In addition, the mean of spot return and forward premium is approximately close to zero for all currencies. In particular, the mean of spot return is negative for CNY, JPY, KRW and SGD while the mean of forward premium is also negative for CNY, HKD, JPY, SGD and TWN.

[29] The LSTR is estimated using a Gauss econometric software package.

The total observations are 174, with a sample size of from 30 January 1997 to 30 September 2011, excluding for INR (data was available from 30 October 1998 to 30 September 2011), KRW (data was available from 30 February 2002 to 30 September 2005) and CYN & MYR (data was available from 30 July 2005 to 30 September 2011)[30]. In the linear framework, we also divide the sample into 4 sub-periods in order to investigate the effect of key financial events (i.e. 1997 Asian crisis and subprime crisis) that would affect the forward bias and to avoid the issue of structural breaks that would alter our estimated results. In table 4.2, the first sub-period is the Asian crisis (AC) covers the period from 01/1997 to 12/1998. The second sub-period is post Asian crisis (PAC) from 01/1999 to 12/2007 where currencies are recovering from the financial crisis. Next, the third sub-period is from 01/2008 to 12/2009 where the economies are in recession due to subprime crisis (SUB). The fourth sub-period is post subprime (PSUB) from 01/2010 to 09/2011.

[30] Malaysian ringgit is temporary fixed exchange rate from 1 September 1998 to 21 July 2005 due to the hit of 1997-98 Asian financial crises. For the robustness of the estimation, MYR is used from 07/2005 to 09/2011.

Table 4.1: Summary Statistics of the Exchange rates								
Currencies	Spot Rate				1-month Forward Rate			
	Mean	Max	Min	SD	Mean	Max	Min	SD
CNY	2.02	2.11	1.85	0.09	2.02	2.11	1.85	0.09
HKD	2.05	2.06	2.05	0.00	2.05	0.06	2.05	0.00
IDR	9.05	9.60	7.77	0.32	9.05	9.64	7.78	0.31
INR	3.80	3.94	3.59	0.06	3.81	3.94	3.59	0.07
JPY	4.70	4.97	4.34	0.13	4.70	4.96	4.34	0.13
KRW	7.01	7.34	6.81	0.12	7.01	7.33	6.81	0.12
MYR	1.29	1.69	0.91	0.13	1.29	1.69	0.91	0.13
PHP	3.83	4.03	3.27	0.17	3.84	4.04	3.27	0.17
SGD	0.46	0.62	0.19	0.11	0.46	0.62	0.19	0.11
THB	3.62	3.97	3.22	0.14	3.62	3.97	3.26	0.14
TWN	3.48	3.56	3.31	0.06	3.47	3.56	3.31	0.06
	Spot return				Forward premium			
CNY	-0.0023	0.0041	-0.0209	0.0042	-0.0017	0.0066	-0.0122	0.0029
HKD	0.0000	0.0045	-0.0071	0.0013	-0.0000	0.0115	-0.0018	0.0014
IDR	0.0074	0.6340	-0.3421	0.0863	0.0043	0.1119	-0.1743	0.0316
INR	0.0014	0.0667	-0.0601	0.0173	0.0028	0.0102	-0.0018	0.0019
JPY	-0.0023	0.0857	-0.1554	0.0309	-0.0027	-9 e-05	-0.0059	0.0018
KRW	-0.0010	0.1615	-0.1538	0.0377	0.0007	0.0034	-0.0089	0.0018
MYR	0.0014	0.3569	-0.1338	0.0397	0.0006	0.0156	-0.0032	0.0024
PHP	0.0029	0.1421	-0.0809	0.0281	0.0042	0.0042	-0.0003	0.0032
SGD	-0.0004	0.0774	-0.0575	0.0183	-0.0009	0.0110	-0.0037	0.0015
THB	0.0010	0.2113	-0.2020	0.0363	0.0021	0.0451	-0.0020	0.0049
TWN	0.0006	0.0786	-0.0597	0.0173	-0.0008	0.0100	-0.0090	0.0028

Note that the monthly spot and corresponding forward exchange rates are expressed as dollars per unit of foreign exchange rate and the data is converted into logarithm form. The currencies employed in this study including Chinese yaun (CNY), Kong Kong dollar (HKD), Indian rupee (INR), Indonesian rupiah (IDR), Japanese yen (JPY), South Korean won (KRW), Malaysian ringgit (MYR), Philippines peso (PHP), Singapore dollar (SGD), Taiwanese new dollar (TWN) and Thai baht (THB). Mean, max, min and SD represent an average, maximum, minimum and standard deviation, respectively

Table 4.2: Sub-sample Periods		
Sample Periods	**Date**	**No. of Observations**
Full sample	30 January 1997 – 30 September 2011	174
Asian Crisis (AC)	30 January 1997 – 30 December 1998	22
Post Asian Crisis (PAC)	30 January 1999 – 30 December 2007	107
Subprime (SUB)	30 January 2008 – 30 December 2009	23
Post Subprime (PSUB)	30 January 2010 – 30 September 2011	19

4.5 Empirical results

In this section, the empirical findings will be analyzed including a preliminary exercise to determine the structure of the currencies and the forward rate unbiased hypothesis being tested in linear and nonlinear setting.

4.5.1 Data plot and unit root test

In our preliminary exercise, we examine the structure of the series in which the spot and forward exchange rates are required to be cointegrated. Firstly, we plot the spot and forward exchange rates and the forward discount series to illustrate the characteristics of the series. Secondly, 3 unit root tests are implemented to detect nonstationarity in the series.

4.5.1.1 Data plot

The spot exchange rate (s_t), forward exchange rate (f_t) and the forward discount $(f_t - s_t)$ of 11 Asian currencies are illustrated in figure 4.1 and 4.2, respectively[31].

In figure 4.1, from a visual inspection of the monthly spot and forward exchange rates generally exhibits nonstationary process with a large spike during the 1997-98 Asian financial crises excluding China (CYN) and South Korea (KRW) where the data was only limited. Moreover, the plots of spot and forward exchange rate series also indicate

[31] The visual inspections of CNY and MYR have shown the full sample observation to give an overview of the series. However, the data of these two currencies are discarded the fixed exchange rate period in estimation section.

a large spike surrounding the subprime crisis in 2007 and 2008 for India (INR) and South Korea (KRW). Additionally, all currencies closely follow each other except for Hong Kong (HKD) where the forward exchange rate clearly deviates during the 1997-1998 period.

In contrast to the spot and forward exchange rate series, the forward discount series in figure 4.2 illustrate stationary process for all currencies except for India (INR), Japan (JPY) and the Philippines (PHP). The visual illustration indicates a clearer picture of extreme deviation associated with the 1997-98 Asian financial crisis (HKD, INR, MYR, PHP, SGD, TWN and THB) and 2007-08 Subprime crisis (CYN, INR, JPY and KRW).

Figure 4.1: spot and forward exchange rates

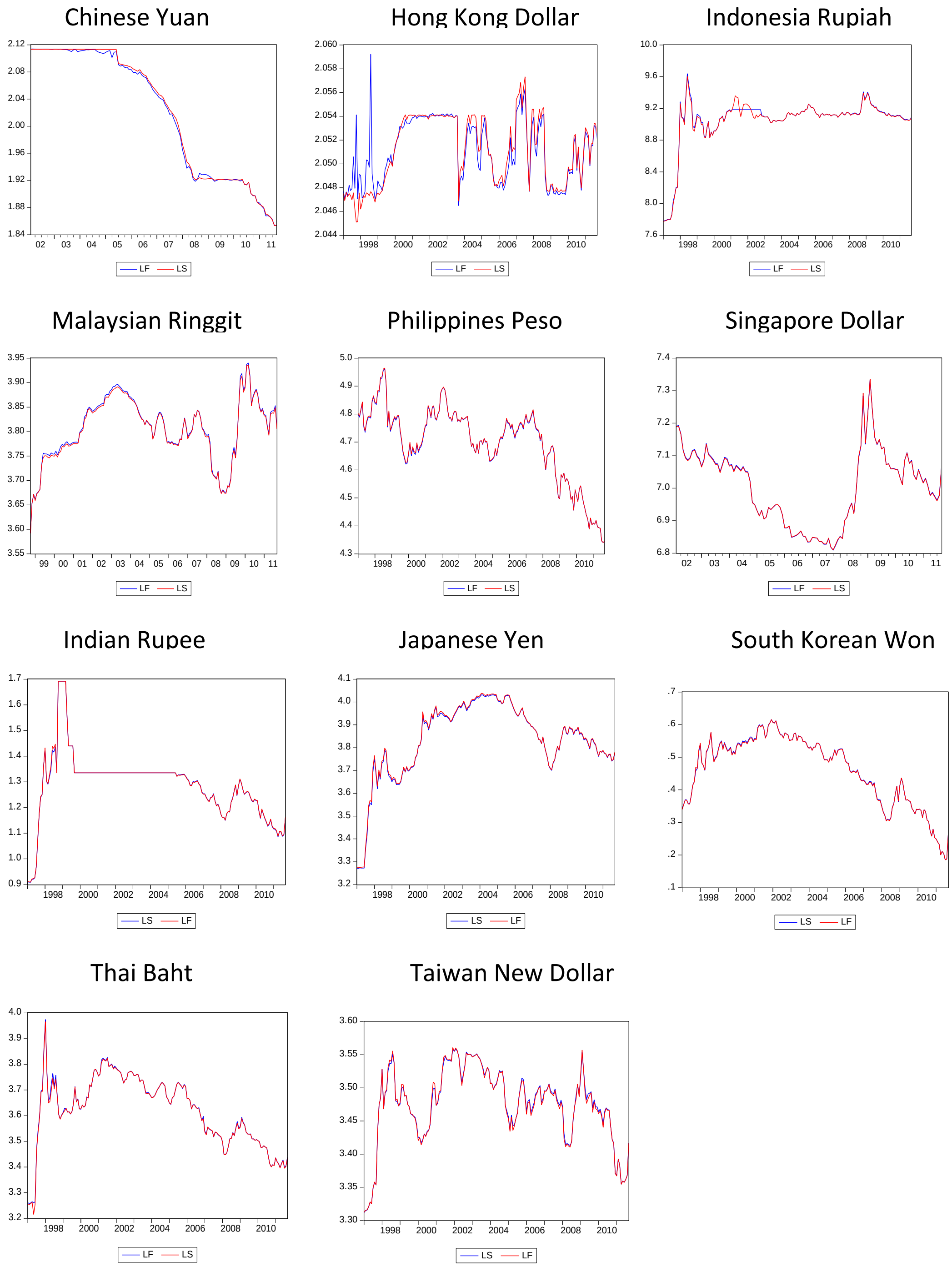
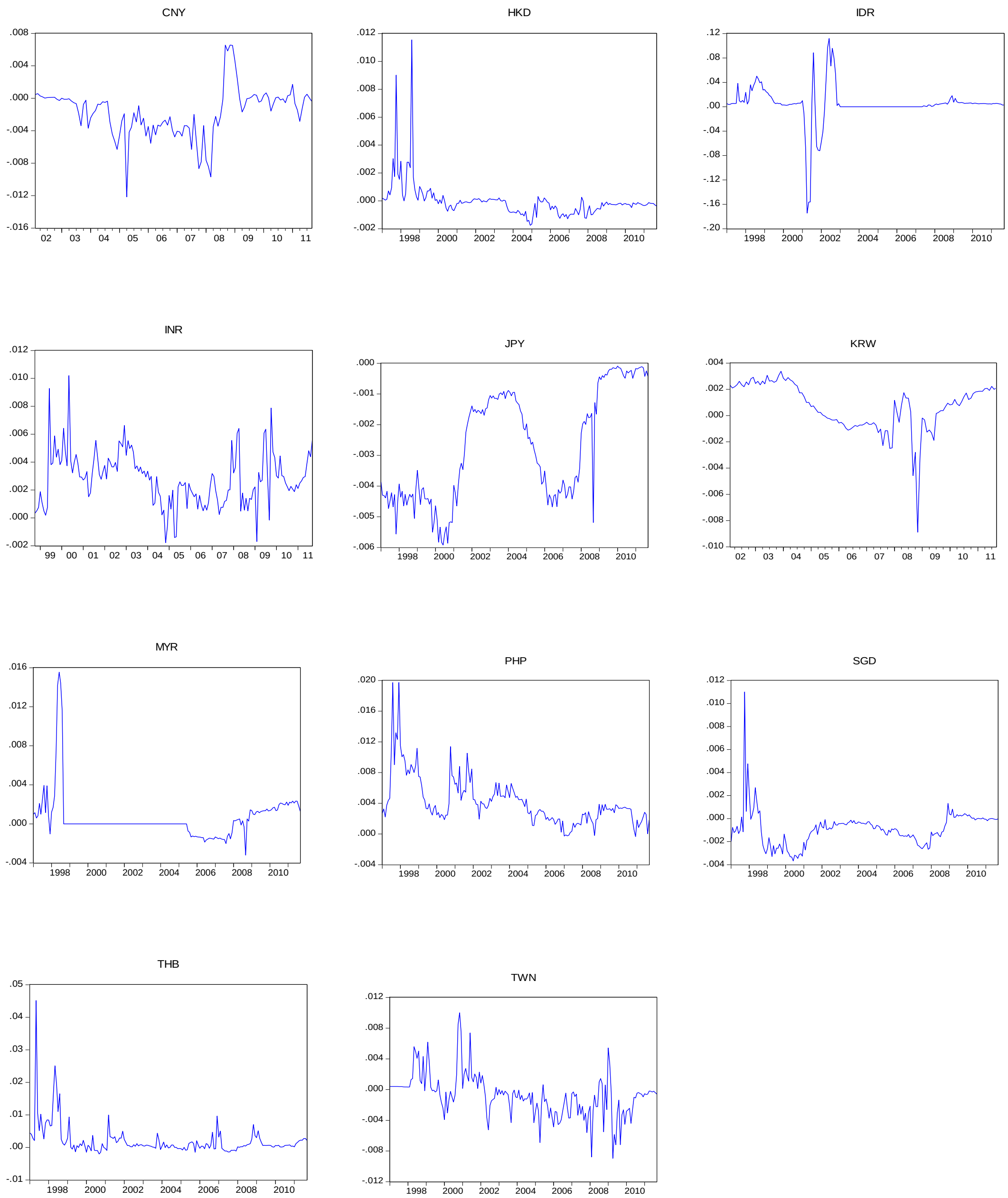


Figure 4.2: Forward discount



4.5.1.2 Unit root tests

In table 4.3, the unit root tests for the spot exchange rate (panel A) and the forward exchange rate (panel B) of all 11 Asian currencies are reported using ADF, PP and KPSS. The result shows that the unit root tests cannot reject the presence of unit root in the full-sample period for 5 currencies where at least 2 out of 3 unit root tests yield the same result. This implies that spot and forward rates of CNY, JPY, KRW, SGD and THB are nonstationary. Moreover, in subsample periods, the unit root tests are significant, which indicate no presence of unit roots for JPY, KRW, SGD and THB. Whereas, the spot and forward exchange rates namely HKD, IDR, MYR, PHP and TWN are stationary in the full sample and subsamples, except the unit roots tests of INR, which exhibits nonstationarity in subsamples. This result might indicate the presence of a structural break; that might cause a rejection of the unit root hypothesis in the full sample.

In addition, table 4.4 presents the unit root test results of spot return in panel A and forward discount in panel B. The finding indicates that the spot return is significant at 1% level in all cases, which shows that the series are stationary. In panel B, the forward premium or discount is highly significant for 7 currencies and 2 currencies are marginally significant in the full sample and some subsamples. Excluding JPY and TWN, the forward premium is not significant in the full sample but appears to be stationary in some subsample periods. In addition, the results indicate that the forward discount becomes nonstationary during the 1997-98 Asian financial crises (6 currencies) and subprime crisis (8 currencies) as the ADF test is not significant at 5%. This implies that the key financial events might alter the stationarity of the forward discount in emerging markets.

In general, we find only 5 spot and forward rate series follow $I(1)$ process. The currencies include CNY, JPY, KRW, SGD and THB. Thus, only 5 currencies are appropriated to model using logistic smooth transition model.

Table 4.3: Unit Roots Test Results on Spot and Forward Exchange Rates

Panel A: Spot Exchange Rates

ADF	Spot										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	0.23	-2.85 *	-4.35 ***	-2.83 *	0.13	-2.08	-2.97 **	-3.76 ***	-0.67	-3.07 **	-3.36 **
AC	-	-6.15 ***	-3.55 **	-	-4.62 ***	-	-5.61 ***	-3.94 ***	-4.05 ***	-3.40 **	-4.49 ***
PAC	5.61	-9.71 ***	-7.78 ***	-1.95	-9.26 ***	-3.81 ***	-7.32 ***	-4.24 ***	-10.38 ***	-5.03 ***	-8.11 ***
SUB	-7.16 ***	-3.86 ***	-3.85 ***	-0.32	-4.33 ***	-5.43 ***	-3.41 **	-4.24 ***	-4.28 ***	-3.92 ***	-3.78 ***
PSUB	1.24	-3.79 **	-4.01 ***	-4.21 ***	-4.96 ***	-3.11 **	-3.68 **	-4.18 ***	-3.22 **	-3.44 **	-2.97 *

PP	Spot										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	0.90	-3.00 **	-4.19 ***	-3.39 **	-0.53	-2.09	-3.15 **	-3.61 ***	-0.72	-2.69 *	-3.03 **
AC	-	-8.35 ***	-3.46 **	-	-4.62 ***	-	-5.84 ***	-3.95 ***	-4.03 ***	-3.30 **	-4.50 ***
PAC	5.54	-10.24 ***	-10.63 ***	-7.74 ***	-9.26 ***	-7.39 ***	-7.17 ***	-9.54 ***	-10.38 ***	-9.90 ***	-7.86 ***
SUB	-11.94 ***	-3.75 **	-3.82 ***	-2.46	-4.31 ***	-5.44 ***	-3.41 **	-4.23 ***	-4.28 ***	-3.89 ***	-3.72 **
PSUB	1.48	-5.57 ***	-3.89 ***	-3.81 **	-4.99 ***	-2.59	-2.93 *	-4.26 ***	-2.95 *	-3.20 **	-2.91 *

KPSS	Spot										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	1.19 ***	0.26	0.53 **	0.20	1.07 ***	0.21	0.44 *	0.57 **	1.07 ***	0.68 **	0.26
AC	-	0.50 **	0.19	-	0.19	-	0.12	0.24	0.13	0.28	0.26
PAC	0.69 **	0.12	0.06	0.55 **	0.06	0.09	0.32	1.01 ***	0.54 **	0.54 **	0.09 ***
SUB	0.48 ***	0.13	0.17	0.48 **	0.09	0.31	0.26	0.42 *	0.14	0.14	0.14
PSUB	0.62 ***	0.27	0.23	0.16	0.08	0.17	0.38	0.31	0.23	0.29	0.20

Note that the Augmented Dickey Fuller (ADF), Phillip-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests are reported in statistic where ***, **, * indicate the statistical significance at the 1%, 5% and 10% level, respectively. The data includes Chinese yuan (CNY), Hong Kong dollar (HKD), Indonesian rupee (IDR), Indian rupiah (INR), Japanese yen (JPY), South Korean won (KRW), Malaysian riggit (MYR), Philippines peso (PHP), Singapore dollar (SGD), Thai baht (THB) and Taiwanese new dollar (TWN). The sample period is divided into Asian crisis (AC), post Asian crisis (PAC), subprime crisis (SUB) and post subprime crisis (PSUB).

Table 4.3: Continued

Panel B: 1-month Forward Exchange Rates

ADF	Forward										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	0.23	-4.92 ***	-4.46 ***	-3.40 **	0.12	-2.02	-2.92 **	-3.77 ***	-0.71	-3.03 **	-3.36 **
AC	-	-8.21 ***	-3.59 **	-	-4.60 ***	-	-5.71 ***	-3.91 ***	-4.26 ***	-3.50 **	-4.49 ***
PAC	4.82	-10.16 ***	-4.34 ***	-7.36 ***	-9.25 ***	-3.81 ***	-7.32 ***	-4.28 ***	-10.41 ***	-5.14 ***	-8.11 ***
SUB	-4.17 ***	-4.08 ***	-3.75 **	-0.26	-4.29 ***	-5.37 ***	-4.37 ***	-4.33 ***	-4.21 ***	-3.99 ***	-3.78 ***
PSUB	1.07	-3.66 **	-4.08 ***	-4.06 ***	-4.96 ***	-3.12 **	-4.37 ***	-4.11 ***	-3.23 **	-3.42 **	-2.97 *

PP	Forward										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	0.91	-4.68 ***	-4.22 ***	-3.41 **	-0.55	-2.08	-3.15 **	-3.62 ***	-0.77	-2.69 *	-3.03 **
AC	-	-9.52 ***	-3.51 **	-	-4.60 ***	-	-6.11 ***	-3.91 ***	-4.25 ***	-3.44 **	-4.50 ***
PAC	10.93	-10.87 ***	-11.97 ***	-7.43 ***	-9.26 ***	-7.38 ***	-7.17 ***	-9.77 ***	-10.42 ***	-10.34 ***	-7.86 ***
SUB	-6.19 ***	-4.02 ***	-3.71 **	-2.40	-4.28 ***	-5.37 ***	-4.36 ***	-4.32 ***	-4.20 ***	-3.95 ***	-3.72 **
PSUB	1.60	-5.70 ***	-3.94 ***	-3.74 **	-4.99 ***	-2.61	-4.36 ***	-4.27 ***	-2.95 *	-3.18 **	-2.91 *

KPSS	Forward										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	1.19 ***	0.21	0.53 **	0.19	1.07 ***	0.22	0.44 *	0.56 **	1.07 ***	0.69 **	0.26
AC	-	0.18	0.19	-	0.19	-	0.13	0.24	0.14	0.29	0.26
PAC	0.69 **	0.14	0.05	0.70 **	0.06	0.09	0.32	0.96 ***	0.55 **	0.49 **	0.09
SUB	0.51 **	0.11	0.17	0.48 **	0.09	0.32	0.17	0.42 *	0.14	0.17	0.14
PSUB	0.62 **	0.27	0.23	0.15	0.08	0.17	0.17	0.29	0.23	0.29	0.20

Note that the Augmented Dickey Fuller (ADF), Phillip-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests are reported in statistic where ***, **, * indicate the statistical significance at the 1%, 5% and 10% level, respectively. The data includes Chinese yuan (CNY), Hong Kong dollar (HKD), Indonesian rupee (IDR), Indian rupiah (INR), Japanese yen (JPY), South Korean won (KRW), Malaysian riggit (MYR), Philippines peso (PHP), Singapore dollar (SGD), Thai baht (THB) and Taiwanese new dollar (TWN). The sample period is divided into Asian crisis (AC), post Asian crisis (PAC), subprime crisis (SUB) and post subprime crisis (PSUB).

Table 4.4: Unit Roots Test Results on Spot Returns (Δs_{t+1}) and Forward Discount $(f_t - s_t)$

Panel A: Spot Returns

ADF	Spot Return										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	-3.02 **	-9.54 ***	-5.76 ***	-4.57 ***	-7.29 ***	-5.23 ***	-4.52 ***	-4.19 ***	-11.63 ***	-5.81 ***	-10.9 ***
AC	-	-6.15 ***	-3.55 **	-4.26 ***	-4.62 ***	-	-5.61 ***	-3.94 ***	-4.05 ***	-3.47 **	-4.49 ***
PAC	-6.07 ***	-9.71 ***	-7.78 ***	-8.65 ***	-9.26 ***	-3.81 ***	-7.32 ***	-4.24 ***	-10.38 ***	-9.75 ***	-7.95 ***
SUB	-1.88	-3.86 ***	-3.85 ***	-1.24	-4.33 ***	-5.43 ***	-4.38 ***	-4.24 ***	-4.28 ***	-3.92 ***	-3.52 **
PSUB	-4.46 ***	-3.79 **	-4.01 ***	-3.78 **	-4.96 ***	-3.11 **	-3.68 **	-4.18 ***	-3.22 **	-2.93 *	-2.92 *

PP	Spot Return										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	-8.11 ***	-14.50 ***	-10.44 ***	-12.7 ***	-13.3 ***	-11.11 ***	-12.91 ***	-11.6 ***	-11.54 ***	-10.38 ***	-10.91 ***
AC	-	-8.35 ***	-3.46 **	-4.29 ***	-4.62 ***	-	-5.84 ***	-3.95 ***	-4.03 ***	-3.47 **	-4.49 **
PAC	-5.70 ***	-10.24 ***	-10.63 ***	-8.70 ***	-9.26 ***	-7.40 ***	-7.17 ***	-9.54 ***	-10.38 ***	-9.75 ***	-7.71 ***
SUB	-3.72 **	-3.75 **	-3.82 ***	-5.03 ***	-4.31 ***	-5.44 ***	-4.37 ***	-4.23 ***	-4.28 ***	-3.92 ***	-3.43 **
PSUB	-5.64 ***	-5.57 ***	-3.89 ***	-6.22 ***	-4.99 ***	-2.59	-2.93 *	-4.26 ***	-2.95 *	-2.56	-2.87 *

KPSS	Spot Return										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	0.34	0.10	0.34	0.24	0.14	0.21	0.26	0.59 **	0.55 **	0.43 *	0.32
AC	-	0.50 **	0.20	0.26	0.19	-	0.12	0.24	0.13	0.27	0.25
PAC	0.29	0.12	0.06	0.60 **	0.06	0.09	0.32	1.01 ***	0.54 **	0.54 **	0.09
SUB	0.52 **	0.13	0.17	0.37 *	0.09	0.31	0.17	0.42 *	0.14	0.17	0.17
PSUB	0.40 *	0.27	0.23	0.22	0.08	0.17	0.38 *	0.31	0.23	0.18	0.21

Note that the Augmented Dickey Fuller (ADF), Phillip-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests are reported in statistic where ***, **, * indicate the statistical significance at the 1%, 5% and 10% level, respectively. The data includes Chinese yuan (CNY), Hong Kong dollar (HKD), Indonesian rupee (IDR), Indian rupiah (INR), Japanese yen (JPY), South Korean won (KRW), Malaysian riggit (MYR), Philippines peso (PHP), Singapore dollar (SGD), Thai baht (THB) and Taiwanese new dollar (TWN). The sample period is divided into Asian crisis (AC), post Asian crisis (PAC), subprime crisis (SUB) and post subprime crisis (PSUB).

Table 4.4: Continued

Panel B : Forward Discount

ADF	Forward Discount										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	-2.95 **	-3.16 **	-6.96 ***	-3.56 **	-0.94	-2.59 *	-2.16	-2.87 *	-2.97 **	-2.82 **	-2.56
AC	-	-3.99 ***	-2.07	-	-5.77 ***	-	-1.02	-2.65 *	-1.67	-3.85 ***	-0.06
PAC	1.66	-3.54 ***	-5.86 ***	-2.72 *	-2.52	0.78	-1.08	-2.56	-1.51	-4.31 ***	-4.29 ***
SUB	-3.93 ***	-1.70	-2.67 *	-3.48 **	-1.47	-2.56	-2.82 *	-1.54	-1.39	-2.08	-3.34 **
PSUB	-4.29 ***	-5.97 **	-0.33	-0.30	-2.85 *	-2.14	-1.82	-2.07	-3.80 **	-0.58	-9.83 ***

PP	Forward Discount										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	-3.94 ***	-8.12 ***	-3.78 ***	-7.25 ***	-1.30	-3.15 **	-3.42 **	-4.25 ***	-7.33 ***	-8.37 ***	-5.99 ***
AC	-	-3.99 ***	-1.92		-5.89 ***	-	-1.89	-2.65 *	-3.77 ***	-3.85 ***	-2.43
PAC	-3.87 ***	-3.38 **	-2.83 *	-4.85 ***	-1.32	-0.43	-1.01	-3.23 **	-1.79	-7.92 ***	-4.16 ***
SUB	-1.85	-2.01	-2.60	-3.48 **	-2.64 *	-2.63	-2.75 *	-2.64 *	-1.23	-2.00	-3.34 **
PSUB	-2.81 *	-3.22 **	-0.37	0.20	-2.85 *	-1.17	-1.89	-2.07	-2.64	-0.65	-1.71

KPSS	Forward Discount										
	CNY	HKD	IDR	INR	JPY	KRW	MYR	PHP	SGD	THB	TWN
Full sample	0.24	0.85 ***	0.08	0.27	0.79 ***	0.48 **	0.32	0.97 ***	0.15	0.64 **	0.93 ***
AC	-	0.17	0.56 **		0.12	-	0.19	0.21	0.16	0.09	0.37 *
PAC	0.53 **	0.74 ***	0.06	0.66 **	0.27	1.02 ***	0.79 ***	0.69 **	0.36 *	0.16	0.85 ***
SUB	0.24	0.51 **	0.17	0.25	0.55 **	0.14	0.41 *	0.39 *	0.54 **	0.32	0.18
PSUB	0.13	0.07	0.43 *	0.27	0.09	0.61 **	0.41 *	0.39 *	0.45 *	0.49 **	0.46 **

Note that the Augmented Dickey Fuller (ADF), Phillip-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests are reported in statistic where ***, **, * indicate the statistical significance at the 1%, 5% and 10% level, respectively. The data includes Chinese yuan (CNY), Hong Kong dollar (HKD), Indonesian rupee (IDR), Indian rupiah (INR), Japanese yen (JPY), South Korean won (KRW), Malaysian riggit (MYR), Philippines peso (PHP), Singapore dollar (SGD), Thai baht (THB) and Taiwanese new dollar (TWN). The sample period is divided into Asian crisis (AC), post Asian crisis (PAC), subprime crisis (SUB) and post subprime crisis (PSUB).

4.5.2 Fama Regression

The estimation results of conventional Fama regression for 11 Asian currencies are reported in table 4.5. The first column represents (i) the full sample period, (ii) Asian crisis period (AC), (iii) post Asian crisis period (PAC), (iv) Subprime period (SUB) and (v) post Subprime period (PSUB). Column 2, 3, 4 present the number of monthly observation (Obs.), constant (a) and slope coefficient (b), respectively. Next, column 5 and 6 report the Wald test on beta individually and jointly constant and slope. In addition, the table also reports the ADF test on forward premium/discount, the Q statistic for the residual at lag 3 and 6 and whether the FRUH should be held or rejected in column 7, 8, 9 and 10, respectively.

On the basis of the FRUH test, we find 4 (HKD, INR, IDR and CNY) Asian currencies that violate the restrictions (a = 0 and b = 1) in the full sample. More specifically, using a joint Wald test, the 4 currencies are rejected at 5% level; hence, the findings indicate the forward bias anomaly. In addition, 7 Asian currencies (MYR, PHP, TWN, JPY, SGD, THB and KRW) clearly pass the individual t-test and the joint Wald test. As a consequence, the null hypothesis of forward rate unbiased holds for these 7 currencies. This result implies that in a full sample, the forward exchange rates of these 7 Asian currencies are the best predictor of future spot exchange rates. Moreover, the Q statistics for residual autocorrelation of CNY, INR, IDR and THB currencies show p-value smaller than 0.05. These findings indicate that modeling spot and forward relationship in linear dynamic specification are not well-specified.

In subsamples, our results indicate that UIP works better during crisis periods, which is in line with the empirical findings of Flood and Rose (2002) and Bai and Mollickb (2010). We find that the FRUH held during the Asian crisis for IDR, SGD and THB while it is rejected in the post Asian crisis. Also, the FRUH held during subprime crisis, which might reflect the fact that Asian currencies (HKD, INR, IDR, SGD, THB and KRW) are affected by this global crisis. In addition, we find that in some subsample period, the hypothesis cannot be rejected even though β widely deviated from the true theoretical value and often in a negative value. This result could be due to the large standard errors of the estimated coefficient that causes the failure of rejection of the unbiased hypothesis.

In summary, the FRUH cannot be rejected for 7 Asian currencies using conventional Fama regressions. This finding indicates that the forward rate of MYR, PHP, TWN, JPY, SGD, THB and KRW is an efficient unbiased predictor for the future spot rate in full-sample from January 1997 to September 2011. The finding also shows that the estimated beta is positive for 8 out of 11 cases while the remaining 3 currencies have negative beta. The 3 currencies are JPY, HKD and INR, which are more developed than the other Asian currencies. In fact, the highest estimate beta is 1.89, whereas the lowest beta is -0.89. Our finding contradicts prior studies of major currencies, where consistently negative beta coefficients are found. However, our result is in line with the empirical finding of Frankel and Poonawala (2010), which showed that the forward discount bias in emerging countries is less severe than the developed currencies as the evidence that we obtain negative beta for more developed currencies in Asia. Similar to the Flood and Rose (2002) and Bai and Mollick (2010) outcomes, we discover that the financial crises affect the forward discount bias in which the FRUH is upholding during financial crises.

Table 4.5: FRUH tests by Fama regression
Model: $\Delta s_{t+1} = a + b(f_t - s_t) + \varepsilon_{t+1}$

Currency	Obs.	a	b	Wald test		ADF	Q(3)	Q(6)	FRUH
				b=1	a=0,b=1	FP[lag]			
CNY									
Full sample	115	-0.0015 *** (0.0004)	0.4611 *** (0.1234)	19.08 ***	10.67 ***	-2.95 [4] **	0.00	0.00	Reject
AC	-	-	-	-	-	-	-	-	-
PAC	70	-0.0003 (0.0006)	0.5659 *** (0.1607)	7.29 ***	5.70 ***	-1.55 [3]	0.25	0.48	Reject
SUB	24	-0.0025 *** (0.0009)	0.6792 ** (0.2009)	2.55	4.97 **	-3.93 [5] ***	0.59	0.36	Reject
PSUB	115	-0.0015 *** (0.0004)	0.4611 *** (0.1234)	19.08 ***	10.67 ***	-2.95 [4] **	0.00	0.00	Reject
JPY									
Full sample	176	-0.0050 (0.0042)	-0.8903 (1.3120)	2.08	1.04	-0.94 [2]	0.91	0.12	Hold
AC	23	-0.0095 (0.1345)	-1.5624 (30.26)	0.007	0.02	-5.77 [0] ***	0.98	0.97	Hold
PAC	108	-0.0048 (0.0053)	-1.4931 (1.5167)	2.70	2.18	-2.52 [6]	0.59	0.24	Hold
SUB	24	0.0107 (0.0109)	14.94 (6.2929)	4.91 **	2.89 *	-1.47 [1]	0.78	0.86	Reject
PSUB	21	0.0026 (0.0117)	45.77 (42.69)	1.09	1.97	-2.85 [0] *	0.69	0.75	Hold
KRW									
Full sample	115	-0.0016 (0.0037)	0.9082 (1.9251)	0.002	0.11	-2.59 [1] *	0.19	0.32	Hold
AC	-	-	-	-	-	-	-	-	-
PAC	70	-0.0042 (0.0026)	-0.8658 (1.4052)	1.76	4.19 **	0.78 [1]	0.65	0.22	Reject
SUB	24	0.0151 (0.0149)	7.2786 (6.1185)	1.05	0.78	-2.57 [0]	0.81	0.94	Hold
PSUB	21	0.0028 (0.0257)	-1.4819 (16.31)	0.02	0.02	-2.14 [4]	0.52	0.59	Hold

Table 4.5: Continued									
Currency	Obs.	a	b	Wald test		ADF	Q(3)	Q(6)	FRUH
				b=1	a=0,b=1	FP[lag]			
SGD									
Full sample	176	-0.0004 (0.0016)	0.0318 (0.9191)	1.13	0.62	-2.97 [8] **	0.73	0.83	Hold
AC	23	0.0072 (0.0062)	-0.1476 (2.1640)	0.28	0.74	-1.68 [1]	0.60	0.61	Hold
PAC	108	-0.0038 (0.0021)	-1.7477 (1.1926)	5.31 **	2.67 *	-1.51 [3]	0.99	0.82	Reject
SUB	24	0.0006 (0.0107)	1.8821 (5.8773)	0.02	0.04	-1.39 [0]	0.73	0.73	Hold
PSUB	21	-0.0033 (0.0055)	-10.69 (40.30)	16.09 ***	8.04 ***	-3.80 [2] **	0.76	0.79	Reject
HKD									
Full sample	176	0.00003 (0.00009)	-0.0367 (0.0727)	203.39 ***	101.83 ***	-3.16 [12] **	0.21	0.53	Reject
AC	23	0.00003 (0.0002)	-0.0179 (0.0609)	279.51 ***	209.82 ***	-3.99 [0] ***	0.33	0.66	Reject
PAC	108	-0.000009 (0.0001)	-0.2391 (0.22433)	30.51 ***	19.83 ***	-3.54 [0] ***	0.32	0.46	Reject
SUB	24	-0.0002 (0.0005)	0.1215 (0.9410)	0.87	0.64	-1.70 [2]	0.98	0.99	Hold
PSUB	21	0.000008 (0.0011)	-0.7205 (4.3504)	0.16	0.80	-5.97 [4] ***	0.66	0.67	Hold
IDR									
Full sample	176	0.0067 (0.0066)	0.1627 (0.2059)	16.53 ***	8.38 ***	-6.96 [1] ***	0.01	0.00	Reject
AC	23	0.1216 (0.0672)	-3.4259 (2.6086)	2.88	1.75	-2.07 [0]	0.24	0.46	Hold
PAC	108	0.0013 (0.0045)	0.1955 * (0.1171)	47.23 ***	23.64 ***	-5.86 [1] ***	0.20	0.10	Reject
SUB	24	0.0127 (0.0217)	-1.8533 (2.8232)	1.02	0.72	-2.67 [0] *	0.61	0.64	Hold
PSUB	21	0.0433 (0.0220)	-9.3038 ** (4.3564)	5.59 **	6.86 ***	-0.33 [0]	0.31	0.68	Reject

Table 4.5: Continued									
Currency	**Obs.**	**a**	**b**	**Wald test**		**ADF**	**Q(3)**	**Q(6)**	**FRUH**
				b=1	**a=0,b=1**	**FP[lag]**			
INR									
Full sample	155	0.0037 (0.0025)	-0.8148 (0.7220)	6.32 **	3.69 **	-2.85 [2] **	0.01	0.00	Reject
AC		-	-	-	-	-	-	-	-
PAC	108	0.0009 (0.0018)	0.0860 (0.5255)	3.03 *	2.87 *	-2.72 [2] *	0.01	0.01	Reject
SUB	24	0.0100 (0.0091)	-2.1111 (2.3776)	1.71	0.87	-3.48 [0] **	0.11	0.16	Hold
PSUB	21	0.0004 (0.0194)	-1.3522 (6.2888)	0.14	0.78	-0.29 [0]	0.28	0.24	Hold
MYR									
Full sample	74	-0.0022 (0.0022)	0.4123 (1.4492)	0.16	0.66	-1.22 [1]	0.27	0.47	Hold
AC	-	-	-	-	-	-	-	-	-
PAC	29	0.0113 (0.0112)	10.9443 (7.8120)	1.62	1.84	-1.98 [3]	0.52	0.11	Hold
SUB	24	0.0027 (0.0051)	-2.4532 (4.3813)	0.62	0.33	-2.82 [0] *	0.81	0.59	Hold
PSUB	21	-0.0216 (0.0299)	9.5946 (15.5262)	0.31	0.65	-1.82 [0]	0.26	0.48	Hold
PHP									
Full sample	176	-0.0051 (0.0034)	1.8986 *** (0.6517)	1.90	1.15	-2.87 [1] *	0.47	0.85	Hold
AC	23	-0.0195 (0.0258)	4.0992 (2.5773)	1.45	0.98	-2.65 [0] *	0.98	0.99	Hold
PAC	108	0.00007 (0.0037)	0.1080 (0.8182)	1.19	2.15	-2.56 [1]	0.08	0.04	Hold
SUB	24	0.0290 (0.0113)	-9.3971 ** (4.0798)	6.49 **	3.39 *	-1.54 [2]	0.84	0.77	Reject
PSUB	21	0.0085 (0.0082)	-4.7826 (3.1301)	3.41 *	2.55	-2.07 [0]	0.40	0.49	Hold

Table 5.5: Continued									
Currency	**Obs.**	**a**	**b**	**Wald test**		**ADF**	**Q(3)**	**Q(6)**	**FRUH**
				b=1	**a=0,b=1**	**FP[lag]**			
THB									
Full sample	176	-0.0009 (0.0029)	0.9539 * (0.5517)	0.01	0.08	-2.82 [13] *	0.02	0.07	Hold
AC	23	0.0057 (0.0264)	0.9564 (1.9210)	0.00	0.04	-3.85 [0] ***	0.52	0.84	Hold
PAC	108	0.0008 (0.0019)	-1.8447 ** (0.8716)	10.65 ***	5.73 ***	-4.31 [2] ***	0.78	0.68	Reject
SUB	24	0.0006 (0.0053)	-0.7374 (2.344)	0.55	0.37	-2.08 [1]	0.78	0.97	Hold
PSUB	21	-0.0094 (0.0058)	6.2251 (4.4150)	1.40	1.33	-0.58 [0]	0.28	0.63	Hold
TWN									
Full sample	176	0.0011 (0.0013)	0.6147 (0.4628)	0.69	0.89	-2.56 [5]	0.28	0.37	Hold
AC	23	0.0102 (0.0079)	-2.2033 (3.4224)	0.88	0.85	-0.06 [5]	0.98	0.65	Hold
PAC	108	0.0004 (0.0012)	0.3968 (0.4311)	1.96	1.25	-4.29 [0] ***	0.12	0.06	Hold
SUB	24	0.0023 (0.0049)	1.1525 (1.1564)	0.02	0.13	-3.32 [0] **	0.75	0.92	Hold
PSUB	21	-0.0043 (0.0062)	-1.318 (3.3109)	0.49	0.29	-9.83 [3] ***	0.66	0.65	Hold

Note that the table shows the results from estimating the conventional Fama regression. The standard error associated to the estimate value of constant (a) and slope coefficient (b) is reported in the parenthesis. Wald statistic is reported for testing the individual slope coefficient and the joint hypothesis a = 0 and b = 1. Moreover, p-values are reported for Q(k) statistics residual test. Augmented Dickey Fuller test (ADF) is tested the unit root in the forward premium and the optimal lag determined from AIC criteria is reported in the square brackets. ***, ** and * represent statistically significant at 1%, 5% and 10% confident interval, respectively. The sample period is divided into Asian crisis (AC), post Asian crisis (PAC), subprime crisis (SUB) and post subprime crisis (PSUB).

4.5.3 Error Correction Model

In this section, we test the FRUH by using an error correction model; results are reported in table 4.6. In contrast to the previous findings by Fama regression, the estimation results show that the FRUH are rejected for 10 out of 11 Asian currencies. This implies that the forward rate is a biased predictor of the future spot rate in Asian markets. Specifically, the joint Wald tests are highly significant, which induce the FRUH to be rejected in full and subsample periods, except for MYR where the FRUH cannot be rejected in the full sample but is rejected in the subsamples. The findings also indicate no sign of residual autocorrelation in the error correction specification, with the exception of CNY and IDR. In this study, we observe that 5 currencies (CNY, SGD, MYR, JPY and TWN) yield positive beta (but not close to unity), excluding THB, KRW, HKD, IDR, INR and PHP that contain negative value of beta. The estimated beta ranges between -0.97 to 1.81, which is similar to the estimated beta from Fama regressions. Moreover, the disequilibrium term obtained from the spot and forward rate regression (in level specification) exhibits stationary behavior for both full and subsamples. The ECM estimation also gives smaller standard deviation comparing to the estimation results from Fama regression. Thus, the larger the standard deviation obtained in table 4.5 could prevent the rejection of the FRUH even though the estimated coefficient deviates from the unity.

In summary, our findings confirm that using an error correction term, the forward exchange markets are biased. The estimation results obtained from the ECM seem better than the estimation results from Fama regression due to smaller standard deviation and better Q statistics. This study supports the argument of Baillie (1989) and the findings of Barnhart and Szakmary (1991) that Fama regression is misspecified and error correction model is superior in estimating the spot and forward relationship. Additionally, in subsample analysis, the error correction model rejects the FRUH for all cases, therefore, the effect of key financial crises (the 1997 Asian financial crisis and the subprime crisis) on the forward discount cannot be observed. Moreover, based on unit root tests in table 4.3, spot and forward exchange rates of 5 currencies are found to be nonstationary. Also, the significant error correction term in this analysis has confirmed that the spot and forward rates of CNY, JPY, KRW, SGD and THB are cointegrated.

Table 4.6: FRUH tests by Error correction specification
Model: $\Delta s_{t+1} = a + b(f_t - \beta s_t) + \Delta s_{t+k} + \Delta f_{t+k} + \varepsilon_{t+1}$

Currency	Obs.	a	b	Wald test		ADF	Q(3)	Q(6)	FRUH
				b=1	a=0,b=1	Coin[lag]			
CNY									
Full sample	114	-0.0023 *** (0.0004)	0.0105 (0.1023)	95.50 ***	64.00 ***	-10.06 [0] ***	0.00	0.00	Reject
AC	-	-	-	-	-	-	-	-	-
PAC	69	-0.0018 *** (0.0004)	-0.0902 (0.1294)	70.93 ***	45.16 ***	-7.44 [0] ***	0.00	0.00	Reject
SUB	23	-0.0023 ** (0.0009)	-0.2836 (0.2574)	24.87 ***	15.25 ***	-3.54 [0] **	0.02	0.02	Reject
PSUB	114	-0.0023 *** (0.0004)	0.0105 (0.1013)	95.50 ***	64.00 ***	-10.06 [0] ***	0.00	0.00	Reject
JPY									
Full sample	172	-0.0080 (0.0042)	1.8146 (1.2993)	0.39	3.26 **	-6.91 [4] ***	0.94	0.62	Reject
AC	22	-0.0017 (0.0109)	-0.1953 (0.2466)	23.49 ***	11.88 ***	-4.08 [0] ***	0.98	0.95	Reject
PAC	107	-0.0002 (0.0024)	0.0578 (0.0989)	90.68 ***	45.34 ***	-8.83 [0] ***	0.68	0.46	Reject
SUB	23	-0.0068 (0.0084)	-0.1667 (0.2405)	23.53 ***	11.88 ***	-4.02 [0] ***	0.58	0.19	Reject
PSUB	20	-0.0082 (0.0053)	-0.1802 (0.2354)	25.14 ***	13.64 ***	-4.69 [0] ***	0.95	0.69	Reject
KRW									
Full sample	113	-0.00004 (0.0032)	-0.8266 * (0.4423)	17.06 ***	8.69 ***	-4.84 [2] ***	0.12	0.20	Reject
AC	-	-	-	-	-	-	-	-	-
PAC	66	0.0011 (0.0046)	-1.0171 (0.7433)	7.36 ***	9.73 ***	-3.43 [4] **	0.71	0.31	Reject
SUB	23	0.0092 (0.0145)	-0.2922 (0.2251)	32.96 ***	16.66 ***	-5.16 [0] ***	0.78	0.92	Reject
PSUB	20	-0.0002 (0.0080)	-0.2329 (0.3032)	16.54 ***	8.43 ***	-2.96 [0] *	0.59	0.67	Reject

Table 4.6: Continued									
Currency	**Obs.**	**a**	**b**	**Wald test**		**ADF**	**Q(3)**	**Q(6)**	**FRUH**
				b=1	**a=0,b=1**	**Coin[lag]**			
SGD									
Full sample	175	-0.0005 (0.0014)	0.0630 (0.0795)	138.84 ***	69.42 ***	-11.77 [0] ***	0.84	0.90	Reject
AC	22	0.0068 (0.0064)	-0.0304 (0.2372)	18.87 ***	10.07 ***	-4.22 [0] ***	0.59	0.61	Reject
PAC	107	-0.0015 (0.0012)	0.0117 (0.0947)	108.83 ***	55.15 ***	-10.25 [0] ***	0.96	0.80	Reject
SUB	23	0.0101 (0.0043)	-2.7654 *** (0.7679)	24.05 ***	12.52 ***	-2.53 [3]	0.64	0.72	Reject
PSUB	20	-0.0050 (0.0056)	-0.3557 (0.3380)	16.09 ***	8.04 ***	-3.31 [0] **	0.72	0.76	Reject
HKD									
Full sample	167	0.00006 (0.0001)	-0.1526 (0.0952)	146.35 ***	73.37 ***	-3.16 [9] **	0.99	1.00	Reject
AC	22	0.00001 (0.0002)	-0.5608 *** (0.2131)	53.65 ***	26.85 ***	-2.75 [0] *	0.95	0.97	Reject
PAC	107	0.00006 (0.0001)	-0.0646 (0.0918)	134.52 ***	67.53 ***	-7.58 [0] ***	0.17	0.32	Reject
SUB	23	-0.0003 (0.0003)	0.0181 (0.2183)	20.24 ***	10.45 ***	-3.89 [0] ***	0.46	0.33	Reject
PSUB	20	0.0001 (0.0003)	-0.4282 (0.2484)	33.05 ***	16.58 ***	-3.98 [0] ***	0.39	0.14	Reject
IDR									
Full sample	163	0.0014 (0.0045)	-0.4693 ** (0.2282)	42.45 ***	21.03 ***	-3.72 [13] ***	0.40	0.00	Reject
AC	22	0.0557 (0.0457)	0.1631 (0.2249)	13.85 ***	7.71 ***	-3.48 [0] **	0.70	0.81	Reject
PAC	107	0.0004 (0.0045)	-0.1617 (0.0796)	213.16 ***	106.58 ***	-7.02 [0] ***	0.13	0.14	Reject
SUB	23	0.0006 (0.0108)	0.0616 (0.2275)	17.01 ***	4269.7 ***	-3.68 [0] **	0.54	0.62	Reject
PSUB	20	-0.0035 (0.0033)	-0.2939 (0.2716)	22.70 ***	11.49 ***	-3.93 [0] ***	0.61	0.58	Reject

Table 5.6: Continued									
Currency	Obs.	a	b	Wald test		ADF	Q(3)	Q(6)	FRUH
				b=1	a=0,b=1	Coin[lag]			
INR									
Full sample	149	-0.0008 (0.0013)	-0.9763 *** (0.2945)	45.05 ***	23.12 ***	-3.93 [6] ***	0.73	0.92	Reject
AC	-	-	-	-	-	-	-	-	-
PAC	107	-0.0003 (0.0010)	-0.9708 *** (0.3200)	37.92 ***	20.16 ***	-6.25 [3] ***	0.96	0.56	Reject
SUB	23	-0.0531 (0.0293)	-14.167 * (7.3188)	4.29 *	2.79 *	-0.25 [4]	0.78	0.81	Reject
PSUB	20	0.0032 (0.0079)	-2.7569 (1.7083)	4.84 *	4.55 **	-1.54 [4]	0.65	0.33	Reject
MYR									
Full sample	72	-0.0006 (0.0027)	-0.7726 (0.6858)	6.68 **	5.61 ***	-3.81 [2] ***	0.30	0.41	Reject
AC	-	-	-	-	-	-	-	-	-
PAC	28	-0.0046 (0.0021)	0.0979 (0.1959)	0.25	13.43 ***	-4.62 [0] ***	0.92	0.60	Reject
SUB	23	0.0025 (0.0045)	0.0082 (0.2169)	20.90 ***	10.65 ***	-4.17 [0] ***	0.84	0.60	Reject
PSUB	20	-0.0025 (0.0052)	-0.9885 * (0.5046)	15.53 ***	9.07 ***	-4.76 [1] ***	0.26	0.21	Reject
PHP									
Full sample	167	-0.00004 (0.0019)	-0.5592 * (0.3387)	22.49 ***	11.57 ***	-4.11 [9] ***	0.66	0.67	Reject
AC	22	0.0180 (0.0128)	0.0254 (0.2411)	16.34 ***	9.10 ***	-4.17 [0] ***	0.93	0.96	Reject
PAC	107	-0.0002 (0.0019)	-0.7736 (0.6000)	8.74 ***	4.38 **	-4.85 [3] ***	0.83	0.44	Reject
SUB	11	0.0148 (0.0075)	-0.1529 (0.3308)	12.15 ***	6.85 **	-4.59 [0] ***	0.74	0.16	Reject
PSUB	20	-0.0018 (0.0043)	-1.0177 (0.6228)	10.49 ***	7.28 ***	-3.89 [1] ***	0.40	0.31	Reject

Table 4.6: Continued									
Currency	**Obs.**	**a**	**b**	**Wald test**		**ADF**	**Q(3)**	**Q(6)**	**FRUH**
				b=1	**a=0,b=1**	**Coin[lag]**			
THB									
Full sample	168	-0.0009 (0.0021)	-0.2574 (0.3749)	11.25 ***	5.72 ***	-5.11 [8] ***	0.38	0.15	Reject
AC	22	0.0158 (0.0195)	0.1109 (0.2358)	14.22 ***	7.46 ***	-3.52 [0] **	0.55	0.82	Reject
PAC	107	-0.0012 (0.0020)	0.5023 (1.0131)	0.24	0.49	-4.85 [2] ***	0.99	0.75	Hold
SUB	23	0.0004 (0.0043)	0.0653 (0.2230)	17.57 ***	8.79 ***	-3.83 [0] ***	0.99	0.99	Reject
PSUB	20	-0.0035 (0.0042)	-0.1483 (0.2797)	16.86 ***	8.52 ***	-3.64 [0] **	0.54	0.89	Reject
TWN									
Full sample	175	0.0006 (0.0013)	0.1107 (0.0795)	125.26 ***	62.82 ***	-11.19 [0] ***	0.55	0.62	Reject
AC	22	0.0072 (0.0065)	-0.0941 (0.2337)	21.92 ***	11.49 ***	-4.49 [0] ***	0.87	0.80	Reject
PAC	107	0.00007 (0.0012)	0.2231 ** (0.0976)	63.39 ***	31.70 ***	-8.09 [0] ***	0.96	0.66	Reject
SUB	23	-0.00003 (0.0043)	0.1793 (0.2289)	12.86 ***	6.43 ***	-3.66 [0] **	0.87	0.96	Reject
PSUB	20	-0.0023 (0.0047)	0.0243 (0.2857)	11.66 ***	5.83 **	-2.92 [0] *	0.67	0.68	Reject

Note that the table shows the results from estimating the error correction model. The standard error associated to the estimate value of constant (a) and slope coefficient (b) is reported in the parenthesis. Wald statistic is reported for testing the individual slope coefficient and the joint hypothesis a = 0 and b = 1. Moreover, p-values are reported for Q(k) statistics residual test. Augmented dickey fuller test (ADF) is tested the unit root in the error correction term and the optimal lag determined from AIC criteria is reported in the square brackets. ***, ** and * represent statistically significant at 1%, 5% and 10% confident interval, respectively. The sample period is divided into Asian crisis (AC), post Asian crisis (PAC), subprime crisis (SUB) and post subprime crisis (PSUB).

4.5.4 Logistic Smooth Transition Regression

Unlike the empirical studies of Sarno, Valente and Leon (2004), Ballie and Kilic (2005), Amri (2008) and Bonga-Bonga (2009) who use nonlinear least square (NLS), in this study, we use a maximum likelihood estimator (MLE) to estimate the smooth transition parameters that maximize the likelihood function. In this study, the lagged forward premium is selected as the transition variable. From table 4.3, unit root tests suggest that spot and forward rates of CNY, JPY, KRW, SGD and THB can be modeled using nonlinear smooth transition regression. However, the possibility of structural break in the data could cause the rejection of the unit root hypothesis in the case of HKD, IDR, INR, MYR, PHP and TWN. Hence, in this section, we estimate the LSTR using both nonstationary and stationary series. The results are reported in table 4.7 and 4.8, respectively.

4.5.4.1 LSTR results using nonstationary series

In table 4.7, the estimation of LSTR for CNY, JPY, KRW, SGD and THB are reported. We find that 3 out of 5 currencies show nonlinear behavior. In fact, the transition parameter (γ) is significant at 5% level for KRW, SGD and THB. The estimated location parameter (c) appears to be small but significantly different from zero for these currencies[32]. These findings show that the midpoint of a smooth transition for KRW is below zero while it is above zero for SGD and THB. Moreover, based on t statistic, the FRUH is rejected in the upper regime at 10% level for KRW while the test rejects the same null hypothesis in the lower regime at 1% level for SGD and THB. In addition, the FRUH is also tested, in each regime, using the joint restriction $\alpha = 0$ and $\beta = 1$ by Wald statistics, yielding the same results.

To ensure the validity of LSTR, we also perform various diagnostic tests, which are the Q statistics on residuals and square residuals, parameter constancy and tests of no remaining nonlinearity. The finding indicates that SGD and JPY pass all various diagnostic tests but the LSTR cannot capture nonlinearity for JPY. Moreover, the result shows some evidence of residual autocorrelation in the case of CNY and parameter

[32] The estimated c parameter indicates the midpoint between the two extreme regimes.

inconstancy in the case of THB. Additionally, KRW fails to reject heteroskedasticity and no remaining nonlinearity tests in this analysis. Therefore, the estimation of LSTR using nonstationary data seems to adequately capture nonlinearity and instability only for SGD.

Table 4.7: Estimation results of LSTR model (nonstationary series)

	CNY	JPY	KRW	SGD	THB
α_1	-0.0006 (0.0009)	-1.2287 *** (0.4187)	-0.2950 (0.2456)	1.5031 (1.2779)	1.2277 (3.5768)
β_1	0.0006 (0.0026)	-4.2218 *** (1.4773)	-1.3948 (1.4295)	-1.2266 (3.6340)	0.4123 (3.5768)
α_2	-0.2490 *** (0.0618)	5.2960 ** (11.6195)	1.9535 (1.7342)	-0.4779 *** (0.1779)	0.0297 (0.1529)
β_2	0.5742 *** (0.1671)	22.6521 ** (11.6195)	9.0013 * (6.4142)	-2.5720 *** (1.1309)	-1.7736 * (1.1178)
γ	0.5595 (0.6867)	0.6404 (2.5781)	3.7489 ** (1.9035)	66.60 ** (31.6670)	9.3366 ** (4.8792)
c	0.9395 (1.4154)	-3.4908 (13.1558)	-0.3313 ** (0.1982)	0.0441 *** (0.0129)	0.5440 *** (0.0877)
Log Likelihood	47.00	-419.79	-269.55	-324.87	-383.99
T stat (β=1)					
t(β_1=1)	-	-3.5347 [0.00]	-1.6752 [0.10]	-0.6351 [0.53]	-0.1643 [0.87]
t(β_2=1)	-2.5488 [0.01]	1.8634 [0.07]	1.2474 [0.22]	-8.3088 [0.00]	-2.4814 [0.01]
Wald stat (α=0,β=1)					
Regime 1	-	12.5234 ***	9.9047 ***	1.3912	0.1356
Regime 2	16.45 ***	3.4868	2.2405	10.1938 ***	6.8603 **
Diagnostic tests					
Q1(3)	0.00	0.69	0.12	0.46	0.12
Q1(6)	0.00	0.07	0.18	0.60	0.34
Q2(3)	0.14	0.26	0.00	0.75	0.07
Q2(6)	0.42	0.61	0.00	0.90	0.26
PC	21.60 [0.12]	0.78 [0.99]	2.20 [0.99]	5.14 [0.99]	32.08 [0.01]
NRN	4.56 [0.97]	2.32 [0.99]	28.38 [0.00]	0.55 [0.99]	13.98 [0.30]
Sample	116	177	116	177	177

Note that the estimated standard errors are in parenthesis below the estimates of constant (α_1, α_2) and slope (β_1, β_2) of regime 1 and 2. γ is the transition parameter while c is the location coefficient. ***, ** and * represent statistically significant at 1%, 5% and 10% level; t(β_1=1) and t(β_2=1) are the 2 tails t-statistic for the hypothesis of estimate beta equal to unity. Wald statistic tests the joint hypothesis $\alpha = 0$ and $\beta = 1$ in each regime. Moreover, Q1(k) and Q2(k) are reported in p-value, which are the residual Ljung-Box statistic and the squared residual Ljung-Box at lag k. P-values are also reported in squared bracket for PC and NRN, which are the chi-square statistics for the null hypothesis of parameter inconstancy and for the null hypothesis of no remaining nonlinearity. PC and NRN is compared to the chi-square with 3(k+1) =15 degree of freedom and 3p=12 degree of freedom, respectively.

4.5.4.2 LSTR result using stationary series

Table 4.8 shows the estimation results of LSTR for HKD, INR, IDR, PHP, TWN and MYR. The results indicate that the transition parameters of HKD, IDR and PHP are significantly different from zero. This finding implies that the LSTR can capture the nonlinear relationship of these 3 currencies. Moreover, the estimated c is negatively significant at 5% level for HKD while the estimated c is positively significant at 1% for IDR and PHP. These results show that the midpoint between the two extreme regimes is above zero for the case of HKD and below zero for the cases of IDR and PHP. In addition, the t test rejects the hypothesis of $\beta = 1$ in the lower regime for HKD, IDR and PHP. Similarly, the Wald test also rejects the joint hypothesis of zero constant and unity slope for all cases in the lower regime.

Furthermore, the validity of LSTR is also confirmed by the various diagnostic tests for HKD and PHP. In particular, the results show that Q statistics on residuals and square residuals of these 2 currencies are larger than 0.05. The null hypotheses of parameter constancy and no remaining nonlinearity are also obtained. This result shows some evidence of residual autocorrelation at lag 6 in the case of IDR. Hence, the findings suggest that the estimations of LSTR using stationary data appear to be adequate capture nonlinearity in the spot and forward relationship of HKD and PHP. The results also point out that the data might be nonstationary but the ADF test could not detect the unit root when the series contain structural breaks.

In order to clearly illustrate the nonlinear model, we plot the transition function against the transition variable for each series including both the LSTR with stationary and nonstationary series. In figure 4.3, the illustration shows that the logistic function is well defined for 6 currencies that exhibit nonlinearity (significant transition parameter). The transition between the two regimes is relatively sharp for SGD as it has the highest smoothness parameter equal to 66.6. The other nonlinear models such as IDR (γ=11.54), THB (γ=9.34), PHP (γ=6.43), HKD (γ=5.85) and KRW (γ=3.75) have a smoother transition as the estimate transition parameters are smaller.

Table 4.8: Estimation results of LSTR model (stationary series)

	HKD	INR	IDR	PHP	TWN	MYR
α_1	0.0081 *** (0.0032)	-0.3826 *** (0.0966)	4.7991 (3.8058)	0.5910 (4.1512)	0.0680 (0.4467)	0.9598 (1.7926)
β_1	-0.0113 (0.0164)	1.1805 *** (0.2293)	-0.7213 (0.8953)	2.0855 (3.7644)	1.3493 (1.3230)	2.2396 (10.9916)
α_2	-0.0129 (0.0263)	0.6855 * (0.4237)	0.2846 (0.2938)	0.0943 (0.2560)	-0.0020 (0.1406)	-0.8222 *** (0.2741)
β_2	-0.2582 (0.3120)	-1.5932 (1.2012)	0.2521 *** (0.0996)	-0.2589 (0.6807)	0.0197 (0.3187)	-2.5283 (1.7554)
γ	5.8540 ** (2.8924)	0.9545 (1.0114)	11.5402 ** (5.1714)	6.429 *** (2.0027)	3.6417 (2.8765)	6.1533 (8.0355)
c	-0.0773 ** (0.0451)	0.6743 * (0.4515)	0.7193 *** (0.0617)	0.9269 *** (0.1093)	0.1431 (0.2038)	0.2131 (0.2716)
Log Likelihood	173.50	-286.99	-520.54	-376.73	-322.05	-137.39
T stat (β=1)						
$t(\beta_1=1)$	-	0.7870 [0.43]	-1.9226 [0.06]	0.2883 [0.77]	0.2640 [0.79]	0.1128 [0.91]
$t(\beta_2=1)$	-4.0326 [0.00]	-2.1588 [0.03]	-7.5105 [0.00]	-1.8494 [0.07]	-3.0759 [0.00]	-2.0100 [0.05]
Wald stat (α=0,β=1)						
Regime 1	-	38.4176 ***	3.7554	1.2044	0.1433	0.4916
Regime 2	17.8107 ***	4.7645 *	61.6928 ***	7.8155 **	17.6226 ***	9.6151 ***
Diagnostic tests						
Q1(3)	0.05	0.01	0.14	0.23	0.21	0.32
Q1(6)	0.17	0.00	0.03	0.25	0.38	0.50
Q2(3)	0.41	0.00	0.93	0.83	0.02	0.58
Q2(6)	0.82	0.00	0.96	0.75	0.00	0.87
PC	1.31 [0.99]	0.27 [1.00]	10.10 [0.81]	9.63 [0.84]	1.47 [0.99]	6.98 [0.96]
NRN	0.88 [0.99]	0.12 [1.00]	1.39 [0.99]	21.17 [0.05]	1.31 [0.99]	6.82 [0.87]
Sample	177	168	177	177	177	75

Note that the estimated standard errors are in parenthesis below the estimates of constant (α_1, α_2) and slope (β_1, β_2) of regime 1 and 2. γ is the transition parameter while c is the location coefficient. ***, ** and * represent statistically significant at 1%, 5% and 10% level, respectively. $t(\beta_1=1)$ and $t(\beta_2=1)$ are the 2 tails t-statistic for the hypothesis of estimate beta equal to unity. Wald stat is the Wald statistic for testing the joint hypothesis $\alpha = 0$ and $\beta = 1$ in each regime. Moreover, Q1(k) and Q2(k) are reported in p-value , which are the residual Ljung-Box statistic and the squared residual Ljung-Box at lag k. P-values are also reported in squared bracket for PC and NRN, which are the chi-square statistics for the null hypothesis of parameter inconstancy and for the null hypothesis of no remaining nonlinearity. PC and NRN is compared to the chi-square with 3(k+1) =15 degree of freedom and 3p=12 degree of freedom, respectively.

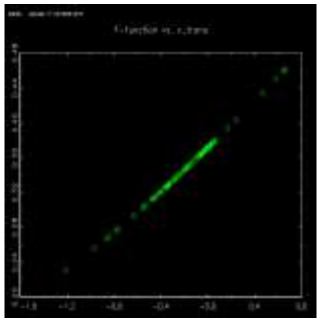
Moreover, we also plot the transition function against time, which is shown in figure 4.4. Interestingly, the transition probability is relatively close to 1 during the Asian crisis as it is clearly exhibited for THB (7/1997-10/1998), IDR (7/1997-7/1999), PHP (8/1997-5/1998) and SGD (11/1997-10/1998). Also, IDR has a high transition probability of being in upper regime when the transition function is close to one from 11/2008 to 4/2009, which is during the Subprime crisis. Apart from this period, the plots clearly show that the observations are in the lower regime most of the time where the transition probability is relatively close to zero. Similar to Sarno, Valente and Leon (2004) and Baillie and Kilic (2006), we obtain a few observations in the upper regime while the majority of the observations belong to the lower regime. The result implies that the forward bias is persistent and dominant in the lower regime, which causes the FRUH to be rejected by the data. The previous empirical findings of Sarno et al. (2004), Ballie and Kilic (2006) and our results suggest that the FRUH is more likely to hold in the upper regime (forward premium) and the forward bias anomaly is more likely to occur in the lower regime (forward discount).

In summary, the estimation of LSTR with the lagged forward premium as the transition variable indicates that 6 out of 11 spot and forward exchange rates exhibit strong nonlinearity. The LSTR is also able to capture nonlinearity in the incorrect unit root specification even though we previously found stationarity in the spot and forward rates. The validity of the model has been confirmed by various diagnostic tests. This finding casts doubt on the power of ADF test that fail to detect the unit root in some series. Moreover, the estimate slope coefficients from both regimes give mixed signs in which we cannot draw a clear inference on whether the Asian forward markets are (more or less) biased.

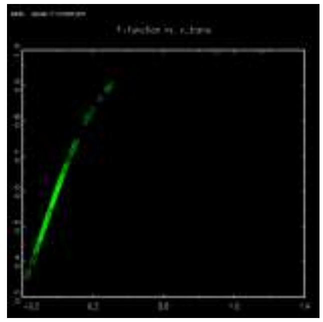
In the next section, we perform out-of-sample forecasting to compare whether linear or nonlinear models would give better out-of-sample prediction of future spot rate.

Figure 4.3: Estimated Transition function over transition variable

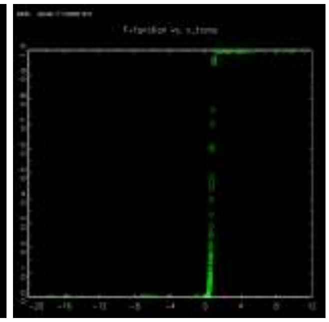
CNY



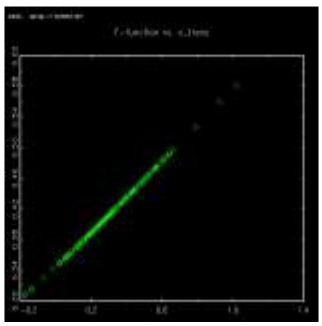
HKD



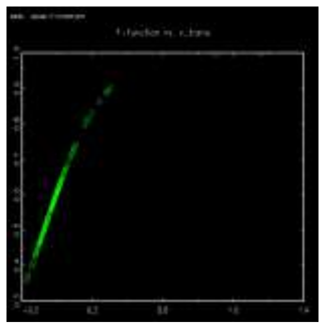
IDR



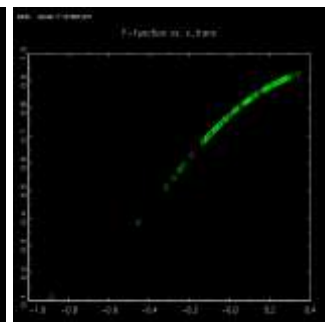
INR



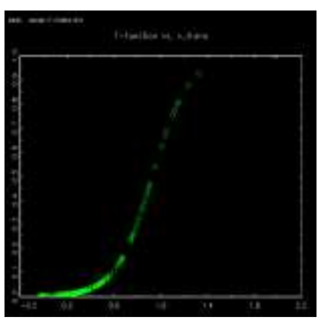
JPY



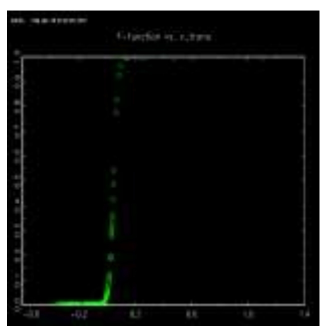
KRW



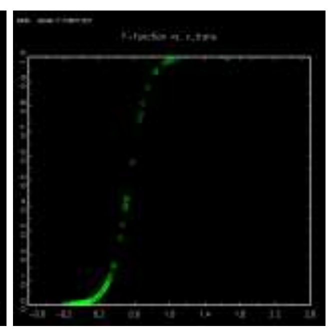
PHP



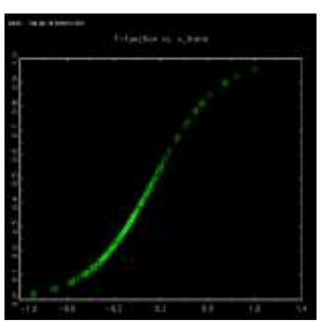
SGD



THB



TWN



MYR

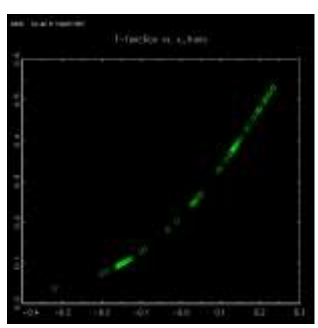
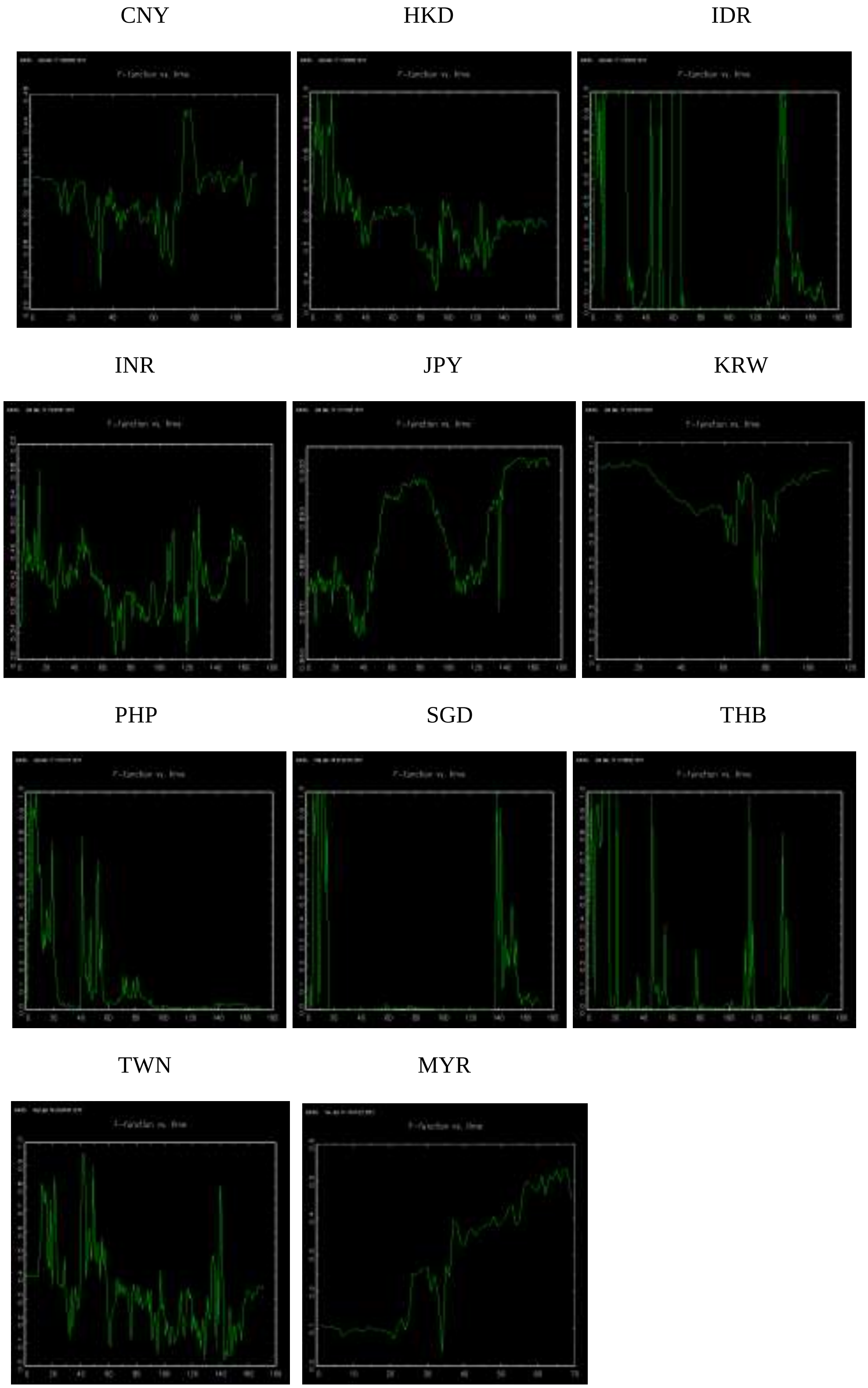


Figure 4.4: Estimated Transition function over time



4.6 Forecasting simulation and results

The purpose of this forecasting exercise is to test the predictability of the logistic smooth transition model. In the previous section, we discovered strong nonlinearity in the data for at least 6 Asian currencies (HKD, IDR, PHP, THB, KRW and SGD). In this section, we conduct one step-ahead forecast from 10/2009 to 9/2011 for all currencies using LSTR, Fama regression and ECM. Theoretically, the forward exchange rate should be the best predictor of the future spot rate, assuming that the FRUH hold. Thus, the forecast performance of LSTR is compared to 2 benchmark models, which are the Fama regression and the ECM. The competing forecasting models are described as follow;

Model 1: Logistic smooth transition model (from equation 4.6); the optimal one-step-ahead forecast at forecast origin t is

$$\hat{s}_{t+1} = f_t + [\alpha_1 + \beta_1(f_{t,1} - s_t)][1 - F(z_t;\gamma,c)] + [\alpha_2 + \beta_2(f_{t,1} - s_t)]F(z_t;\gamma,c) + u_{t+1} \tag{4.8}$$

where $\hat{s}_{t+1}$ is the one-step-ahead forecast of spot exchange rate at forecast origin t.

Model 2: Linear Fama model (from equation 4.4); the optimal one-step-ahead forecast at forecast origin t is

$$\hat{s}_{t+1} = f_t + \alpha + \beta(f_t - s_t) + u_{t+1} \tag{4.9}$$

Model 3: Linear Error correction model (from equation 4.5); the optimal one-step-ahead forecast at forecast origin t is

$$\hat{s}_{t+1} = f_t + a + b(f_t - \beta s_t) + \left\{ \sum_{i=1}^{k-1} \delta_{st} \Delta s_{t-i+1} + \sum_{i=1}^{k-1} \delta_{ft} \Delta f_{t+i-1} \right\} + u_{t+1} \tag{4.10}$$

In the forecasting evaluation, we appraise the forecasting performance of each forecasting model based on firstly, how well the forecasting model predicts relative to the actual value and secondly, how well the nonlinear model forecast relative to the linear model.

The first forecasting appraisal is the popular mean square error (MSE).

$$MSE = (1/n)\sum_{i=1}^{n} e_{t+1,i}^{2} \tag{4.11}$$

where the forecast error ($e = s_{t+1} - \hat{s}_{t+1}$) is the difference between the actual and forecast spot rate at time t+1, n is 24 months and i is 1 step-ahead.

The second forecasting evaluation is the Theil's inequality coefficient, which is used to indicate which forecasting model is better than the benchmarking model in terms of equal forecasting accuracy. The Thiel's coefficient or U coefficient is formulated as follow:

$$U = \frac{\sqrt{\Sigma(s_{t+1,i} + \hat{s}_{t+1,i})^{2}}}{\sqrt{\Sigma(s_{t+1,i})^{2}} + \sqrt{\Sigma(\hat{s}_{t+1,i})^{2}}} \tag{4.12}$$

If the Theil's coefficient is zero, this implies perfect forecast while the forecasting performance of the competing models are not different if the Theil's coefficient is one.

The results of forecast comparison in terms of MSE and Thiel's coefficient are summarized in table 4.9. The results indicate that the LSTR used to forecast nonlinear currencies can outperform the linear models for HKD, IDR and PHP. However, the LSTR is outperformed by linear models for KRW, SGD and THB. Based on MSE, the LSTR shows the smallest loss for HKD, IDR and PHP, which reveals that the LSTR is the best forecaster against the linear Fama regression and ECM as the forecast is approximately close to the actual spot rate. Moreover, the LSTR also outperform with the CNY where we previously found no presence of nonlinearity. However, the Fama regression appears to be the best forecaster for INR, KRW, THB, TWN and MYR while JPY and SGD are best predicted by ECM. In addition, the relative ratio of MSE also tells the same story. For example, there is a gain on forecasting performance of 43% when the LSTR is used against Fama regression for HKD and 14% against ECM. Whereas, the LSTR loses the forecast accuracy of 92% against Fama regression and 90% against ECM for THB.

Moreover, the Theil's inequality coefficients for all 3 forecasters are approximately close to zero for all currencies except for SGD. The finding suggests that the forecasting models perfectly predict the future spot rate. However, the LSTR appears to be the best forecaster as Theils's coefficient is smaller than the competing models for HKD, IDR, PHP and TWN. Moreover, Fama regression is the most accurate predictor for CNY, INR, KRW and MYR while ECM is superior to competing models for JPY, SGD and THB.

Table 4.9: Forecasting performance at 1 Step ahead

Model/Currencies	CNY	HKD	INR	IDR	JPY	PHP	KRW	SGD	THB	TWN	MYR
MSE											
LSTR	**0.0177**	**0.000007**	0.0432	**0.2141**	8.2965	**0.0025**	0.3683	0.2477	0.0413	0.0339	0.0920
Fama	0.0183	0.000010	**0.0106**	0.7017	0.1496	0.0519	**0.0017**	0.0038	**0.0035**	**0.0082**	**0.0907**
ECM	0.0370	0.000008	0.0112	0.7011	**0.1289**	0.0374	0.0125	**0.0037**	0.0042	0.0377	0.1611
Thiel's coefficient											
LSTR	0.0412	**0.0007**	0.0069	**0.0179**	0.0673	**0.0003**	0.0688	0.9952	0.0814	**0.0079**	0.2103
Fama	**0.0369**	0.0010	**0.0010**	0.0388	0.0575	0.0079	**0.0012**	0.4359	0.0208	0.0093	**0.2085**
ECM	0.0535	0.0009	0.0131	0.0387	**0.0243**	0.0049	0.0135	**0.3975**	**0.0153**	0.0276	0.2428

Note that the mean square error (MSE) and Thiel's coefficient are reported for logistic smooth transition regression (LSTR), Fama regression (Fama) and error correction model (ECM). The bold number indicates the smallest value.

4.7 Conclusion

This chapter has examined the spot return and the forward premium relationship for 11 Asian currencies, using conventional linear (Fama regression and error correction model) and nonlinear regressions (Logistic smooth transition regression with the transition variable being the lagged forward premium). A large amount of literatures have tested the forward rate unbiased hypothesis using conventional linear (i.e. Fama, 1984; Froot & Thaler, 1990; Baillie & Bollerslev, 1989; and Barnhart & Szakmary, 1991) and nonlinear regressions (i.e. Sarno, Valente & Leon, 2004; Bailie & Kilic, 2006; Amri, 2008) on major currencies. On the other hand, there is a limited number of studies that have tested the unbiased hypothesis in the emerging currencies using linear (i.e. Flood & Rose, 2002; Jeon & Seo, 2003; Franken & Poonawala, 2010; Bai & Mollickb, 2010) and nonlinear models (i.e. Bonga-Bonga, 2009). The previous empirical studies often rejected the unbiased hypothesis where the slope coefficient is deviated from the true value of one.

Conventional Fama regression indicated that 7 Asian currencies (MYR, PHP, TWN, JPY, SGD, THB and KRW) appear to support the forward rate unbiased hypothesis as the joint hypothesis $\alpha=0$ and $\beta=1$ hold for the full-sample analysis. The estimated beta is mostly positive except for more developed currencies (JPY, HKD and INR), thus supporting the empirical findings of Frankel and Poonawala (2010) that the forward bias is less pronounced in developing countries. Moreover, the estimation of error correction model showed that the forward rate unbiased hypothesis is rejected in all cases except for MYR. However, error correction model seems to be a better estimate the spot and forward relationship than the Fama regression based on smaller standard errors. Thus, this result supported the argument of Ballie (1989) and the findings of Barnhart and Szakmary (1991) that the error correction model is superior to Fama regression. The finding of stationary error correction term (of nonstationary spot and forward rates) also indicated that spot and forward rates of CNY, JPY, KRW, SGD and THB are cointegrated. Furthermore, the logistic smooth transition regression indicated that the spot and forward relationship of 6 Asian currencies are nonlinear. Our finding is in line with Sarno, Valente and Leon (2004) and Ballie and Kilic (2006) empirical studies. We found that the majority of the observations remained in the lower regime where the forward rate unbiased hypothesis is most likely to be rejected. On the other hand, a few observations occurred in the upper regime where the unbiased hypothesis is more likely to hold. Thus, this finding suggested that the unbiased hypothesis does not hold all the time where the more frequent observations induced the rejection in the Asian currencies.

Moreover, our findings also support the Flood and Rose (2002) and Bai and Mollick (2010) outcomes, that the financial crises do affect the forward bias where the FRUH is upholding during financial crises. In fact, a sub-sample analysis using Fama regression showed that the forward rate unbiased hypothesis hold during Asian crisis for IDR, SGD and THB while HKD, INR, IDR, SGD, THB and KRW hold during subprime crisis. Similarly, the logistic smooth transition regression also provided high transition probability of being close to one during the Asian crisis for IDR, PHP and THB and during Subprime crisis for IDR.

In addition, the forecasting performance showed some evidence of superior forecasting accuracy of the nonlinear LSTR over the linear conventional Fama regression and error correction model.

CHAPTER V

THE EXPECTATION HYPOTHESIS OF TERM STRUCTURE OF ASIAN INTEREST RATES USING SMOOTH TRANSITION MODELS

5.1 Introduction

The expectation hypothesis (EH) of the term structure of interest rates states that the long-term interest rate is the average of the expectation of the market participants on the short-term interest rates over the holding period of the long-term bond plus a constant risk premium (Thornton, 2003). The implication of the EH of the term structure provides useful information with respect to arbitrage opportunities (Shen, 1998). Understanding such relationship is also crucial as monetary policy makers use the interest rates to stabilize the economy. Consequently, the EH is one of the widely tested the hypothesis of the term structure of interest rates literature using a variety of linear and nonlinear models.

The empirical study of Fama and Bliss (1987) examined the expectation hypothesis using the US. Treasury bonds at various maturities (1 to 5 years). The long-term change in short-term rates is regressed on the spread between the forward rate and the current spot rate. The finding indicated that the positive slope of the forward-spot spread was informative to forecast the changes in the short-term rate, in this case, the 1-year spot rate. However, the estimated slope is not found to be equal to the true theoretical value, which is required by the expectation theory, thus, rejecting the hypothesis. Moreover, Campbell and Shiller (1991) reported a contribution towards the rejection of the EH based on the yield spread between US bonds of different maturities. Campbell and Shiller (1991) found paradoxical results. On one hand, the estimation of the long-term changes in the short-term rate gave positive slope of the term structure, which implied a predictive power of the term structure. On the other hand, the estimation of the short-term changes in the long-term rate yielded negative slope. Thornton (2003) advocated that the common findings of Campbell-Shiller paradoxical result was due to the construction of the tests (when the EH does not hold).

Despite the fact that the EH does not hold in a majority of cases (based on linear single equation and VAR approach), the subsequent empirical studies have shown the favorable evidence towards the EH in a nonlinear fashion. For example, Psaradakis, Sola and Spagnolo (2006) tested the expectation hypothesis of the term structure of G7 interest rates. The result indicated that the EH cannot be rejected when the data is estimated by Markov regime switching model. The forecasting result also revealed that the Markov switching model has an ability to predict changes in the short-term rate in the correct direction as required by the expectation theory. The finding also suggested that the conventional regression of the term structure has regime-dependent parameters. Moreover, Krishnakumar and Neto (2010) provided favorable contribution toward the EH using a three-regime threshold error correction model. The finding showed that the joint expectation hypothesis and uncover interest parity cannot be rejected in the case of Switzerland relative to Germany where the interest rates appear to be cointegrated at least in one of the regimes. Hung and Siklos (2001) used linear and nonlinear smooth transition error correction models to examine the term structure of interest rates for Canada, the UK, the US, Germany, Switzerland and Sweden. The results indicated that the changes in short-term interest rates are well approximated by the exponential smooth transition model. The smooth transition exhibits slow symmetric behavior around the location parameter. Moreover, Hung and Siklos (2001) suggested that the central bank policy and the regime shift in the long time-series could be the source of nonlinearity in the term structure of interest rates. Furthermore, McMillan (2004) employed several nonlinear models such as nonlinear model of Escribano and Granger (1998), threshold autoregressive (TAR), moment-TAR (MTAR) and smooth transition models (logistic and exponential smooth transitions). The findings indicated that nonlinear models are better to approximate the UK interest rate than the linear ECM. In fact, a logistic smooth transition error correction model is superior to other nonlinear models based on both estimation and forecasting performance. Moreover, McMillan (2004) found asymmetric nonlinear adjustment in the data, which reflects the asymmetric action of the market agents and monetary policy makers responding to the situation when the short-term interest rate is above or below the long-term rate.

In emerging countries, some studies have tested the EH in the Asian market using a linear model, in particular volatility and cointegration models. Gerlach (2003) found supportive evidence toward the EH in the Hong Kong market using the GARCH model. The finding indicated that the estimated slope of the term structure was unity and the presence of the risk premium was significant. Gerlach (2003) concluded that the term premium and the spread of interbank rates are unbiased but cannot predict the future changes in the short-term rate accurately. In contrast, Liau and Yang (2009) found no evidence supporting the EH in the Taiwanese money market based on the same methodology of Gerlach (2003). This result showed that the time-varying risk premium is not significant in this market. In other word, the spread cannot be used to forecast the future changes in the short-term rates. Liau and Yang (2009) suggested that a possible reason why the EH does not hold in the Taiwan market could be due to the unsounded government bond (i.e. illiquid bond market and the restriction on bond volume issue, which limit the upper bound of long-term rate) and a tight control of interest rate. Thus, this bond market does not reflect the true information of the market.

Additionally, Shen (1998) tested the EH on the term structure of Taiwan interest rates in a cointegration framework. He examines 10-day short rate and 30, 90 and 180-day long commercial paper rates. The result reveals that the EH does not hold for a shorter maturity pairs (10-30 day). Whereas, the EH cannot be rejected for a longer maturity pairs (10-90 day and 10-180 day). Shen (1998) points out that the noise contained in high frequency data could cause the rejection of the EH in shorter maturity pairs. Moreover, the empirical study of Shivam and Jayadev (2005) provided favorable evidence toward the EH in India, using a cointegration framework. The finding indicated that the spread exhibits mean reversion property, which is slowly correcting to the long-run equilibrium in India.

In addition, the central bank intervention could be one of the sources that induce the nonlinearity in the term structure of interest rates. Previous empirical studies (see, van Dijk and Franses, 2000; Enders and Siklos, 2001; and McMillan, 2004) showed some evidence of asymmetric intervention in periods of rising and falling inflation (McMillan, 2008). The results indicated that the adjustment of short term rate is faster when it is exceeded by the long term rate, which is indicative of rising future inflation (McMillan, 2008). Additionally, Haug and Siklos (2001) advocated that the action of central banks induces nonlinear adjustment and the presence of structural breaks in the term structure of interest rates. Moreover, the Malaysian central bank increased the interest rate during the 1997-98 Asian financial crisis to protect their currency (Hiebert, 1997; Liau and Yang, 2009). Therefore, the presence of nonlinearity might also cause the EH to be rejected. Alternatively, the nonlinearity of the term structure can also arise from risk adverse investors who require higher premium to hold risky long term bond in the period of falling rates than in the period of rising rates (McMillan, 2008). In addition, the presences of transaction costs also cause nonlinearity in the term structure as the investors will delay their arbitrage activity until the deviation is sufficiently large enough to offset these costs (Anderson, 1997).

To the best of my knowledge, only the empirical study of Kuo and Enders (2004) provided favorable evidence toward the EH based on nonlinear TAR and momentum-TAR in the Japanese interest rate market. The result also indicated the presence of asymmetric behavior of the term structure of Japanese interest rate at different maturities. However, no empirical studies have studied the behavior of the term structure in other Asian emerging interest rate markets using nonlinear model. In addition, there are many market agents responding to the deviation of the term structure of interest rate at different times, the economic variable (i.e. the term structure) would take some time to switch from one regime to another. Thus, the smooth transition model might be appropriated to be employed as the model allows the transition to occur in a smooth manner. It is of our aim to investigate the term structure of interest rates using logistic and exponential smooth transition models to capture nonlinearity in Asian interest rate markets that could arise from the central bank intervention, risk adverse investor and the presence of transaction cost.

The main purpose of this study is to investigate the expectation hypothesis of the term structure of 6-month and 3-month interest rates in Hong Kong, Malaysia, the Philippines and Thailand. Additionally, we aim to examine whether the term structure is better explained by nonlinear models rather than the conventional linear models. In this study, we employ linear conventional term structure regression, linear error correction models and smooth transition models with logistic and exponential functions, which allow to capture asymmetric and symmetric adjustment, respectively. McMillan (2004) pointed out that the logistic smooth transition model can capture sign asymmetry (different behavior occurs depending on whether the deviations are positive or negative) while the exponential smooth transition model enables to capture size nonlinearity (different behavior occurs for small and large deviations from equilibrium regardless of sign). The approximation of each model is evaluated based on several diagnostic tests including Ljung-Box (1978) Q-statistics on residual and squared residual. Additionally, the parameter constancy and no remaining nonlinearity tests are accounted to ensure that the smooth transition models are well specified. Moreover, an out-of-sample forecast is also conducted to show whether the nonlinear models can better describe the Asian interest rates.

The remainder of the study is organized as follows. Section 5.2 discusses the expectation hypothesis of the term structure literatures on various markets using linear and nonlinear models. The empirical framework is outlined in section 5.3. In section 5.4, we describe the property of interest rate data. Moreover, in section 5.5, the empirical result reports the estimation results of implemented models while the out-of-sample forecast performance is showed in section 5.6. Finally, the conclusion is summarized in section 5.7.

5.2 Literature review

The implications of the expectation hypothesis (EH) of the term structure of interest rates have been tested extensively in advance countries while limited evidence has been shown in emerging countries. In this section, the empirical literatures of both advance and emerging countries are reviewed using a variety of approaches to test the expectation hypothesis of the term structure.

5.2.1 Term structure evidence from Advance countries

5.2.1.1 The linear evidence in advanced economies

The study of Fama and Bliss (1987) tested the EH of the term structure of interest rates in respect to the predictability of the term structure. Extending the previous studies on U.S Treasury bills that have maturities of less than one year, the authors employed annual U.S Treasury bonds with the maturities up to 5 years.

The first regression is used to estimate the term premium in the 1-year return on a long term bond. The term-premium regression is formulated as it follows:

$$rx_{t+1}^{(n)} = \alpha + \beta(f_t^{(n)} - y_t^{(n)}) + \varepsilon_{t+1}^{(n)} \tag{5.1}$$

where $(rx_{t+1}^{(n)})$ is the 1-year return on n-year bond[33]. The authors run a regression of the 1-year excess return on n-year bond against the spread between the forward and spot rate of the same 1-year maturity $(f_t^{(n)} - y_t^{(n)})$. Under the pure expectation hypothesis, the constant and the slope coefficients (α and β) should be zero and one, respectively. Thus, this hypothesis implies no expected excess return on long term bond over the short term bond.

The authors found positive slope coefficient of the term-premium regression. In particular, the estimated slope is relatively close to unity at 1-year maturity. The finding also indicated that the term premium fluctuate the most at 1-year maturity, which confirmed the empirical finding of Fama (1984a) that the forward rate cannot predict the short term changes in the case of U.S Treasury bills. Moreover, the autocorrelation test indicated that the forward-spot spread became positive in the period of strong business activity while the spread became negative in the period of recession.

The second regression is to equate the changes in future spot rate on the forward-spot spread, which is formulated as follow:

$$y_{t+1}^{(n)} - y_t^{(n)} = a + b\left(f_t^{(n)} - y_t^{(n)}\right) + \varepsilon_{t+1}^{(n)} \tag{5.2}$$

[33] Fama and Bliss (1987) set n = 2 to 5-year bond, which represent as the long term bond.

If this forecasting regression yields the estimated slope coefficient greater than zero, the forward-spot spread has the power to forecast the future changes in the 1-year spot rate. The result indicated that the spread has an ability to predict changes in 1-year spot rate at 2 to 5 years ahead. As the forecasting horizon rose, the R^2 increased approximately to 0.5; thus, this result indicated an improvement of predictability of the term structure. The authors concluded that an improvement of the forecasting power over the longer horizon is due to the slow mean reversion of the spot rate.

Moreover, Campbell and Shiller (1991) also provided evidence against the expectation hypothesis of the term structure. The authors used single equation and vector autoregressive model to estimate the yield spread between bonds of different maturities. Campbell and Shiller (1991) employed continuously compounded yield on riskless discount bonds with different maturities. For the short-term rates, 0, 1, 2, 3, 4, 5, 6, and 9 months are used while 1, 2, 3, 4, 5 and 10 years are used for the long-term bond. The data is calculated by McCulloch (1990) in the period from January 1952 to February 1987[34]. Unlike Fama and Bliss (1987) used the forward-spot spread, the yield spread between bonds of different maturities is employed, which is formulated as follow:

$$\left(1/_k\right)\sum_{i=0}^{k-1} R^m_{t+m} - R^m_t = a + \beta\left(R^n_t - R^m_t\right) + e_t \qquad (5.3)$$

where R^m and R^n represent the short term and long term bond, respectively; k is an integer of n/m. In this equation, the long-term change in the short-term rate is equated on the spread between the long-term and short-term rates. Similar to the empirical finding of Fama and Bliss (1987), the EH cannot be rejected if the estimated slope coefficient (β) is unity. In fact, the regression yielded positive slope coefficients, which were significantly different from zero. However, the test rejected the EH at the short end while accepted the EH at the long end of the term structure. This finding implied that the slope of the yield curve has predictive power for the short-term rate (Thornton, 2003). Moreover, the authors ran a regression of the short-term change in the long-term rate against the long-short term spread, which is formulated as follow:

[34] The monthly pure discount bond yields for U.S Government securities are calculated by McCulloch (1990) cover the period from December 1946 to February 1987.

$$R_{t+m}^{n-m} - R_t^n = \mu + \lambda\left(\frac{m}{n-m}\right)(R_t^n - R_t^m) + \varepsilon_t \tag{5.4}$$

Similarly, the estimated slope coefficient (λ) is tested; if the slope of the term structure is equal to the true theoretical value of one, the EH holds. However, in contrast to equation (5.3), this regression yielded negative slope coefficients. This finding indicated that the negative estimated slope of the term structure mislead the prediction of changes in the longer-term yield over the life of the shorter-term bond. Therefore, the authors conclude that

"we thus see an apparent paradox: the slope of the term structure almost always gives a forecast in the wrong direction for the short-term change in the yield on the longer bond but gives a forecast in the right direction for long-term changes in short rates" (Campbell and Shiller, 1991, p. 505).

Furthermore, the authors employed the VAR model to examine the movement of the spread in relation to the prediction of changes in short term rates (Campbell and Shiller, 1991). The result showed positively large value, which implied that the actual spread and the estimated theoretical spread are positively correlated. In addition, the finding of Campbell and Shiller (1991) also provided evidence supporting the result of Fama and Bliss (1997) that the forecasting power of the term structure to predict changes in the short term rate improves as the forecast horizon increased. The result also indicated the deterioration of forecasting power when the maturities less than 1 year. In particular, the authors obtained the estimated slope coefficients exhibited a "U-shapes" pattern, which showed the minimum level of forecasting power was between 9 and 12 months, and then the forecasting ability started to improve. In contrast, the U-shaped pattern did not appear in the long-term yields. In fact, as the horizon increased, the estimated coefficients became increasingly negative.

Furthermore, Thornton (2003) attempted to test the empirical findings of Campbell and Shiller (1991) using the same data with an extension sample period, which covers from January 1952 to February 1991. Employing Campbell and Shillier (1991) methodology, the author found similar results of Campbell and Shiller (1991) for the period from 1952:01 to 1987.02. In particular, the conventional regression (equation 5.3) yielded positive beta coefficients of the term structure in the majority of cases. The estimated beta coefficients are relatively larger in the short and long periods than in the intermediate period. This finding indicated a U-shape pattern or "smile" as it was named by Roberds and Whitman (1999). This finding suggested that the EH is more likely to hold in short and long periods of maturities while the same hypothesis is more likely to be rejected in the intermediate periods. On the contrary, the contrarian regression (equation 5.4) yielded negative slope coefficients (λ) for every pair of long-term and short-term at different maturities. As the horizon increased, the estimated λ became increasingly negative.

In addition, Thornton attempted to provide the explanation toward the paradoxical results of Campbell and Shiller (1991) by conducting the Monte Carlo experiments. The results suggested that both tests (equation 5.3 and 5.4) tended to generate consistent results with the Campbell-Shiller paradoxical results when the EH does not represent the true data generating process (DGP) for the long-term rate. The author concluded that when the EH does not hold, the estimated slope of one test will be bias toward unity while the estimated slope of other test will be negative. The author also pointed out several implications of his research, which will be summarized as the following;

- The common findings of paradoxical results are due to the construction of the tests when the EH does not hold.
- The sizes of the estimated slope coefficients and the adjusted R-squares from both tests are not sufficient to be used for testing the validity of the EH in which these tests often reject this hypothesis.
- Thornton's (2003) finding showed that both tests produce biased estimates in the direction of the Campbell and Shiller (1991) paradox when the EH is rejected. This result is a complement to the finding of Bekaert et al. (2001) that the estimated slopes are positively biased in the small sample when the EH cannot be rejected. Thus, the evidence of both empirical studies entailed that the violation of EH is much more pronounced using small sample distributions than the asymptotic distributions.

- The finding suggested that the paradoxical results of Campbell and Shiller do not provide predictability of the term structure for either long-term changes in the short-term rate or short-term changes in the long-term rate. But the results showed that the EH does not represent the true data generating process. Thus, the predictability of the term structure could be influenced by other factors that determine the long-term rate and this should be included in the specification of the test.

In summary, the previous literatures using McCulloch data provided similar findings against the validity of the EH using single equation and VAR-based approaches. Therefore, there would be no reason to expect any systematic changes in findings based on the same data. In the next section, the evidence of the EH of the term structure investigating in various advance economies have demonstrated a nonlinear fashion.

5.2.1.2 The nonlinear evidence in Advance economies

The empirical study of Hung and Siklos (2002) investigated the term structure of interest rates using linear and nonlinear smooth transition error correction models. Monthly interest rates from Canada, the UK, the US, Germany, Switzerland and Sweden are used. The data spans the period from 1960 to 1998. The preliminary finding indicated that the interest rates are cointegrated based on Johansen's vector error correction model and Engle and Granger ECM. Moreover, the authors estimated smooth transition model using both logistic and exponential transition functions with various transition variables (domestic spread, error correction term, the US spread, inflation, output gap and real GDP growth). However, the domestic spread appears to be the best candidate in this analysis. The results revealed that the changes in short-term interest rates are better estimated by the exponential smooth transition model, which implied that the smooth transition tends to show symmetric behavior around the location parameter. In particular, the hypothesis of linearity is rejected in all cases in which the expectation hypothesis is also rejected for all countries. The authors suggested that the action of central bank policy makers and the regime shift in the long time series could cause nonlinearity in the term structure of interest rates.

Moreover, Kuo and Enders (2004) investigated the long run relationship between Japanese interest rates of different maturities using a nonlinear approach. The weekly series of daily, one-month and three-month Euro-yen deposit rates were examined over the period of July 1985 to October 1998. Threshold autoregressive model and the momentum-threshold model were implemented, which allowed for asymmetric adjustment toward a long-run equilibrium. The result showed supportive evidence of the EH in the sense that the spread reflected the rational expectation of the future changes in short-term interest rates. The Japanese rates of different maturities are also found to be cointegrated, and the term structure adjustments are asymmetric. Moreover, the authors employed the error correction model to determine the nature of the adjustment process. The result showed that the error correction model with asymmetric adjustment was significant in the pair of Euro 3-month and daily spot rates. This finding indicated that the euro-yen spot rates adjusted strongly to the positive disequilibrium from the long-run equilibrium and moderately to the negative disequilibrium (Kuo and Enders, 2004). On the other hand, the 3-month rate only adjusted when the short-term deviation was negative. The results also indicated that the spot rate adjusted toward the long-run equilibrium more than the 3-month rate.

In addition, the study of McMillan (2004) also used nonlinear models to estimate and forecast the term structure of short and long-term UK interest rates. The daily and yearly interbank rates over the period from January 1975 to June 2003 are utilized. Several models, such as the nonlinear model of Escribano and Granger, threshold autoregressive (TAR), moment-TAR (MTAR) and smooth transition models (logistic and exponential smooth transitions) were considered to capture the nonlinear cointegration and error correction mechanism of the interest rates. The estimations from these nonlinear models are compared to the standard linear ECM. The findings revealed evidence of cointegration relationship between short and long-term UK interest rates. Moreover, the long-term rate Granger caused the short-term rate and no reversion direction. This result can be seen as the evidence favoring the validity of the EH although the author did not test this hypothesis directly. As a result, the specification tests indicated that this data is better explained by the nonlinear models over the linear ECM. However, a logistic smooth transition error correction model appeared to be the best performer in terms of parameter estimation and forecasting. In fact, out-of-sample forecasting showed small but significant forecasting improvement for LSTR over the linear model. This finding suggested that the asymmetric nonlinear adjustment is smoothly changed from one regime to the other, and this adjustment process depends upon the sign of disequilibrium (McMillan, 2004). The author pointed out that the finding of asymmetric nonlinear behavior of the term structure reflected the actions of the monetary policy makers and the market agents toward the movement of the short-term rate relative to the long-term rate. In fact, the author found the negative disequilibrium term is reverted faster than the positive disequilibrium term. This finding indicated that the monetary policy makers and the market agents might respond faster when the long-term interest rate exceeds the short-term rate.

The next empirical study of Psaradakis, Sola and Spagnolo (2006) indicated that the expectation hypothesis of the term structure cannot be rejected when using Markov regime switching model, which allows for time-varying risk premium. The quarterly 3-month and 6-month interest rates for G7 counties, including the U.S (from 1960 to 2000), Germany and the UK (from the middle of 1970 to 2000), Canada, France, Italy and Japan (from the early 1980 to 2000) are examined. The findings showed that the conventional regression of the term structure had regime-dependent parameters and the explanatory variables are correlated to the disturbance in each regime. To overcome the endogenous variables problem, the instrument variable is employed in the Markov switching model. Thus, 6 out of 7 countries cannot reject the EH for 3 and 6-month maturity rates. The estimated coefficients are approximately close to the true values with tighter confidence intervals. Moreover, the Markov switching model has the ability to forecast the changes in the short-term rate in the correct direction.

In a more recent empirical study, Krishnakumar and Neto (2012) attempted to test the expectation hypothesis and uncover interest rate parity (UIP) together in a nonlinear framework. Theoretically, given that the expectation hypothesis is held, the uncover interest rate parity (UIP) should be held in a short and long horizon. Krishnakumar and Neto (2012) tested these two theoretical hypotheses jointly in cointegrated framework with nonlinear and symmetric disequilibrium. The authors estimated a multivariate three-regime threshold vector error correction model (TVECM) where the long run relationship follows the unit root process and develops the reduced rank test to capture the cointegrated relationship in each regime. Moreover, a no-cointegration test is also implemented following the methodology of Caner and Hansen (2001). The monthly interest rate series of Switzerland relative to the U.S and Switzerland relative to Germany is used covering the period from January 1993 to October 2008. The authors used 1, 3 and 6-month money market rates as the short-term interest rates while 10 years government bond rate is used as the long-term rate. The findings indicated the presence of threshold cointegration in the employing samples. In the case of Switzerland relative to Germany, the estimation detects the cointegrating relationship at least in one or both regimes and accepts the joint hypotheses of EH and UIP. In the case of Switzerland relative to the U.S, there is an existence of one cointegrating relationship and the joint hypotheses are rejected. The findings also indicated the evidence of asymmetry disequilibrium as it deviates outside the band of inaction where no-cointegration exists in this band.

In summary, the empirical studies have shown mixed evidence, either supporting or opposing the expectation hypothesis in advance economic countries, using a variety of linear and nonlinear models. In the next section, we will discuss the previous literatures that have tested the expectation hypothesis in the emerging economies, especially those in Asian countries.

5.2.2 Term structure evidence from Asian countries

The previous literatures have addressed the mixed evidence of the expectation hypothesis of the term structure mainly in a linear framework while there is limited evidence using nonlinear model to examine the term structure in Japan and no evidence in other Asian countries particularly in emerging Asian countries. In this section, we will review the previous linear literature based on 2 main methods that test the EH by capturing the volatility of the interest rate and the cointegration.

5.2.2.1 The Expectation hypothesis and volatility

Gerlach (2003) tested the expectation hypothesis in Hong Kong and employed a GARCH model to measure the time-varying risk premium. Monthly interbank rate of Hong Kong is examined during the period from January 1992 to February 2001 at 1, 3, 6, 9 and 12-month maturity. Firstly, the expectation hypothesis is tested using the general method of moment (GMM), which allows the error to be heteroscedasticity. This obtained error is governed by moving average process. As a result, the EH is rejected in this data as the estimated slope is significantly different from unity and the negative constant is insignificantly different from zero. Thus, the nonzero constant implies the time-varying risk premium. Moreover, the author applied GARCH model to estimate the volatility of the 1-month rate, which measures the risk premium. The term premium is assumed to be proportional to the logarithm of the variance of innovation to the 1-month rate (Gerlach, 2003). The result showed that the volatility of 1-month rate is generally low in this market. However, the volatility rose dramatically during the 1997 Asian crisis and the speculative attack in the latter half of 1998. Furthermore, the author re-estimated the previous regression including the variance of shocks to the 1-month rate, which obtained from GARCH model. The findings showed better estimation, which supported the EH. In particular, the EH is held for 6, 9 and 12-month rates while the hypothesis is rejected for 3-month rate. The slope of volatility is also significant for all cases. However, the author pointed out that the estimated slope of logarithm volatility of the 1-month rate could be biased due to an errors-in-variables problem. Therefore, the instrumental variable is used to overcome of such problem, which is suggested by Pagan and Ullah (1988). The author re-estimated the regression and replaced the logarithm volatility by the logarithm of square of the fitted error in ARCH model with 2 lags. The result indicated even larger estimated slope and more significant relative to the previous regression incorporate with implied volatility in all cases (except for 3-month rate). Thus, the EH cannot be rejected for 6, 9 and 12-month rates as the estimated slope of the term structure is one. In addition, the slopes of square variance are highly significant, which imply that the risk premium remains highly significant in this analysis. Therefore, the author concluded that the term premium and spread of interbank rates in Hong Kong are unbiased. However, they poorly predict the future short term rates.

Moreover, Liau and Yang (2009) adopted Gerlach (2003)'s methodology to test the expectation hypothesis in the Taiwanese money market. The authors used monthly commercial paper interest rates for 30, 60, 90, 120, 180 and 365-days maturities. The full sample covers from January 1994 to December 2005. Moreover, the authors also concern the presence of structural break in the data as the sample covers the period of turmoil. Thus, the sample is divided into 2 subsamples based on the economic downturn in 2000, which are the high interest rate (January 1994 to May 2000) and low interest rate (June 2000 to December 2005). Following Gerlach's (2003) empirical study, the authors firstly examined the EH of the term structure in the Taiwanese money market using GMM. Then, the logarithm variance of 30-days interest rate is estimated using GARCH model. Then, the logarithm of variance is replaced by the square of fitted residual to overcome the bias estimate as proposed by Pagan and Ullah (1988). As a result, the estimated slope of the term structure is significantly different from zero and one. Thus, the EH is rejected for all cases in the full sample. Moreover, the EH is also rejected for both sub-sample periods. In contrast to Gerlach's (2003) empirical findings, Liau and Yang (2009) discovered insignificant negative slope of the variance of the 30-day rate for 30, 60, 90 and 120-day rates. This finding implied that the time-varying risk premium does not appear in this market while it appears to remain in the longer horizons of 180 and 365-day rates. Moreover, the result also indicated that there is no structural change between the high and low interest rate periods even though the interest rate has decreased during the economic downturn in mid-2000. The authors suggested that the reasons behind this finding could be due to the unsounded government bond and a tight control of interest rate. In Taiwan market, the government bonds are held by certain number of institution investors in a high volume, which causes the destruction of price mechanism. Also, the bond market is restricted on the issue volume in which the long-term interest rate cannot move up in relation to excess demand of money. The bond market is also illiquid; thus, the government bond market does not reflect the information of the short- and long-term interest rates (Liau and Yang, 2009).

5.2.2.2 The Expectation hypothesis and cointegration

In emerging markets, the empirical study of Shen (1998) tested the expectation hypothesis in a cointegration framework. The author applied Johansen's maximum likelihood approach to test the validity of the EH in Taiwanese money market. The commercial paper rates are collected from August 1983 to October 1992. The author used 10-day as a short-term rate and 30, 90 and 180-day as a long-term rate. In Johansen's cointegration test without a constant term, the estimated slope of spread is approximately close to the estimated coefficients obtained from the OLS method. Moreover, the test rejects the null hypothesis of no cointegrating vectors for 3 pairs and also indicates that a system of money market rates contains one cointegrating vector. In addition, the EH is held for all cases, and the likelihood ratio statistic cannot reject the null hypothesis that cointegrating vector is (1, -1). Furthermore, the EH are also confirmed by the Granger and causality test as there is only one Granger causality flow from the spread to the change in the short-rate. This result implies that the spread contains useful information, which causes changes in the short-term rate. However, the Wald statistics reject the null hypothesis of the term structure expectation for shorter maturity pairs (10-30 days pair) while the EH is held for the longer maturity pairs (10-90 day and 10-180 day pairs). Moreover, the level variance ratio also supports the Wald statistic. In fact, the ratio is equal to 1.227 for the 10-180 day pair, which is the closest to theoretical value of unity.

Moreover, Shivam and Jayadev (2005) investigated the term structure of interest rates in Indian money market. The sample data includes 90-day commercial paper rate, overnight call money rate, overnight MIBOR, secondary market yield of 90-day Treasury bill and secondary market yield of 1-year Treasury bill. These 5 rates are collected from September 2001 to June 2003. Firstly, the authors used Johansen's technique to test for the co-movement in the yields of Indian money market rates. The result indicated that the whole system of money market rates is cointegrated as they are driven by a common stochastic trend. The finding also supported the EH in this market. Secondly, the ECM is used to determine the causal structure and the speed of adjustment toward the long run equilibrium. If the disequilibrium term is positive (negative), the rates should increase (decrease). The result indicated significant error correction term, which showed that the spread contains mean-reversion property. Thus, the deviation of the change in the short term rates will reverse back to their long run equilibrium. The property of ECM also provides the benefit to the market investors. For instance, the error correction mechanism of the spread helps to forecast the change of the money market rates in the short-term rate. Moreover, it can be used as the criterion to select the valuable investment instrument as the ECM provides the speed of adjustment and the direction of re-correction in the short rate. In fact, the authors found small value of adjustment coefficients in which indicated that the deviation of money market rates appeared to be slowly correcting to the long run equilibrium in India.

Moreover, Holmes, Otero and Panagiotidis (2010) employed a panel data approach to examine the term structure in seven Asian countries including Hong Kong, Korea, Japan, Malaysia, the Philippines, Singapore and Thailand. The quarterly 3-month deposit rates and long-term government bond are examined from the period of Q4:1995 to Q4:2008. Unlike the existing panel unit root test, the authors adopted Hadri and Rao (2008) methodology, which tests the national term structures for the joint stationarity rather than joint non-stationarity. By doing this, the Hadri and Rao method can identify which variable influences the rejection of the null hypothesis of joint stationarity. As a consequence, the finding indicated supportive evidence toward the EH when the panel approach is allowed for structural breaks and cross sectional dependency. In particular, the panel unit root test cannot reject the joint stationarity hypothesis, which indicates that the Asian term structures are stationary. The result also showed that the forward rate is an unbiased predictor of the future spot rate. Hence, the Asian financial markets are found to be efficient in this analysis.

In addition, Nugroho (2011) tested the EH in Indonesian bank rate using cointegration framework. The 30 (short-term), 90 (medium-term) and 180-day (long-term) Sertifkat bank Indonesia rates are examined covering the period from January 2005 to January 2011. The preliminary finding showed that the relationship between 30-day and 180-day interest rates is significantly negative. Then, the author applied OLS regression of the long-term rate on the short-term rate in level. The Wald statistic showed that the constant and slope coefficients are not significantly equal to zero and one. Thus, the EH cannot be held in the Indonesian market, which means that the short-term (30-day) rate is not efficient in predicting the future long-term (180-day) rate. Moreover, the estimated residual obtained from OLS regression also appears to continue auto correlated between the residual across all lags, which shows that the historical interest rate contains significant information. Hence, the determination of today's interest rate is influenced by the historical data. Furthermore, the Johansen cointegration model cannot detect any cointegrating relationship between 30 and 90-day interest rates while the cointegrating relationship is exhibited for the 30 and 180-days interest rates. Hence, the finding of cointegrating relationship suggested that the long-term pair is efficient while the medium-term pair is not. However, this result contradicted to the result of ECM; the estimation gave insignificant speed of adjustment of disequilibrium term for 30 and 180-days rate. This result indicated that the short-term rate has low power to influence the long-term rate. The author concluded that the short-term rate is not the best forecaster of the medium-term interest rate as the cointegrating relationship is not presented between the two rates while the efficiency of the term structure between 30 and 180-days rate holds.

In summary, we observe mixed evidence of the expectation hypothesis of the term structure of interest rates in the emerging economies. The common findings using linear models provide the evidence against the expectation theory. As evidence of the EH in a nonlinear framework is limited, it is of our interest to examine the term structure of Asian interest rates whether the nonlinear model is better approximated the data than the common linear model.

5.3 Empirical framework

5.3.1 Linear models

The expectation theory of the term structure of interest rate is the relationship between the long-term interest rate (r_{2t}) and the short-term interest rate (r_{1t}). The expectation hypothesis is formulated as followed:

$$r_{2t} = \frac{1}{2} E_t[r_{1t} + r_{1,t+1}] + v_t \tag{5.5}$$

This equation shows the relationship between long-term and short-term interest rates in the way that the long-term rate is the average of the current and the expectation of the future short-term rate plus the term premium or estimation error (v_t). However, although this term premium can vary across maturities, it is assumed to be constant through time. Then, the expectation theory of the term structure can be expressed in terms of the spread $(r_{2t} - r_{1t})$ as:

$$\Delta r_{1,t+1} = a + b(r_{2t} - r_{1t}) + e_{t+1}, \qquad b = 2 \tag{5.6}$$

As described in Campbell and Shiller (1991), the spread is a constant risk premium plus an optimal forecast of changes in future interest rates. The expectation hypothesis of the term structure can be tested by regressing the change of the short-term interest rates $(\Delta r_{1,t+1})$ on the spread between the long and short-term interest rates. Then, under the rational expectation and risk neutrality, the expectation hypothesis is held if the estimated slope of the term structure equals to two $(b = 2)$ with zero constant (a = 0)[35]. This implies the rational expectation of the future short-term rate plus the absence of risk premium. This equation is a conventional regression, which is widely tested in the literature using the ordinary least square (OLS) estimator.

Moreover, some literature documents the cointegration property for a variety of countries using conventional term structure regression (Hall, Anderson and Granger, 1992, Siklos and Wohar, 1997). Let us suppose that yields are integrated of order one and the spread is stationary; thus, the long and short-term interest rates are cointegrated with a vector (1, -1). The deviation of the spread from the long-run equilibrium represents the arbitrage opportunity.

---

[35] If a = 0 and $b = 2$, equation 5.6 is derived from equation 5.5 as the following;

$$r_{1,t+1} - r_{1t} = 2r_{2t} - 2r_{1t}$$
$$r_{1,t+1} + r_{1t} = 2r_{2t}$$
$$r_{2t} = \frac{r_{1t} + r_{1,t+1}}{2}$$

Moreover, a standard linear error correction model (ECM) is also implemented to measure the error correction mechanism of the term structure of interest rates. The ECM can be formulated as follow:

$$\Delta r_{1,t+1} = a + b(r_{1,t} - \beta_0 - \beta_1 r_{2,t}) + \left\{ \sum_{i=1}^{k-1} \delta_{r1t} \Delta r_{1,t} + \sum_{i=1}^{k-1} \delta_{r2t} \Delta r_{2,t} \right\} + u_{t+1} \tag{5.7}$$

where $(r_{1,t} - \beta_0 - \beta_1 r_{2,t})$ is the error correction term, $\sum_{i=1}^{k-1} \delta_{r1t} \Delta r_{1,t}$ and $\sum_{i=1}^{k-1} \delta_{r2t} \Delta r_{2,t}$ are the lags of changes in 3-month and 6-month interest rates, k is the number of lags and u_{t+1} is a white noise disturbance term with mean of zero. Hence, the expectation hypothesis tests the hypothesis that $a = b - 2 = 0$, as in equation (5.5). In fact, the estimate of slope (b) also represents the speed of adjustment of error correction term where a large value indicates a faster adjustment toward the long-run equilibrium. If b is significantly different from zero, the result implies the 3-month and 6-month interest rates are cointegrated. Additionally, Granger causality can also be identified from this equation, in which the significant adjustment coefficient indicates that long-term rate Granger causes the short-term rate.

5.3.2 Nonlinear smooth transition models

Several reasons have been considered in order to explain why the relationship between long and short-term might be nonlinear. For example, Anderson (1997) suggested that the transaction costs of the bond at different maturities are different and might change over time. Additionally, the delayed response of market agents might also cause nonlinearity as they wait for the deviation of the term structure to be sufficiently large enough to offset the transaction cost (McMillan, 2004). Moreover, Fama (1984a) found that the risk premium is time varying and also displays nonlinear behavior. Haug and Siklos (2001) also pointed out that the action of monetary policy makers influences the term structure of interest rates might cause structural breaks and the adjustment might be nonlinear. Thus, the presence of nonlinearity could induce the rejection of the EH (McMillan, 2004).

In this study, we employ smooth transition models (logistic and exponential functions) introduced by Granger and Terasvirta (1993) and by Terasvirta (1994) to account for a possible nonlinearity behavior in Asian markets. The smooth transition models are appropriate in this analysis due to the fact that the models do not assume an abrupt switch from one regime to the other to occur in the market where a large number of investors participate at different time base on their own expectation. Thus, the change in regime perhaps smooth rather than discrete (Tarasvirta, 1994).

The smooth transition model is given by

$$\Delta r_{1,t+1} = [\alpha_1 + \beta_1(r_{2t} - r_{1t})][1 - F(z_t;\gamma,c)] + [\alpha_2 + \beta_2(r_{2t} - r_{1t})]F(z_t;\gamma,c) + \varepsilon_{t+1} \quad (5.8)$$

where $F(z_t;\gamma,c)$ is the transition function bounded between 0 and 1 and u_{t+1} is a zero mean, stationary disturbance term. The smooth transition model allows different type of behavior depending on the transition function. The most popular transition function includes the logistic and exponential functions.

The logistic function is given by:

$$F(z_t;\gamma,c) = \left(1 + exp\left(-\gamma(z_t - c)\right)\right)^{-1} \text{ with } \gamma > 0, \quad (5.9)$$

where (z_t) is the transition variable, which is the term structure of interest rates or the spread $(r_{2t} - r_{1t})$, c is the location parameter (point to where the transition takes place) and γ is a smooth transition parameter. The logistic function changes monotonically with the transition variable from 0 to 1. Moreover, this function allows the parameters to move asymmetrically around c. When $\gamma \to \infty$, $F(z_t;\gamma,c)$ approaches 1 thus, the logistic smooth transition regression (LSTR) becomes a threshold model while the LSTR model reduces to a linear model of equation (5.6) when $\gamma \to 0$ and $F(z_t;\gamma,c)$ approaches zero. The LSTR model can capture asymmetric behavior when either the deviations are positive or negative (McMillan, 2004).

Moreover, the exponential function is given by:

$$F(z_t;\gamma,c) = 1 - \exp\left(-\gamma(z_t - c)^2\right) \text{ with } \gamma > 0, \quad (5.10)$$

In contrast to logistic function, the exponential function allows the parameters to change symmetrically around c. The ESTR model becomes a linear if $\gamma \to 0$ and $\gamma \to \infty$ [36]. The ESTR model is also able to capture different behavior occurs for small and large deviations (McMillan, 2004).

The Wald statistic is used to test jointly whether the expectation hypothesis ($\alpha = 0, \beta = 2$) holds in each regime. Moreover, individual t-test statistics are also employed to test whether the coefficient of the spread is significantly different from zero and two. Additionally, several diagnostic tests such as the residual Ljung-Box statistic, the squared residual Ljung-Box statistic, parameter constancy test, no remaining nonlinearity test are used to ensure the validity of the nonlinear model.

5.4 Data

We use quarterly 3-month and 6-month Treasury bills. The 3-month rate represents the short-term rate and 6-month rate represents the long-term rate for Hong Kong (from Q1:1997 to Q1:2012), the Philippines (from Q1:1992 to Q1:2012), Malaysia (from Q3:1997 to Q1:2012) and Thailand (from Q1:2002 to Q1:2012)[37]. The data is collected from DataStream except for Thailand where the data is retrieved from the Bank of Thailand. All the data of interest rates are transformed into logarithm form.

5.4.1 The unit root test

First of all, a preliminary exercise is conducted to determine the order of integration of the 3-month and 6-month interest rate series. We employ the augmented Dickey Fuller (ADF) test[38]. In cointegration context, the short and long interest rates are required to be cointegrated of the same order.

In table 5.1, the summarized result of unit root tests are reported for Hong Kong, Malaysia, the Philippines and Thailand. The ADF test cannot reject the unit root

[36] The LSTR and ESTR are estimated by maximum likelihood estimation using Gauss econometric programming.
[37] In Thailand Treasury bills, we obtain daily data. As we use quarterly data, we use the middle rate within each 3 months.
[38] We run the unit root and choose Akaike criterion's automatic lag selection starting from 9 lags.

hypothesis in the 3-month interest rate (r_1) for Hong Kong and the Philippines while the same null hypothesis holds in the 6-month interest rate (r_2) for Hong Kong, the Philippines and Thailand. These findings imply that the short and long-term interest rates are nonstationary for Hong Kong and the Philippines. Moreover, based on the spread between the long and short-term interest rates (r_2-r_1), the tests significantly reject the null hypothesis of unit root for all cases except for the Philippines. Therefore, preliminary tests show that the interest rate series of Hong Kong appears to be consistent the cointegration theory. In fact, the 3-month and 6-month interest rates for Hong Kong have a linear combination, which have stationary long run equilibrium. However, previous empirical studies address the issue that the power of the ADF test is reduced in the presence of structural break in the time-series. Therefore, the series of Malaysia, the Philippines and Thailand are also analyzed in a nonlinear framework.

Table 5.1: The Result of Unit root Test

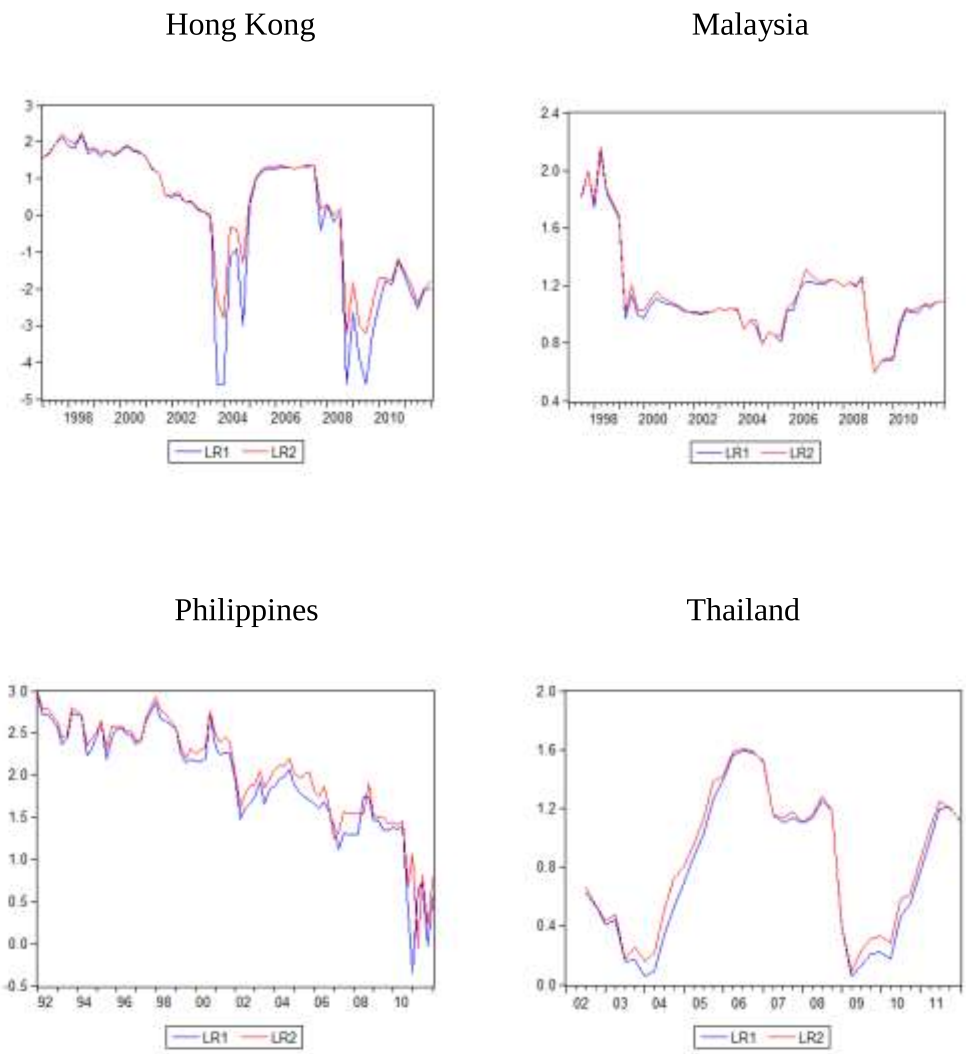
	Hong Kong	**Malaysia**	**Philippines**	**Thailand**
	Augmented Dickey Fuller Test (ADF)			
r_{1t}	-2.3641	-5.3005 ***	-0.3517	-3.6368 **
r_{2t}	-1.7569	-5.3297 ***	1.4719	-2.0357
(r_{2t}-r_{1t})	-3.3159 **	-2.8702 *	-1.0393	-3.3050 **

Note that r_{1t}, r_{2t} and (r_{2t}-r_{1t}) represents 3-month Treasury bill rate, 6-month Treasury bill rate and the spread between the short and long-term rates. ***, **, * indicates significantly at 1%, 5% and 10% respectively.

5.4.2 Visual inspection

The visual inspections showed in figure 5.1 and 5.2 indicate big fluctuations of the data, which provide some evidence of structural break. In figure 5.1, the 3-month and 6-month interest rates of 4 countries appear to be non-stationary. The underlying trend of interest rates appears to be downward throughout the sample under review for all countries, except Thailand. The two different maturities closely followed each other but the short-term rate is slightly lower than the long-term rate. Additionally, in figure 5.2, the illustration of spread between the two rates shows several outstanding changes. Particularly, the spread of Hong Kong exhibits large spike during 2004 and 2009 while several changes occur in Malaysia during the periods 1998, 2005 and 2010. Also, the Philippines have constant variation of the spread and a large spike at the end of the sample (during 2010). Similarly, the spread of Thailand also exhibits several changes throughout the sample period; the largest spike occurs during the period 2004-2005. Based on a visual inspection and the ADF test, the unit root test result is likely to be sensitive to the presence of the structural break in our sample. Therefore, nonlinear model can be used to take into account for structural instability and breaks in the data.

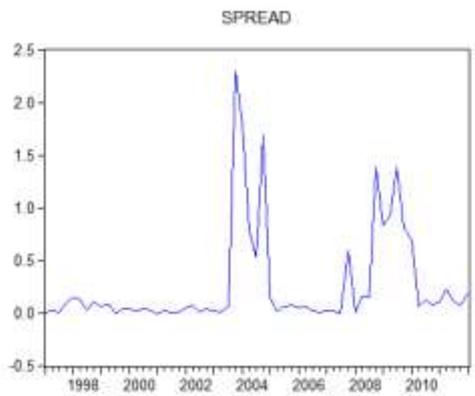
Figure 5.1: 3-month and 6-month Treasury bill rates



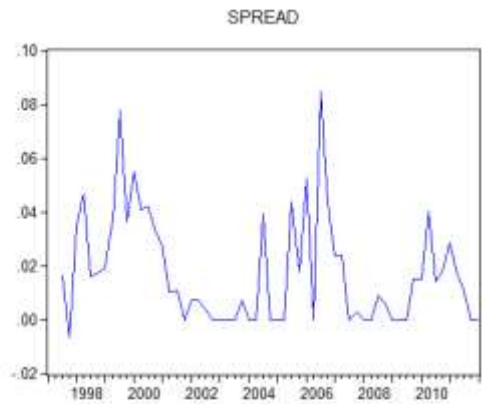
Note that LR1 and LR2 represent 3-month and 6-month Treasury bill rates in logarithm form, respectively.

Figure 5.2: The spread of long term and short term interest rate (r_{2t}-r_{1t})

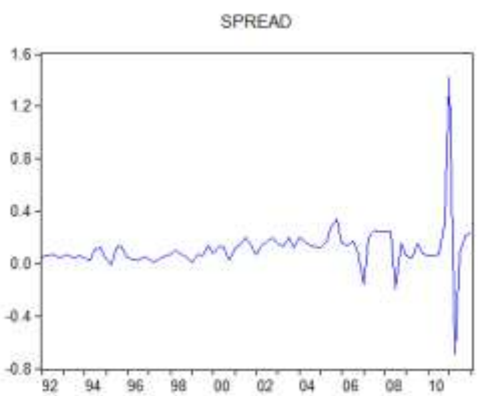
Hong Kong



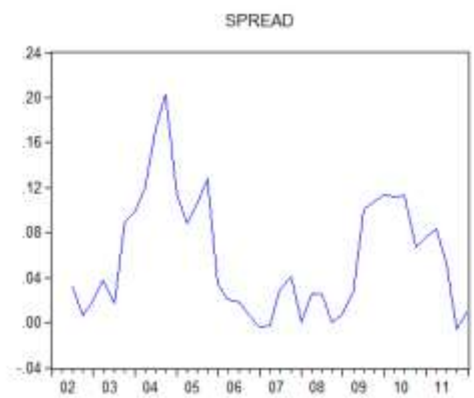
Malaysia



Philippines



Thailand



5.5 Empirical results

5.5.1 Linear Regression

In this section, a linear modeling approach is used to test the expectation hypothesis of the term structure of interest rates with 3-month and 6-month maturities in a bivariate setting. The OLS estimation results of dynamic term structure regression (equation 5.6) are reported in table 5.2. The estimation results show similar findings to the previous empirical studies that used data on advance economies. The results show positive estimated slope coefficients of the term structure, which are significantly different from zero, except for Malaysia. This finding indicates that the spread of Hong Kong, the Philippines and Thailand contains useful information to forecast the future changes in the 3-month interest rates. The positive slope also implies the correct forecasting direction, as required by the expectation theory. Moreover, the Wald statistic cannot reject the expectation hypothesis of $\beta = 2$ for Malaysia and Thailand. However, the joint Wald test on the constant and slope coefficient ($\alpha = 0, \beta = 2$) indicates that the EH is rejected in all cases. This result implies that the positive slope substantially deviates from the true theoretical value. Specifically, in the case of Malaysia and Thailand, the Wald test cannot reject the hypothesis on $\beta = 2$ but significantly reject the joint hypothesis on $\alpha = 0, \beta = 2$. This finding suggests that the cause of rejection could be due to the presence of the term premium, which is nonzero. Generally, our findings provide evidence against the expectation theory for all cases. The linear OLS estimations appear to describe the data well for Hong Kong and Thailand with relatively low standard errors of 1.09 and 0.27, respectively. The diagnostic tests confirm the robustness of these 2 estimations as the Ljung-Box statistic of residual and square residual give value larger than 0.05. Moreover, the diagnostic tests also indicate linear and nonlinear dependency for Malaysia and the Philippines. In particular, the Q-statistics on residuals and squared-residuals show p-values smaller than 0.05 for Malaysia and the Philippines, respectively.

Table 5.2: OLS estimation result of dynamic linear regression

	Hong Kong	Malaysia	Philippines	Thailand
α	-0.3396	-0.0275	-0.0887	-0.1173
	**		***	***
	(0.1606)	(0.0263)	(0.0329)	(0.0422)
β	1.0336	0.8330	0.5304	2.1709
	***		***	***
	(0.2827)	(0.9733)	(0.1481)	(0.5314)
Standard Error	1.0930	0.1501	0.2540	0.1713
		Wald Test		
β=2	11.6831	1.4375	98.4423	0.1034
	***		***	
α=β-2=0	14.9467	3.7337	88.9587	7.4774
	***	**	***	***
		Diagnostic Tests		
Q1(4)	4.8175	12.390	5.0148	1.7561
	[0.307]	[0.015]	[0.286]	[0.781]
Q1(8)	8.5216	14.957	6.4537	3.7527
	[0.384]	[0.060]	[0.597]	[0.879]
Q2(4)	1.9593	4.2018	36.136	0.3506
	[0.743]	[0.379]	[0.000]	[0.986]
Q2(8)	3.4102	4.6984	36.244	0.4873
	[0.906]	[0.789]	[0.000]	[1.00]

Note that ***, **, * represent significant at 1%, 5% and 10% respectively. α and β are the constant and slope coefficients. The standard errors corresponding to estimated coefficient are in the parenthesis. Wald test is the Wald statistic for testing the expectation hypothesis β=2 and α=β-2=0. P-values are in square brackets, which are reported for diagnostic tests. Q1(k) is the residual Ljung-Box statistic at lag k and Q2(k) is the squared-residual Ljung-Box statistic at lag k.

5.5.2 Error correction model

The estimation result using error correction models is summarized in table 5.3. In contrast to the previous finding, in table 5.2, the estimated slope coefficient is negative and significantly different from zero for all countries except for Malaysia. Thus, including insignificant error correction term, the ECM would generate estimation noise rather than helping to explain the relationship of Malaysian interest rates. Moreover, the ADF test shows that the error correction term significantly reject the unit root hypothesis for Hong Kong, Malaysia and Thailand. These findings indicate that the long run relationship of these 3 countries is stationary except for the Philippines. Additionally, the significant error correction term also indicates that the 6-month interest rate Granger causes the 3-month interest rate. In other words, the market participants can determine the short-term rate based on the long-term rate. In addition, the estimated slope reflects the speed adjustment of disequilibrium term in which the bigger absolute value shows a faster error correction adjustment towards the long run equilibrium. Particularly, Thailand appears to contain the biggest absolute value (slope of error correction term = |-2.09|), which implies that the short-run deviation is reversed back to the long run equilibrium faster than the other countries. However, the disequilibrium adjustments of Hong Kong, Malaysia and the Philippines have a similar speed, as the ECM yields closely similar estimates, which are |-1.27|, |-1.29| and |-1.20| , respectively.

Moreover, the Wald test significantly rejects the expectation hypothesis of $\beta = 2$ and the joint hypothesis of $\alpha = 0, \beta = 2$ for all cases. Furthermore, the standard error of ECM is similar to the one we obtained from table 5.2. The diagnostic tests also tell the similar story that Malaysia tends to have serial autocorrelation in the residual series while the Philippines appears to have problems of heteroscedasticity. This finding implies that the linear ECM cannot explain the term structure of interest rates successfully in Malaysia and the Philippines.

In summary, using the conventional term structure regression and error correction model, we find that the expectation theory does not hold in Hong Kong, Malaysia, the Philippines and Thailand. The EH is rejected in the latter model for all cases while it holds in the conventional term structure regression for Thailand when tested on the slope individually. Our findings indicate the presence of linear and nonlinear dependency in the case of Malaysia and the Philippines. Hence, in the next section, the smooth transition models (logistic and exponential smooth transition) are implemented to examine for the potential nonlinearity relationship of the term structure.

Table 5.3: Estimation result of ECM				
	Hong Kong	**Malaysia**	**Philippines**	**Thailand**
α	-0.0143	-0.0186	-0.0276	0.0096
	(0.1452)	(0.0196)	(0.0271)	(0.0296)
β	-1.2744 ***	-1.2854	-1.1952 ***	-2.0893 **
	(0.3565)	(1.1977)	(0.2323)	(0.9131)
Standard Error	1.09	0.15	0.24	0.18
EC	-8.1014 ***	-3.1192 **	-1.4326	-3.3337 **
	0 lag	1 lag	10 lags	4 lags
		Wald Test		
β=2	84.37 ***	7.52 ***	189.11 ***	20.06 ***
α=β-2=0	43.12 ***	4.10 **	95.69 ***	10.07 ***
		Diagnostic Tests		
Q1(4)	3.70	8.81	2.05	4.07
	[0.45]	[0.07]	[0.73]	[0.40]
Q1(8)	7.96	9.19	4.02	7.58
	[0.44]	[0.33]	[0.86]	[0.48]
Q2(4)	1.36	1.78	13.89	0.75
	[0.85]	[0.78]	[0.01]	[0.95]
Q2(8)	2.60	2.02	17.09	1.34
	[0.96]	[0.98]	[0.03]	[0.99]

Note that ***, **, * represent significantly at 1%, 5% and 10% respectively. α and β are the constant and slope coefficients. The standard errors corresponding to estimated coefficient are in parenthesis. Wald test is the Wald statistic for testing the expectation hypothesis β=2 and α=β-2=0. P-values are in square brackets, which are reported for diagnostic tests. Q1(k) is the residual Ljung-Box statistic at lag k and Q2(k) is the squared-residual Ljung-Box statistic at lag k. Augmented dickey fuller test (ADF) is reported for testing the presence of unit root in the error correction term.

5.5.3 Logistic smooth transition model

Based on the fact that ADF test has a low power to detect the unit root when the time-series contains structural break, and on the visual inspection (figure 5.1 and 5.2) that also indicates some evidence of structural break in our sample. In this section, we are going to implement a nonlinear approach.

In table 5.4, the estimations of LSTR are reported for Hong Kong, Malaysia, the Philippines and Thailand, respectively. The result shows that the estimate α_1 is significantly different from zero for 3 countries (excluding Thailand), while α_2 is only significant for Hong Kong and Thailand. Additionally, the positive slope (β_1) is significantly different from zero for all 4 countries in the first regime while the sign of β_2 in regime 2 is mixed and only significant for Hong Kong. Moreover, the LSTR gives positive estimate of transition parameter (γ) except for Thailand. Thus, the LSTR cannot be used to explain the relationship of the term structure of Thailand's interest rates. Additionally, 2 out of 3 (positive) estimated smoothness parameters are significant at 5% level. The rejection of zero smoothness transition parameter ($\gamma = 0$) implies that Hong Kong and Malaysia data support the nonlinearity hypothesis. Moreover, the estimate location parameter (c) is positive and approximately close to zero for all cases. However, only the estimate c for Hong Kong ($c = 0.76$) and Malaysia ($c = 0.03$) are significantly different from zero. The estimate c indicates the midpoint between the two extreme regimes where the logistic function is equal to 0.5; in this case, the midpoint of the smooth transition is slightly above zero.

Additionally, the expectation hypothesis is tested based on the individual t-test and jointly, (using Wald test) to examine whether the slope in each regime is significantly different from two, and the constant is different from zero. It turns out that the EH cannot be rejected in the first regime based on individual t-test while it is significantly rejected at 1% level in the second regime. Moreover, based on the joint Wald test on constant and slope, the result indicates that the EH is rejected in both regimes for Hong Kong while the same null hypothesis is only rejected in the second regime for Malaysia. Generally, based on these two tests, the EH is significantly rejected in regime 2 (lower regime where the transition function is approaching zero) for Hong Kong and Malaysia while the EH holds in the first regime (upper regime) for Malaysia.

In addition, we perform various diagnostic tests to ensure the robustness of the LSTR. In particular, the presence of nonlinearity in Hong Kong and Malaysia is well captured by using nonlinear LSTR. The diagnostic tests such as Q-statistics on residual and squared residual, parameter constancy and no remaining nonlinearity confirm such findings. Moreover, an improvement of the p-value of both Ljung-Box Q-statistics also favors the LSTR over the linear dynamic regression and the linear ECM for Hong Kong and Malaysia (excluding the Philippines and Thailand). Particularly, we obtain significant improvements for modeling Malaysian interest rates using nonlinear smooth transition model rather than the linear model. However, in the case of the Philippines, the LSTR does not appear to be the best specification even though the LSTR pass serial autocorrelation, parameter constancy and no remaining nonlinearity tests.

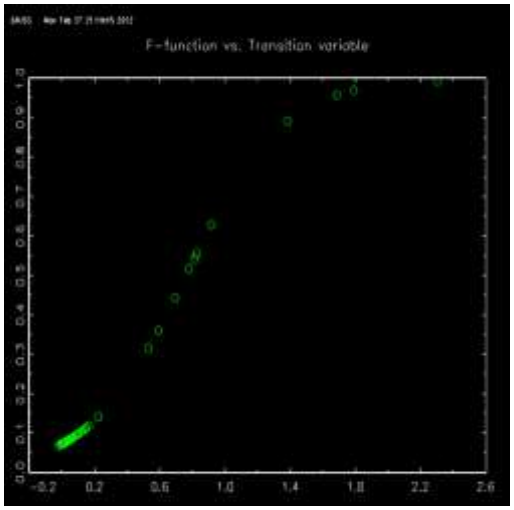
Table 5.4: Estimation result of LSTR				
	Hong Kong	**Malaysia**	**Philippines**	**Thailand**
α_1	-2.9776 ***	-0.1502 *	-0.0802 ***	0.0049
	(0.9339)	(0.0974)	(0.0223)	(0.0345)
β_1	2.6883 ***	3.1579 *	0.7137 ***	1.0879 ***
	(0.7292)	(2.3558)	(0.0741)	(0.3724)
α_2	-0.0962 ***	0.0072	-0.0915	-0.3957 **
	(0.0468)	(0.0072)	(0.0759)	(0.1907)
β_2	1.1698 ***	-0.2405	0.0006	-8.1279
	(0.2710)	(0.4637)	(0.4827)	(39.7875)
γ	3.3689 **	58.3191 **	3.2639	-151.8036
	(1.8196)	(32.0893)	(2.9961)	(133.4912)
c	0.7613 **	0.0324 ***	0.0038	0.0009
	(0.3320)	(0.0111)	(0.1684)	(0.0095)
Log Likelihood	-39.41	59.69	9.49	23.38
$t(\beta_1=2)$	0.9439	0.4915	-17.3518	-2.4489
	[0.35]	[0.62]	[0.00]	[0.02]
$t(\beta_2=2)$	-3.0637	-4.8321	-4.1424	-0.2546
	[0.00]	[0.00]	[0.01]	[0.80]
		Wald Stat (α=0, β=2)		
Regime 1	18.4764 ***	4.3089	545.5065 ***	19.5157 ***
Regime 2	24.7149 ***	29.4133 ***	26.5910 ***	5.0139 *
		Diagnostic tests		
Q1(4)	4.24	1.45	1.84	4.24
	[0.37]	[0.84]	[0.76]	[0.37]
Q1(8)	7.41	2.99	3.98	7.29
	[0.49]	[0.93]	[0.86]	[0.50]
Q2(4)	0.96	0.38	22.13	1.59
	[0.92]	[0.98]	[0.00]	[0.81]
Q2(8)	1.79	0.65	22.99	1.77
	[0.99]	[0.99]	[0.00]	[0.99]
PC	2.89	5.60	3.60	0.83
	[0.99]	[0.99]	[0.99]	[0.99]
NRN	3.85	0.02	15.03	0.28
	[0.98]	[1.00]	[0.24]	[0.99]
Sample	61	59	81	39

Note that estimated standard errors are in parenthesis below the corresponding parameter estimates of constant ($\alpha_{1,}$ α_2) and slope ($\beta_{1,}$ β_2) of regime 1 and 2. γ is the transition parameter while c is the location coefficient. ***, ** and * represent statistically significant at 1%, 5% and 10% level, respectively. $t(\beta_1=1)$ and $t(\beta_2=1)$ are the 2 tails t-statistic for the hypothesis of estimate beta equal to two. Wald stat is the Wald statistic for testing the joint hypothesis $\alpha = 0$ and $\beta = 2$ in each regime. Moreover, p-values are reported in square brackets. The diagnostic tests including Q1(k) and Q2(k) are the residual Ljung-Box statistic and the squared residual Ljung-Box at lag k, respectively. Also, PC and NRN are the chi-square statistics for the null hypothesis of parameter inconstancy and for the null hypothesis of no remaining nonlinearity. PC and NRN is compared to the chi-square with 3(k+1) =15 degree of freedom and 3p=12 degree of freedom, respectively.

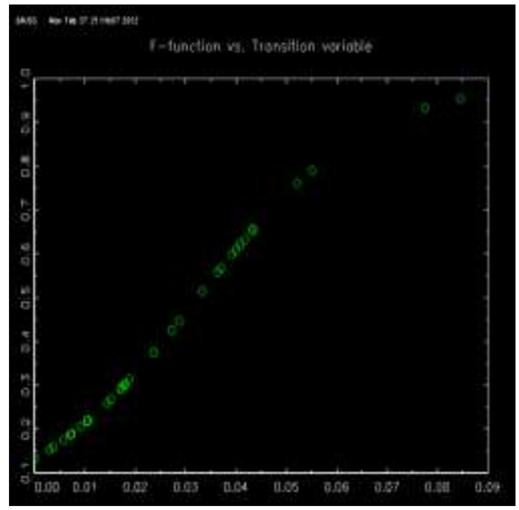
Furthermore, we plot the transition function against the transition variable in figure 5.3. The graph shows that the logistic function is well defined for Hong Kong and Malaysia as we find significant transition parameter as shown in table 5.4. Moreover, the transition between the two regimes of Hong Kong (γ = 3.3689) is relatively smoother than the Malaysia case (γ = 58.3191) as the transition parameter is smaller. This implies that the transition function of Hong Kong slowly changes from one regime to another while it appears to be faster in the case of Malaysia. Moreover, the illustration of the Philippines case also shows a smoothness transition even though the positive smooth transition parameter is not significant. The plot of the Philippines transition function shows that the majority of the observations lines between 0.5 and 0.8 and a few observations approach the transition probability of 1 and zero. In addition, we also plot the transition function against time in figure 5.4, which shows several changes between the two extreme regimes occur during the sample span. The graphs of Hong Kong and Malaysia show that the majority of the observations are in the lower regime most of the time while a few observations occur in the upper regime. In particular, the illustration of Hong Kong indicates that the transition probability is close to one during the period from Q4:2003 to Q2:2005 and Q1:2009-Q2:20010. A part from these periods, the majority of the observations are in the zero neighborhoods. This finding indicates that the expectation hypothesis is most likely to be rejected in the lower regime for Hong Kong as the majority of the observations line in this regime. In the case of Malaysia, the graph also indicates that the observations stay in the lower regime more than the upper regime. In particular, the transition probability is close to one during the period from Q3:1998-Q4:1999 and Q2:2006-Q2:200. Thus, in this case, the EH is likely to hold in the upper regime and to be rejected in the lower regime. Moreover, the plot of the transition function against time does not clearly show the separation of the two regimes in the case of the Philippines. The majority of observations occur in the middle range between 0.4 and 0.8. Lastly, the transition probability attained one most of the time for the case of Thailand, which indicates that the expectation hypothesis of the term structure is likely to hold in this country. This period includes Q1:2006-Q1:2007 and Q3:2007-Q3:2011. This graph also indicates that the nonlinear adjustment of Hong Kong and Malaysia are asymmetric.

Figure 5.3: Estimated transition function vs. Transition variable (Logistic function)

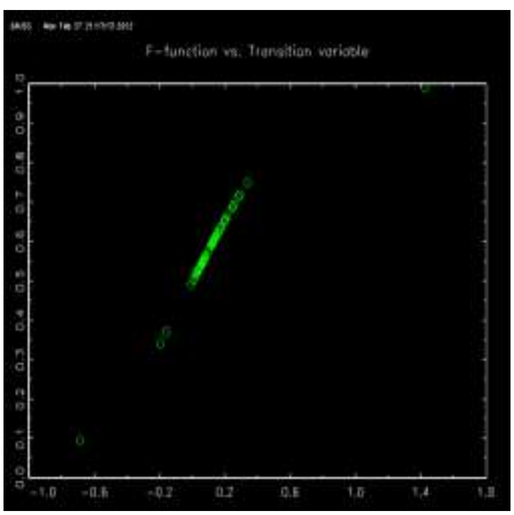
Hong Kong



Malaysia



Philippines



Thailand

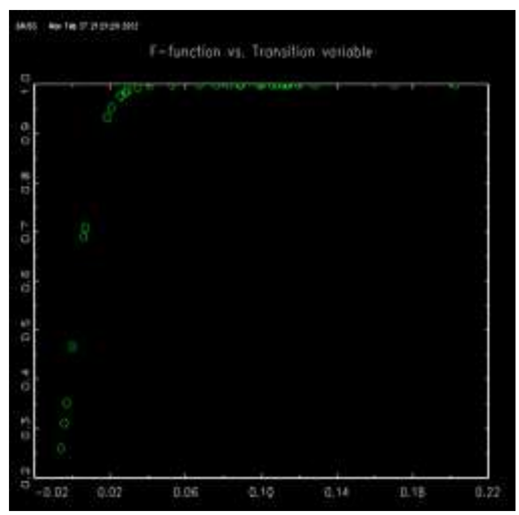
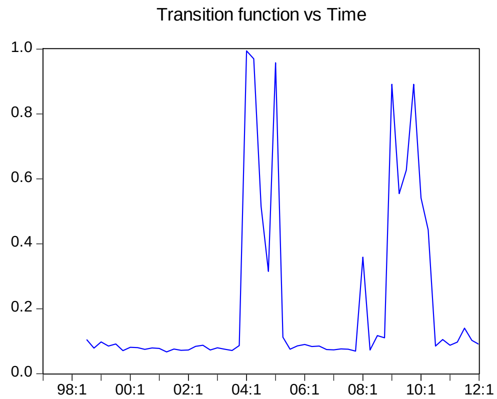
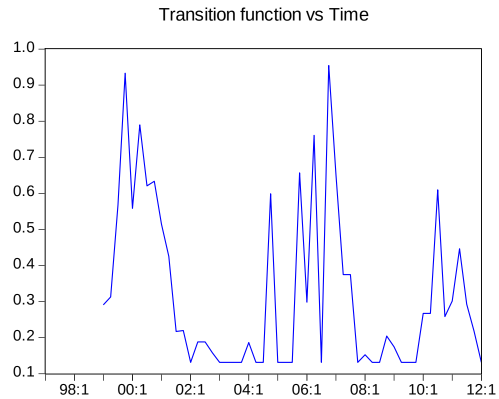


Figure 5.4: Estimated transition function over time (Logistic function)

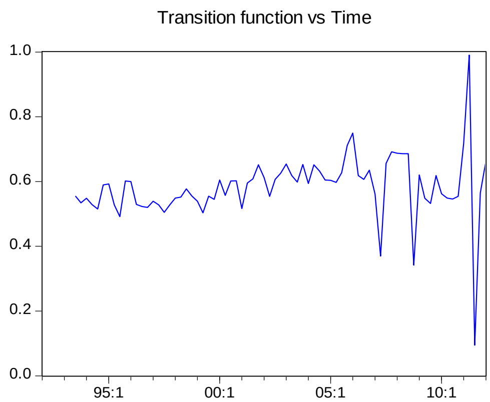
Hong Kong



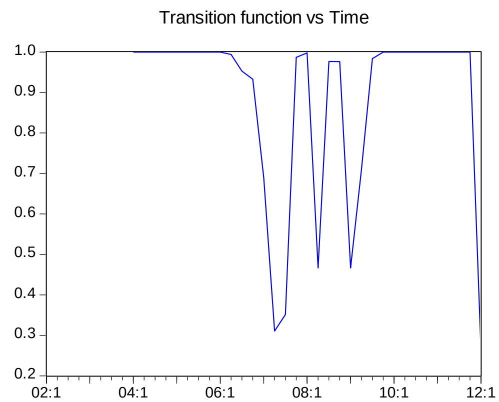
Malaysia



Philippines



Thailand



5.5.4 Exponential smooth transition model

The previous literature has shown evidence of nonlinear behavior of the term structure of interest rates in major countries. Hung and Siklos (2002) found symmetric nonlinear relationship while McMillan (2004) and Kuo and Enders (2004) found asymmetric nonlinear relationship. Finding whether the nonlinear adjustment is asymmetric or symmetric would lead to better understand the action of the market agents and monetary policy makers. Thus, in this section, we employ exponential smooth transition regression, which allows for symmetric adjustment.

The estimation results of the ESTR are reported in table 5.5. We find that 2 out of 4 countries that the term structure of interest rates exhibit nonlinearity; these are Hong Kong and the Philippines. The estimated α_1 is significantly different from zero for all cases while α_2 is only significant for Hong Kong. Additionally, the estimated slope (β_1) is also positive and significant for all countries, whereas β_2 is significant for Hong Kong and Thailand. Moreover, the estimate smooth transition parameter (γ) is positive for all cases, but it is only significant (at 5%) for Hong Kong and marginally significant (at 10%) for the Philippines. Thus, the rejection of zero smoothness parameter implies that the ESTR does well capturing the nonlinearity relationship of the term structure for Hong Kong but marginally explained the term structure relationship for the Philippines. Moreover, the location parameter (c) is positive and significant at 1% level for all countries, except for Malaysia where we obtain a negative estimate.

Furthermore, based on individual t-test, the expectation hypothesis is rejected in the second regime for Hong Kong while the test rejects the EH in both regimes for the Philippines. In addition, the joint Wald statistics show large values, which significantly reject the EH in both regimes for Hong Kong and the Philippines.

Table 5.5: Estimation result of ESTR

	Hong Kong	Malaysia	Philippines	Thailand
α_1	-1.9779	-0.1547	-0.1581	-0.4882
	***	*	**	***
	(0.6754)	(0.0997)	(0.0901)	(0.1295)
β_1	2.2158	3.3061	0.7452	18.0752
	***	*	**	*
	(0.6155)	(2.4645)	(0.3269)	(12.1389)
α_2	-0.2136	0.0071	0.0168	-0.0031
	***	(0.0070)	(0.0177)	(0.0317)
	(0.0511)			
β_2	4.2197	-0.2072	-0.0617	1.1579
	***			***
	(0.8966)	(0.4244)	(0.0895)	(0.3455)
γ	56.3026	203.95	1.4022	25.8977
	**		*	
	(31.0679)	(213.81)	(1.0485)	(21.5721)
c	0.0318	-0.0252	0.7609	0.1158
	***		***	***
	(0.0122)	(0.0207)	(0.2312)	(0.0334)
Log Likelihood	-36.7379	59.7316	11.4162	22.2728
$t(\beta_1=2)$	0.3506	0.5299	-3.8374	1.3242
			***	*
$t(\beta_2=2)$	2.4756	-5.2008	-23.0399	-2.4370
	***	***	***	***
		Wald Stat (α=0, β=2)		
Regime 1	20.1739	4.2361	46.7064	14.7125
	***		***	***
Regime 2	18.0912	33.4744	628.61	19.5663
	***	***	***	***
		Diagnostic tests		
Q1(4)	0.6572	1.5472	11.5052	3.7554
	[0.96]	[0.82]	[0.02]	[0.44]
Q1(8)	2.6071	3.1109	13.5440	6.9780
	[0.96]	[0.93]	[0.09]	[0.54]
Q2(4)	0.2624	0.4392	42.9535	0.8248
	[0.99]	[0.98]	[0.00]	[0.94]
Q2(8)	0.6442	0.7287	44.0162	1.1415
	[0.99]	[0.99]	[0.00]	[0.99]
PC	1.40	5.22	-	9.68
	[0.99]	[0.99]		[0.84]
NRN	4.41	-	14.90	0.28
	[0.97]		[0.25]	[0.99]
Sample	61	59	81	39

Note that estimated standard errors are in parenthesis below the corresponding parameter estimates of constant (α_1, α_2) and slope (β_1, β_2) of regime 1 and 2. γ is the transition parameter while c is the location coefficient. ***, ** and * represent statistically significant at 1%, 5% and 10% level, respectively. $t(\beta_1=1)$ and $t(\beta_2=1)$ are the 2 tails t-statistic for the hypothesis of estimate beta equal to two. Wald stat is the Wald statistic for testing the joint hypothesis $\alpha = 0$ and $\beta = 2$ in each regime. Moreover, p-values are reported in square brackets. The diagnostic tests including Q1(k) and Q2(k) are the residual Ljung-Box statistic and the squared residual Ljung-Box at lag k, respectively. Also, PC and NRN are the chi-square statistics for the null hypothesis of parameter inconstancy and for the null hypothesis of no remaining nonlinearity. PC and NRN is compared to the chi-square with 3(k+1) =15 degree of freedom and 3p=12 degree of freedom, respectively.

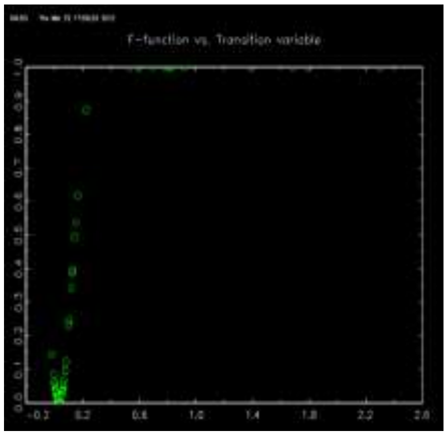
In addition, diagnostic results reveal that the ESTR of Hong Kong, Malaysia and Thailand pass all the tests. As for the logistic case, these include Q-statistics on residuals and squared residuals, parameter constancy and no remaining nonlinearity. We also obtain larger p-value for Q-statistics, which indicate that the ESTR can approximate the interest rate series better than standard linear models. However, the positive smoothness transition parameters of Malaysia and Thailand are not significantly different from zero. In addition, the estimation of the Philippines appears to be puzzling. Even though, the ESTR can capture nonlinearity (at 10% level) in the term structure of the Philippines interest rates, the model still suffers from serial autocorrelation and heteroscedasticity.

We plot the transition function against the transition variable to illustrate the exponential function in figure 5.5. The graph illustrates a bell-shape for Hong Kong, the Philippines and Thailand. In fact, the bell-shape of Hong Kong (γ = 56.3028) is narrower than the Philippines (γ = 1.4022) as the value of the smoothness transition between the regimes is bigger. This illustration indicates faster changes of the transition function of Hong Kong from one regime to the other. The plot of Thailand also exhibits a bell-shape with the smooth transition parameter is 25.8977, but it is not statistically significant. Moreover, the limiting transition probability of one is attained in all cases except for Thailand.

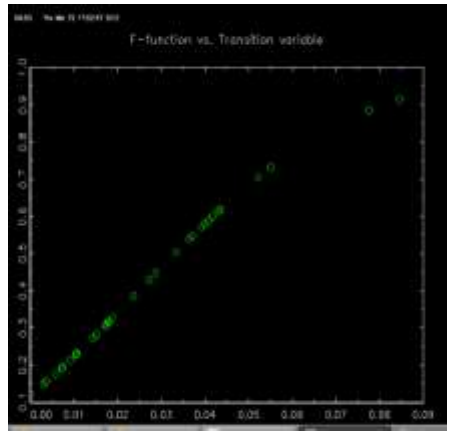
Furthermore, we plot the estimate transition function over time of each country in figure 5.6. The graphs exhibit frequently changes between the regimes. The majority of the observations are in the lower regime where the probability is close to zero. Particularly, the plot reveals that the transition probability for Hong Kong is attained zero during the periods Q1:1998-Q4:2003, Q3:2005-Q2:2007 and Q2:2010-Q1:2011. The graph of Malaysia shows zero transition probabilities during the periods Q2:2001-Q2:2004, Q1:2005-Q3:2005 and Q4:2007-Q1:2010. Finally, the transition function of the Philippines frequently changes between the two regimes. It fluctuates between 0 and 0.5 throughout the sample for Thailand.

Figure 5.5: Estimated transition function vs. Transition variable (Exponential function)

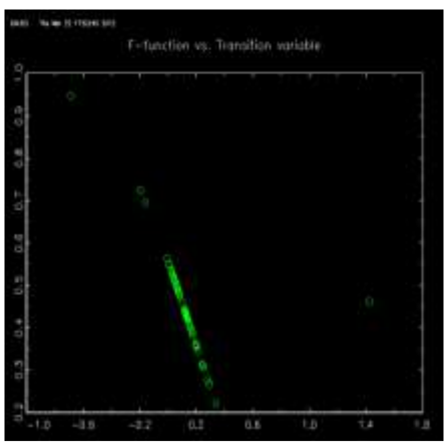
Hong Kong



Malaysia



Philippines



Thailand

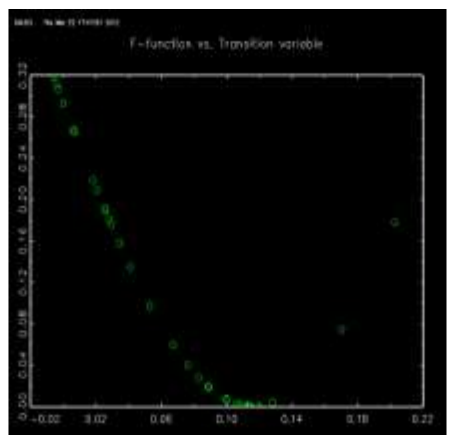
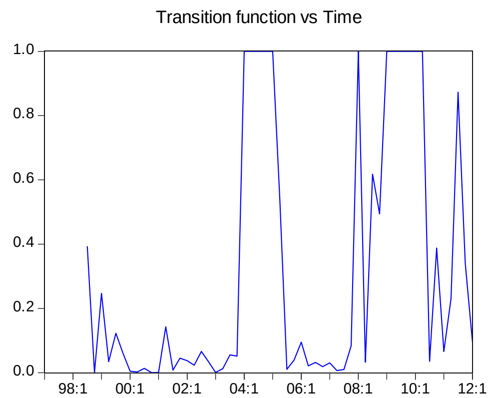
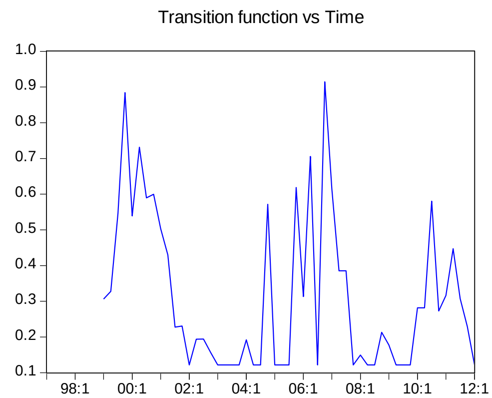


Figure 5.6: Estimated transition function over time (Exponential function)

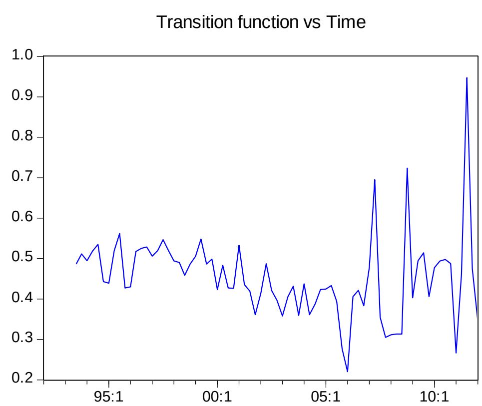
Hong Kong



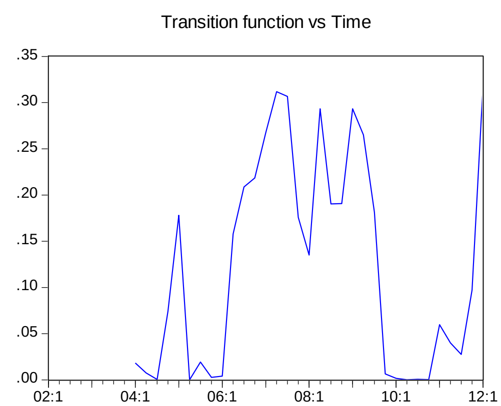
Malaysia



Philippines



Thailand



In summary, our findings provide evidence against the expectation theory using nonlinear model where the EH is rejected at least in one of the regimes. Moreover, we find that the LSTR is able to capture nonlinearity relationship in the term structure of interest rates for Hong Kong and Malaysia. While the ESTR is able to explain such a relationship for Hong Kong, we find weak evidence of nonlinearity for the Philippines. Based on statistically estimations, using linear and nonlinear models, the LSTR outperforms linear alternatives and ESTR in terms of describing the term structure of Hong Kong and Malaysia. Whereas, the term structure of Thailand interest rate appears to be well approximated by using linear conventional regression. Additionally, none of the models can be used to explain the Philippines data significantly, except for the ESTR.

In the next section, we compare our analysis with the forecasting performances of linear and nonlinear models. This will confirm whether the best estimation model in each sample would also give the best out-of-sample prediction.

5.6 Out-of-sample exercise

In this section, we aim to study whether the term structure of interest rates in Asian markets is better explained by linear or nonlinear models in terms of forecasting performance. In this context, we employ conventional dynamic regression, linear error correction model and the smooth transition models with logistic and exponential functions. In the previous section, the estimation results provide evidence against the validity of the expectation theory in various models. The rejection of the expectation hypothesis implies that the term structure is not informative in predicting the future short-term rate. Thus, the short term rate cannot be forecasted. However, the estimation results yield positive slope of the term structure, which indicate a correct forecast direction. Therefore, we conduct a small one-step forecasting to confirm whether the term structure is informative or uninformative in this market.

5.6.1 Forecast simulation and evaluation

In the forecasting exercise, due to the limited number of observations, we conduct one-step ahead for 4 quarters from Q2:2011 to Q1:2012 while the beginning of the sample (until Q1:2011) is used to estimate the model. We conduct a rolling estimation where the sample period is extended after we forecast the future short-term rate for Q2:2011 and continue the same process until we reach the last sample period of Q4:2011 to forecast Q1:2012. The forecasting models are the following:

Model 1: Linear dynamic model (from equation 5.6), the optimal one-step-ahead forecast at forecast origin t is

$$\hat{r}_{t+1} = r_{1t} + a + b(r_{2t} - r_{1t}) + u_{t+1} \tag{5.11}$$

where $\hat{r}_{t+1}$ is the one-step-ahead forecast of the short-term interest rate at the next quarter based on the available information at the forecast origin t.

Model 2: Linear error correction model (from equation 5.7), the optimal one-step-ahead forecast at forecast origin t is[39]

$$\hat{r}_{t+1} = r_{1t} + a + b\left(r_{1,t} - \beta_0 - \beta_1 r_{2,t}\right) + u_{t+1} \tag{5.12}$$

Model 3: Logistic smooth transition model (from equation 5.8 and 5.9), the optimal one-step-ahead forecast at forecast origin t is

$$\hat{r}_{t+1} = r_{1t} + [\alpha_1 + \beta_1(r_{2t} - r_{1t})][1 - F(z_t;\gamma,c)] + [\alpha_2 + \beta_2(r_{2t} - r_{1t})]F(z_t;\gamma,c) + u_{t+1} \tag{5.13}$$

Model 4: Exponential smooth transition model (from equation 5.8 and 5.10), the optimal one-step-ahead forecast at forecast origin t is

$$\hat{r}_{t+1} = r_{1t} + [\alpha_1 + \beta_1(r_{2t} - r_{1t})][1 - F(z_t;\gamma,c)] + [\alpha_2 + \beta_2(r_{2t} - r_{1t})]F(z_t;\gamma,c) + u_{t+1} \tag{5.14}$$

[39] No lags are added since the model did not show any sign of autocorrelation in the residuals.

In the forecasting evaluation, we compare the forecasting performance of nonlinear model relative to linear model in terms of the mean squared error (MSE) and Thiel's inequality coefficient.

5.6.2 Forecast results

The forecasting performances of the linear term structure model, linear error correction model, logistic smooth transition regression and exponential smooth transition regression are compared in terms of mean square error and Thiel's coefficient. The results are reported in table 5.6. Based on point forecast evaluation, the LSTR model can outperform the benchmark models for Hong Kong, Malaysia and the Philippines as the MSE indicates the lowest value. In particular, the MSE yields 0.0284, 0.00003 and 0.0930 for Hong Kong, Malaysia and the Philippines, respectively. This result implies that the prediction of LSTR is approximately close to the actual 3-month interest rate. Additionally, the MSE also indicates that the forecasting performance of the ESTR is equal to the LSTR for Malaysia. However, the nonlinear models are outperformed by the linear conventional term structure model in the case of Thailand. Moreover, the second best forecasting model varies in this analysis. In particular, the second best forecaster for Hong Kong and the Philippines are the conventional term structure regression while the ECM is the second best forecaster for Malaysia and the ESTR for Thailand.

Moreover, the relative ratio of MSE also confirms the forecast accuracy of LSTR model over linear models and ESTR for all cases, excluding Thailand note that previously for the latter we find insignificant smooth transition parameter. The MSE ratio of Hong Kong shows that using LSTR as the forecasting model; we realize some gain of 143%, 596% and 165% against the linear term structure model, ECM and ESTR, respectively. The result also reveals the same story in the case of Malaysia and the Philippines. On the other hand, we obtain the ratio of MSE lower than one when the interest rate of Thailand is forecasted by the LSTR. In particular, we realize a loss of 91%, 62% and 85% over the linear term structure model, ECM and ESTR, respectively. Furthermore, the forecasting performance is also evaluated in terms of Theil's inequality coefficient. The Theil's coefficient yields the lowest value for LSTR in the case of Hong Kong and

Malaysia while the linear conventional term structure model is perfectly forecast the future short-term interest rates for the Philippines and Thailand. However, the forecast evaluation based on Theil's coefficient yields inconsistent result with the previous finding based on MSE for the case of Hong Kong and the Philippines. In Hong Kong, the Theil's coefficient indicates that the perfect forecasters respectively are LSTR, ESTR, ECM and the linear conventional model. The Theil's coefficient also shows the accurate forecasting models respectively are the linear model, LSTR and the ECM in the case of the Philippines.

In summary, the out-of-sample prediction results indicate that the logistic smooth transition model outperforms the benchmark models in the case of Hong Kong and Malaysia. The predictability of the LSTR approach also confirms that the term structures of these 2 series are better explained by nonlinear model where we find the presence of nonlinearity in the data. Moreover, our finding provides supportive evidence towards the rejection of the expectation hypothesis. This implies that the term structure of interest rates contains predictive information, which can help to forecast the future changes in the short-term rate in this analysis.

Table 5.6: Out-of-sample forecasting result (1 step ahead)				
	Hong Kong	**Malaysia**	**The Philippines**	**Thailand**
		MSE		
Linear model	0.0690	0.00040	0.2341	**0.0014**
ECM	0.1978	0.00010	0.2446	0.0060
LSTR	**0.0284**	**0.00003**	**0.0930**	0.0160
ESTR	0.0753	**0.00003**	**-**	0.0024
		MSE Ratio		
Linear model	2.43	13.33	2.52	0.09
ECM	6.96	3.33	2.63	0.38
ESTR	2.65	1.00	-	0.15
		Thiel's Coefficient		
Linear model	0.0543	0.0104	**0.0712**	**0.0023**
ECM	0.0435	0.0075	1.0000	0.0237
LSTR	**0.0219**	**0.0015**	0.1453	0.0781
ESTR	0.0274	**0.0015**	**-**	0.0029

Note that the mean square error (MSE) and Thiel's coefficient are reported for each forecasting models including linear term structure model, error correction model (ECM), logistic smooth transition regression (LSTR) and exponential smooth transition regression (ESTR). The bold number indicates the smallest value. Moreover, MSE ratio is the relative forecasting performance of competing model over LSTR where the value greater than 1 indicating that the LSTR is superior.

5.7 Conclusion

A number of studies have tested the expectation theory of the term structure of interest rates and hypothesized that the long-term rate is determined by the expectation of the short-term rate over the holding period of the long-term rate plus a constant risk premium (Thornton, 2003). In other words, the information of the expected short-term rate should be fully reflected in the long-term rate (Liau and Yang, 2009). In this study, we examined the expectation hypothesis of the term structure of Asian interest rates using 3-month and 6-month quarterly Treasury bill rates. The sample included Hong Kong, Malaysia, the Philippines and Thailand. The linear regression, error correction model and smooth transition regressions (logistic and exponential functions) are employed. In general, we found some evidence towards the rejection of the expectation hypothesis in Asian markets using linear and nonlinear frameworks. This implies that the term structure is not informative in predicting the future short-term rate. However, the estimation of linear regression yielded significantly positive slope coefficients for 3 out of 4 countries (Hong Kong, the Philippines and Thailand), which imply the correct forecasting direction as required by the expectation theory. This finding is consistent with the previous literature which studied advance countries, such as Fama and Bliss (1987), Campbell and Shiller (1991) that the estimated slope is positively significant, but it is not large enough to make the expectation hypothesis to hold. Additionally, a linear error correction model provided evidence against the same hypothesis. Based on the results of stationary long run equilibrium and significant estimated slope, the error correction model seems to be well estimating the term structure of interest rates for Hong Kong and Thailand. The finding also indicated the violation of expectation theory as evidence of Granger causality flow from 6-month to 3-month interest rate. Moreover, we found the presence of linear and nonlinear dependency in the case of Malaysia and the Philippines, which indicated that linear models are not appropriate in explaining the term structure of interest rates of these two countries.

When the smooth transition models with the lagged spread between the long- and short-term interest rates as the transition variable are implemented, the expectation hypothesis is still rejected at least in one of the regimes. However, the findings showed that the series are better modeled using nonlinear model than the linear model for Hong Kong and Malaysia. In particular, logistic smooth transition regression outperformed the competing models in terms of a better estimation based on various diagnostic tests. Moreover, the superiority of the logistic smooth transition model is also confirmed by the one-step forecasting performance. The results showed that the logistic smooth transition regression is the best forecaster for Hong Kong and Malaysia based on MSE and Theil's inequality coefficients. While the conventional linear regression best performs in Thailand, the result is inconclusive for the case of the Philippines. Moreover, our finding suggested that the nonlinear behavior of the term structure of Hong Kong and Malaysia is asymmetric, which is similar to the empirical findings of McMillan (2004) and Kuo and Enders (2004), who found asymmetric nonlinear behavior in the UK and Japan interest rates. This finding also indicated that the market participants and policy makers would respond differently towards the short term interest rate relative to the long term interest rate.

CHAPTER VI

CONCLUSIONS

The efficient market hypothesis has been extensively tested in the literatures, dealing with predictability and profitability. In the efficient market, the historical value of one variable should not be able to forecast the future value of another variable, yielding excess returns better than the average return of the market. More recent studies, including the concept of cointegration are also attracting much attention in the literature. Once the cointegration concept is applied to the market efficiency, this hypothesis is tested in the sense that two non-stationary variables should not be cointegrated in an efficient market (Granger, 1986). Engle and Granger (1987) two-step approach is often used to capture the statistical relationship between two nonstationary series. If their long run relationship is stationary, the two nonstationary series are cointegrated. In addition, the error correction model is also widely employed in a cointegration framework as Granger (1986) showed that the cointegration series has an error correction representation. Thus, if the two variables are cointegrated, the error correction term would help to predict the future movement of the series and leads to excess returns.

In the empirical studies, the cointegration concept has been extensively investigated in advance economies while there is limited evidence in emergent countries. The main purpose of this study is to test the weak form efficient market hypothesis in Asian market associated with the cointegration concept in 4 different financial applications.

The main findings of each application will be summarized in the following:

I: Pairs trading

One of the popular Wall Street quantitative methods of speculation since the mid-1980, namely pairs trading, showed the favorable evidence of profitability, which implied that the Stock Exchange of Thailand is not efficient. The concept of pairs trading is simple. Firstly, identify a pair of stocks that tends to move together in the long run. When the spread is deviated from the equilibrium, it exhibits arbitrage opportunity. Thus, the investor buys the undervalued stock and sells the overvalued stock. Once, the spread reverses back; the contrarian trade is performed. The previous literatures such as Gatev et al (1999) and Nath (2003) used the nonparametric distance method on the US market while Do et al (2006) tested on the US, the UK and Australia using residual spread method. Their findings indicated that pairs trading yielded significant profit event after accounted for the transaction cost. In developing countries, the empirical study of Perlin (2007) has confirmed the profitability of pairs trading strategy using the distance method. However, in this application, we employ the Engle and Granger two-step cointegration approach as Vidyamurthy (2004) outlined in his study but had not tested on the profitability of the strategy.

Results showed that 48 pairs are found to be significantly cointegrated, which are the share price series from Resources, Financial, Property & Construction and Services sectors. Moreover, we applied an error correction model to filter out cointegrated pairs that exhibit weak mean reversion property. The most promising pairs are also selected based on Alexander's (2008) cointegration sign criterion. Hence, we had 2 out of 6 pairs that met our criterion. The 4 different trading simulations indicated that these 2 cointegrated pairs are highly profitable. In particular, updated beta can improve the profitability of the strategy. Additionally, the 3 different trading strategies yielded relatively similar returns. Thus, this finding confirmed that the pair trading strategy is a market neutral strategy, which can be employed regardless whether the market is bull or bear. However, in risk and return perspective, the conservative strategy is favorable as the strategy can perform relatively to the other riskier strategies. In addition, the trading performance of correct and mix sign with different speed of adjustment also pointed out that the sign and size of cointegrated pairs do matter in this analysis. As a result, the mix sign with low adjustment speed yielded insignificant returns. This finding indicated that the cointegrated pairs with mix sign might not be truly cointegrated as the mechanism of disequilibrium term does not reverse. We can conclude that the investor can employ a pair trading strategy and earn excess returns as long as the cointegrated pairs have the correct sign.

II: Forecasting performance of error correction model

Based on cointegrating relationship of two variables, we conducted 20 step-ahead forecasts using the error correction model. The cointegrated pairs are classified into correct and mix sign groups referring to the Alexander's (1998) criterion. The forecasting performance of ECM is compared against the random walk and random walk with drift models. In this application, we employed several methods to measure the forecast accuracy. This included point forecast based on prediction errors, relative ratio of prediction errors, winning percentage of ECM over the benchmark models, Theil's inequality coefficient, Clark and West (2007) equal forecast accuracy, direction of changes and forecast encompassing test.

The results indicated that the ECM outperformed both benchmark models in the longer forecasting horizons while it is underperformed in the shorter horizons. This finding supported the previous literatures such as Engle and Yoo (1987), LeSage (1990) and Lin & Tsay (1996) which showed that the error correction mechanism can help to improve the forecast accuracy in the long run. The result also implied that the historical prices of cointegrated counterpart contain predictive information, which helps to forecast the future price of the series. Thus, this finding also supported the implication of Granger (1986) that the two variables cannot find to be cointegrated in an efficient market.

Moreover, the forecasting performance of ECM in the correct sign cointegrated pairs relative to the mix sign cointegrated pairs cast doubt on the power of the augmented Dickey fuller test. The ECM yielded poor forecasts for the mix sign group where 6 out of 9 pairs were outperformed by the benchmark models at all forecasting horizons. On the other hands, the ECM can beat the benchmarks in the correct sign group (i.e. 10 out of 13 cases). Thus, our finding suggested that the mix sign pairs might not have mean reversion property, which is similar to the previous results of pairs trading application.

In addition, the trading simulation based on the prediction of ECM also showed evidence of profitability. Thus, the findings of predictability and profitability using the ECM can be as the evidence of market inefficiency in the stock exchange of Thailand.

III: Forward rate unbiased hypothesis

In the efficient exchange rate market, the future spot rate should be equal to the current forward rate. In this application, we examined the foreign exchange rate hypothesis in 11 Asian exchange rates. The previous findings of Frankel and Poonawala (2010) showed that the forward bias in emerging markets is smaller than the major countries. They also pointed out that exploiting such small bias is uneconomically significant. Therefore, we attempted to test whether we can exploit this bias in Asian market.

The currencies are estimated using linear conventional Fama regression, error correction model and nonlinear logistic smooth transition model. The previous literatures often found negative estimated slope of the forward premium for the advance currencies, which is deviated from the true theoretical value of one; thus, the forward rate unbiased hypothesis is rejected. In this paper, we found that 7 out of 11 cases cannot reject the FRUH using linear Fama regression. In particular, the result showed that the estimated slope is mostly positive. However, we also obtained negative estimated slope for the developed countries such as Japan, Hong Kong and India. Similar to Frankel and Poonawala (2010), our finding showed that the forward bias of a developed country is more severe than a developing country. On the contrary to the estimation of Fama regression, the ECM rejected the FRUH in all cases. This finding indicated that the forward rate is biased. In a nonlinear framework, the logistic smooth transition model with the forward-spot spread as the transition variable can capture nonlinearity relationship between the spot and forward exchange rates (6 out of 11 currencies). The results indicated that the FRUH is rejected at least in one of the regimes based on the restriction of time-invariant constant and unity slope. Similar to the previous findings of Sarno, Valente & Leon (2004) and Ballie & Kilic (2006) tested in major exchange rates; we found that the FRUH does not hold all the time. In fact, the majority of the transition variables remain in the lower regime where the transition function is attained zero. Thus, the FRUH is most likely to reject in the lower regime. Moreover, the forecasting performance also confirmed the existence of the forward premium anomaly in Asian exchange rate markets. Therefore, the forward rate is a biased predictor of the future spot rate in this analysis.

IV: Expectation hypothesis of the term structure of interest rate

In this application, the expectation hypothesis is investigated on the term structure of 3-month and 6-month Treasury bill rates of Hong Kong, Malaysia, the Philippines and Thailand. We tested whether the linear (conventional regression and error correction model) or nonlinear models (smooth transition models with logistic and exponential function) would better explain the term structure of interest rates. The findings indicated some evidence against the expectation hypothesis. In particular, the conventional regression yielded positive estimated slope coefficients for 3 out of 4 cases, which are significantly different from zero. However, the expectation hypothesis of the term structure cannot be held in this analysis because the estimated slope coefficients are not equal to the theoretical value. This finding is consistent with the previous results of Fama and Bliss (1987) and Campbell and Shiller (1991). Moreover, the finding of positive slope coefficient also indicated that the term structure is informative, which can help to predict the future short-term rate. However, we found negative estimated slope of the term structure when using the error correction model. The expectation hypothesis is also rejected in all cases. The finding of significant error correction term also indicated that the expectation hypothesis is violated. In particular, the Granger causality flow from the 6-month to 3-month rates showed that the long-term rate can help to forecast the short-term rate. In addition, we found the presence of linear and nonlinear dependency in the case of Malaysia and the Philippines. Hence, these two countries cannot be explained by the linear models.

In nonlinear framework, the smooth transition models (logistic and exponential functions) showed some evidence against the expectation hypothesis. The expectation hypothesis of the term structure is rejected at least in one of the regimes, especially in the lower regime. Moreover, the various diagnostic tests yielded the results indicating that the term structure of Hong Kong and Malaysia are better explained using logistic smooth transition regression than the linear models. Additionally, the out-of-sample forecasting performance also confirmed that the LSTR is the best forecaster at one-step ahead. Our finding also indicated that the conventional linear regression outperformed the other models in Thailand while none of the models can explain the term structure of the Philippines successfully.

REFERENCES

Alexander and Dimitriu (2002). “The Cointegration Alpha: Enhanced Index Tracking and Long-Short Equity Market Neutral Strategies, *ISMA Finance Discussion Paper* No. 2002-08.

Alexander, C. (2008). “Practical Financial Econometrics”, *John Wiley & Sons,* pp. 201-250.

Alexander, C. O. (1999). “Optimal Hedging Using Cointegration”, *Philosophical Transactions of the Royal Society,* A 357 pp. 2039-2058.

Alexander, Co. O., Giblin, I. and Weddington, W. (2001). “Cointegration and Asset Allocation: A New Active Hedge Fund Strategy”, *Financial Risk and Financial Risk Management,* Vol. 16, pp. 65-89.

Alper, C. E., Ardic, O. P. and Fendoglu, S. (2007). “The Economics of Uncovered Interest Parity Condition for Emerging Markets: A Survey”. *Munich Personal RePEc Archive,* pp. 1-38.

Amisano, G. and Serati, M. (1999). “Forecasting Cointegrated Series with BVAR Models”. *Journal of Forecasting,* vol. 18, pp. 463-476.

Amri, S. (2008). “Analyzing the Forward Premium Anomaly Using a Logistic Smooth Transition Regression Model”. *Economics Bulletin,* vol. 6, no. 26, pp. 1-18.

Anderson, H.M. (1997). “Transactions Costs and Nonlinear Adjustment towards Equilibrium in the US Treasury Bill Market”. *Oxford Bulletin of Economics and Statistics,* vol. 59(4), pp. 465-484.

Andrews, D. W. K. (1991). “Heteroskedasticity and Autocorrelation Consistent Coariance Matrix Estimation”, *Econometrica,* vol. 59, pp. 817-858.

Andrews, D. W. K. (1993). “Tests for Parameter Instability and Structural Change with Unknown Change Point”. *Econometrica,* vol. 61(4), pp. 821-856.

Andrews, D. W. K. and Monahan, J. C. (1992). “An Improved Heteroskedasticity And Autocorrelation Consistent Covariance Matrix Estimator”, *Econometrica,* vol. 60, pp. 953-966.

Arize, A. C. and Malindretos, J. (2008). “Dynamic linkages and Granger Causality between Trade and Budget Deficits: Evidence from Africa”, *African Journal of Accounting, Economics, Finance and Banking Research*, vol. 2, no. 2, pp. 1-19.

Bai, J. (1997). “Estimating Multiple Breaks One at a Time”. *Econometric Theory,* vol. 13, pp. 315-352.

Bai, S. and Mollickb, A.V. (2010). “Currency Crisis and the Forward Discount Bias: Evidence from Emerging Economies under Breaks”. *Journal of International Financial Markets, Institution of Money,* vol. 20, pp. 556-574.

Bai. J. and Perron, P. (1998). “Estimating and Testing Linear Models with Multiple Structural Changes”. *Econometrica,* vol. 66(1), pp. 47-78.

Bai. J. and Perron, P. (2003). “Computation and Analysis of Multiple Structural Change Models”. *Journal of Applied Econometrics,* vol. 18, pp. 1-22.

Baillie, R. and Bollerslev, T. (1989). “Common Stochastic Trends in a System of Exchange Rates”. *Journal of International Money and Finance,* vol. 13, pp. 167-181.

Baillie, R.T. (1989). “Tests of Rational Expectations and Market Efficiency”. *Econometric Reviews,* vol. 8, pp. 151-186.

Baillie, R.T. and Bollerslev, T. (2000). “The Forward Premium Anomaly is Not as Bad as You Think”. *Journal of International Money and Finance”,* vol. 19, pp. 471-488.

Baillie, R.T. and Kilic, R. (2006). “Do Asymmetric and Nonlinear Adjustments explain the Forward Premium Anomaly?” *Journal of International Money and Finance,* vol. 25, pp. 22-47.

Banerjee, A., Dolado, J. J., Galbraith, J. W. and Hendry, D. V. (1993). “Co-integration, Error Correction, and the Econometric Analysis of Non-Stationary Data”, *Oxford University Press,* pp. 157-159.

Bank of Thailand (2008). “Yearly Report on Economic and Monetary Conditions”. Available: http://www.bot.or.th/English/EconomicConditions/Thai/report/Pages/econ_yearly.aspx [26 June 2010].

Bank of Thailand, (2012). “Treasury bills”. Available: http://www.bot.or.th/ [March 2012].

Bansal, R. and Dahlquist, M. (2000). “The Forward Premium Puzzle: Different Tales from Developed and Emerging Economies”. *Journal of International Economics,* vol. 51, pp. 115-144.

Barnhart, S. and Szakmary, A.C. (1991). “Testing the Unbiased Forward Rate Hpothesis: Evidence on Unit Roots, Co-integration and Stochastic Coefficients”, *Journal of Financial and Quantitative Analysis,* vol. 26, pp. 245-267.

Bedi, J., Richards, A. and Tennant P. (2003), “The Characteristics and Trading Behavior of Dual-Listed Companies”, Reserve Bank of Australia Research Discussion Paper No. 2003-06.

Bonga-Bonga, L. (2009). “Forward Exchange Rate Puzzle: Joining the Missing Pieces in the Rand-US Dollar Exchange Market”. *University of Johannesburg,* working paper no. 122, pp. 1-16.

Brooks, C., Rew, A. G. and Ritson, S. (2001). “A Trading Strategy Based on the Lead-lag Relationship between The Spot Index and Futures Contract for the FTSE 100”. *International Journal of Forecasting,* vol. 17, pp. 31-44.

Bruggemann, R. and Riedel, J. (2010). “Nonlinear Interest Rate Reaction Functions for the UK”. *University of Konstanz Department of Economics,* working paper series 2010-15.

Bulkley, G., Harris, R. D. F. and Nawosah, V. (2011). “Revisiting the Expectations Hypothesis of The Term Structure of Interest Rates”. *Journal of Banking & Finance, vol.* 35, pp. 1202-1212.

Camacho, M. (2004). “Vector Smooth Transition Regression Models for US DGP and the Composite Index of Leading Indicators”. *Journal of Forecasting,* vol. 23, pp. 173-196.

Campbell, J. Y. and Shiller, R.J. (1987). “Cointegration and Tests of Present Value Models”. *Journal of Political Economy,* vol. 95, pp. 1062-87.

Campbell, J. Y. and Shiller, R.J. (1991). “Yield Spreads and Interest Rate Movements: A Bird’s Eye View”. *The Review of Economic Studies,* vol. 58, no. 3, pp. 495-514.

Caner, M. and Hansen, B. (2001). “Threshold Autoregression with a Unit-root”. *Econometrica,* vol. 69, pp. 1555-1596.

Carvalho, J.V, Sachsida, A., Loureiro, P.R.A. and Moreira, T.B.S. (2004). “Uncovered interest parity in Argentina, Brazil, Chile and Mexico: A unit root test application with panel data”. *Review of Urban & Regional Development Studies,* vol. 16, pp. 263-269.

Castro, V. (2008). “Are Central Banks following a Linear or Nonlinear (Augmented) Taylor Rule?” *University of Warwick, Department of Economics.*

Cavoli, T. and Rajan, R.S. (2006). “Capital Inflows Problem in Selected Asian Countries in the 1990s Revisited: The Role of Monetary Sterilization”. *Asian Economic Journal,* vol. 20(4), pp. 409-423.

Chinn, M. and Meredith, G. (2004). “Monetary Policy and Long Horizon Uncovered Interest Parity”, *IMF Staff Papers,* vol. 51(3), pp. 409-430.

Choi and Zivot, (2007). “Long Memory and Structural Changes in The Forward Discount: An Empirical Investigation”. *Journal of International Money and Finance,* vol. 26, pp. 342-363.

Choi, J.Y., Salandro, D. and Shastri, K. (1988). “On the Estimation of Bid-Ask Spreads: Theory and Evidence”. *The Journal of Financial and Quantitative Analysis.* Vol. 23, No. 2, pp. 219-230.

Clark, T. E. and West, K. D. (2007). “Approximately Normal Tests for Equal Predictive Accuracy in Nested Models”, *Journal of Econometrics,* vol. 138, pp. 291-311.

Clark, T.E. and McCracken, M.W. (2005). “Evaluating Direct Multistep Forecasts”. *Econometric Reviews,* Vol. 24, pp. 369-404.

Clements, M. P. and Smith, J. (1999). “A Monte Carlo Study of The Forecasting Performance of Empirical SETAR Models”, *Journal of Applied Econometrics,* vol. 14, pp. 123-141.

Cornell, B. (1977). “Spot Rates, Forward Rates and Exchange Market Efficiency”. *Journal of Financial Economics,* vol. 5, pp. 55-65.

Cox, J.C., Ingersoll, J. E. and Ross, S. A. (1981). “A Reexamination of Traditional Hypotheses about the Term Structure of Interest Rates”. *Journal of Finance,* vol. 36, pp. 769-799

Crowder, W.J. (1994). “Foreign Exchange Market Efficiency and Common Stochastic Trends”. *Journal of International Money and Finance,* vol. 13, pp. 551-564.

Diebold, F. X. and Mariano, R. (1995). “Comparing Predictive Accuracy”, *Journal of Business and Economic Statistics,* vol. 13, pp. 253-265.

Do, B., Faff, R., and Hamza, K. (2006) “A New Approach to Modeling and Estimation for Pairs Trading”, *working paper* (Monash University).

Domowitz, I. and Hakkio, W.A. (1985). “Distribution of the Estimators for Autoregressive Time Series with a Unit Root”, *Journal of the American Statistical Association,* vol. 74, pp. 427-431.

Dumas, B. (1992). “Dynamic Equilibrium and the Real Exchange Rate in a Spatially Separated World”, *Review of Financial Studies,* vol. 5, pp. 153-180.

Eitrheim, O, and Terasvirta, T. (1996). “Testing the Adequacy of Smooth Transition Autoregressive Models”. *Journal of Econometrics*, vol. 74, pp. 59-75.

Elliottt, R., van der Hoek, J. and Malcolm, W. (2005). “Pairs Trading”, *Quantitative Finance,* Vol. 5(3), pp. 271-276.

Enders, W. (1995). “Applied Econometric Time Series”, J*ohn Willey & Sons*, pp. 355-400.

Engle, C. (1996a). “A Note on Cointegration and International Capital Market Efficiency”, *Journal of International Money and Finance,* vol. 15, pp. 657-660.

Engle, C. (1996b). “The Forward Discount Anomaly and the Risk Premium: a Survey of Recent Evidence”. *Journal of Empirical Finance*, vol. 3, pp. 123-192.

Engle, R. and Granger, C. (1987). “Co-integration and Error Correction: Representation, Estimation, and Testing”. *Econometrica,* Vol. 55(2), pp. 251-276.

Engle, R. and Yoo, B. (1987). “Forecasting and Testing in Co-integrated Systens”, *Journal of Econometrics,* Vol. 35, pp. 143-159.

Escribano, A. and Granger, C. W. J. (1998). “Investigating the Relationship between Gold and Silver Prices”, *Journal of Forecasting,* Vol. 17, pp. 81-107.

Evans, M. and Lewis, K.K. (1995). “Do Long-term Swings in the Dollar Affect Estimates of the Risk Premia?” *Review of Financial Studies*, vol. 8, pp. 709-742.

Fair, R. C and Shiller, R. J. (1990). “Comparing Information In Forecasts From Econometric Models”, *The American Economic Review,* vol. 80, no. 3, pp. 375-389.

Fair, R. C. and Shiller, R. (1989). “The Informational Context of Exante Forecasts”. *The Review of Economics and Statistics,* vol. 71, pp. 325-331.

Fama, E. F. (1970). “Efficient Capital Markets: A Review of Theory and Empirical Work”, *Journal of Finance,* pp. 383-417.

Fama, E.F. (1984a). "Forward and Spot Exchange Rates". *Journal of Monetary Economics,* vol. 14, pp. 319-338.

Fama, E.F. (1984b). "The Information in the Term structure". *Journal of Financial Economics,* vol. 13, pp. 509-528.

Fama, E.F. and Bliss, R.R. (1987). "The Information in Long-Maturity Forward Rates". *American Economic Review,* vol. 77, pp. 680-692.

Ferreira, A. L. (2004). "Leaning Against Parity". Working paper series 4-13, *University of Kent.*

Flood, R and Rose, A. (2002). "Uncovered Interest Parity in Crisis: the Interest Rate Defense in the 1990s". IMF working paper 01/207.

Frankel, J. (1980). "Tests of Rational Expectations in the Forward Exchange Rate Market". *Southern Economic Journal*, vol. 46 (4), pp. 1083-1101.

Frankel, J. and Poonawala, J. (2010). "The Forward Market in Emerging Currencies: Less Biased than in Major Currencies". *Journal of International Money and Finance,* vol. 29, pp. 585-598.

Frankel, J.A. and Froot, K.A. (1987). "Using Survey Data to Test Standard Propositions regarding Exchange Rate Expectations". *American Economic Review*, vol.77, pp. 133-153.

Franses, P.H. and van Dijk, D. (2003). "Nonlinear Time Series Models in Empirical Finance". *Cambridge university press.*

Fray, G. (2004). "Culture Matters in the Thai Turnaround: Recovery through Reform", *Harvard International Review*, vol. 26 (3).

Froot KA and EM Dabora (1999). "How are Stock Prices Affected by the Location of Trade?", *Journal of Financial Economics*, vol. 53(2), pp 189–216.

Froot, K. and Frankel, J. (1989). "Forward discount bias: is it an exchange risk premium?" *Quarterly Journal of Economics,* vol. 104 (1), pp. 139-161.

Froot, K.A, and Thaler, R.H. (1990). “Anomalies: foreign exchange”. *Journal of Economic Perspectives,* vol. 4, pp. 179-192.

Fujiwara, I. and Koga, M. (2004). “A Statistical Forecasting Method for Inflation Forecasting: Hitting Every Vector Autoregression and Forecasting under Model Uncertainty”, *Monetary and Economic Studies,* Bank of Japan.

Gatev, E., G., Goetzmann, W. and Rouwenhorst, K. (1999). “Pairs Trading: Performance of a Relative Value Arbitrage Rule”, Yale ICF Working Paper, No. 08-03.

Gerlach, S. (2003). “Interpreting the Term Structure of Interbank Rates in Hong Kong”. *Pacific-Basin Finance Journal,* vol. 11, pp. 593-609.

Granger, C. W. J. and Pesaran, M. H. (1999). “Economic and Statistical Measures of Forecast Accuracy”, *Cambridge Working Papers in Economics,* Faculty of Economics, University of Cambridge.

Granger, C.W.J. and Newbold, P. (1974). “Spurious Regression in Econometrics”. *Journal of Econometrics,* Vol. 2, pp. 111-120.

Granger, C.W.J. and Terasvirta, T. (1993). “Modeling Economic Nonlinear relationship”. *Oxford University Press:* Oxford.

Granger, Clive W. J. (1986). “Developments in the Study of Cointegrated Economic Variables”, *Oxford Bulletin of Economics and Statistics,* Department of Economics, University of Oxford, Vol. 48(3), pp. 213-228.

Gregory, A.W. and Hansen, B.E. (1996). “Residual-based Tests for Cointegration in Models with Regime Shifts”. *Journal of Econometrics,* Vol. 70, pp. 99-126.

Gupta, R. (2006). “Forecasting The South African Economy With VARs and VECMs”. *South African Journal of Economics,* Vol. 74, pp. 611-628.

Hadri, K. and Rao, Y. (2008). “Panel Stationarity Test with Structural Breaks”. *Oxford Bulletin of Economics and Statistics,* Vol. 70, pp. 245-269.

Hakkio, C. S., and Rush, M. (1989). "Market Efficiency and Cointegration. An Application to the Sterling and Deutschemark Exchange Markets", *Journal of International Money and Finance,* Vol. 8, pp. 75-88.

Hall, A. D., Anderson, H.M. and Granger, C.W.J. (1992). "A Cointegration Analysis of Treasury Bill Yields". *Review of Economics and Statistics,* Vol. 74, pp. 116-26.

Hansen, B. E. (1992). "Testing for Parameter Instability in Linear Models". *Journal of Policy Modeling,* Vol. 14, pp. 517-533.

Harris, R. I. D. (1995). "Using Cointegration Analysis in Econometric Modeling". *Pearson Education,* pp. 52-133.

Haug, A. A. and Siklos, P. L. (2002). "The Term Spread International Evidence of Non-Linear adjustment". York University, Department of Economics, *Working papers 2002(08).*

Hiebert, M. (1997). "Warning Shot". *Far Eastern Economic Review,* Vol. 160, pp. 80-81.

Hodrick, R. J. and Srivastava, S. (1984). "An Investigation of Risk and Return in Forward Foreign Exchange". *Journal of International Money and Finance,* Elsevier, Vol. 3(1), pp. 5-29.

Holmes, M.J., Otero, J. and Panagiotidis, T. (2010). "The Term Structure of Interest Rates, the Expectations Hypothesis and International Financial Integration: Evidence from Asian Economies". *The Rimini Centre for Economic Analysis, Working paper 10-34.*

Index Mundi (2010). "Thailand GDP-real growth rate". Available: http://www.indexmundi.com/thailand/gdp_real_growth_rate.html [26 June 2010].

Jeon, B.N. and Seo, B. (2003). "The Impact of the Asian Financial Crisis on Foreign Exchange Market Efficiency: The Case of East Asian Countries". *Pacific-Basin Finance Journal,* Vol. 11, pp. 509-525.

Johnston, J. and Dinardo, J. (1997). "Econometric Method", *McGraw-Hill,* pp. 263-282.

Kan, D. and Andreosso-O'Callaghan, B. (2007). "Examination of the Efficient Market Hyoithesis: The Case of Post-crisis Asia Pacific Countries". *Journal of Asian Economics,* Vol. 18, pp. 294-313.

Kasa, K. (1992). "Common Stochastic Trends in International Stock Markets". *Journal of Monetary Economics,* pp. 169-210.

Kawa, L. (2012). "The 10 Hottest Stock Markets in the World". *Business Insider*. Available: http://www.businessinsider.com [30 December 2012].

Kim Eng. (2010) "Investor Information", Available: http://www.kimeng.co.th/inv_type.asp [3 January 2010].

Krasker, W. S. (1980). "The Peso Problem in Testing the Efficiency of Forward Exchange Markets", *Journal of Monetary Economics,* Vol. 6, pp. 269-276.

Krishnakumar, J. and Neto, D. (2012). "Testing Uncovered Interest Rate Parity and Term Structure Using a Three-regime Threshold Unit Root VECM: An Application to the Swiss 'Isle' of Interest Rates". *Oxford Bulletin of Economics and Statistics,* Vol. 74, pp. 180-202.

Kuhl, M. (2010). "Bivariate Cointegration of Major Exchange Rates, Cross-market Efficiency and The Introduction of The Euro". *Journal of Economics and Business,* Vol. 62, pp. 1-19.

Kuo, S.H. and Enders, W. (2004). "The Term Structure of Japanese Interest Rates: the Equilibrium Spread with Asymmetric Dynamics". *Journal of The Japanese and International Economies,* Vol. 18, pp. 84-98.

LeSage, J. P. (1990). "A Comparison of The Forecasting Ability of ECM and VAR Models". *The review of Economics and Statistics,* Vol. 72(4), pp. 664-671.

Levich, R.M. (1979). "Are Forward Exchange Rates Unbiased Predictors of Future Spot Rates?' *Columbia Journal of World Business,* Vol. 14, pp. 49-61.

Lewis, K. K. (1989). "Changing Beliefs and Systematic Rational Forecast Errors with Evidence from Foreign Exchange", *American Economic Review,* Vol. 79, pp. 621-636.

Liau, Y. S. and Yang, J. J. W. (2009). "The Expectation Hypothesis of Term Structure of Interest Rates in Taiwan's Money Market". *International research Journal of Finance and Economics,* Vol. 27, pp. 181-191.

Lim, G and Martin, V. (1995). "Regression-based Cointegration Estimators". *Journal of Economic Studies,* Vol. 22(1), pp. 3-20.

Lin, J. and Tsay, R.S. (1996). "Co-integration Constraint and Forecasting: An Empirical Examination". *Journal of Applied Econometric,* Vol. 11, pp. 519-538.

Lin, Y., McCrae, M. and Gulati, C. (2006) "Loss Protection in Pairs Trading Through Minimum Profit Bounds: A Cointegration Approach". *Journal of Applied Mathematics and Decision Sciences,* Vol. 2006, pp. 1-14.

Litterman, R.B. (1986). "Forecasting with Bayesian Vector Autoregressions: Five years of Experience". *Journal of Business and Economic Statistics,* Vol. 4, pp. 25-38.

Lundbergh, A., Terasvirta, T. and van Dijk, D. (2003). "Time-Varying Smooth Transition Autoregressive Models". *Journal of Business and Economic Statistics,* Vol. 21, no. 1, pp. 104-121.

Luukkonen, R. Saikkonen, P. and Terasvirta, T. (1988). "Testing Linearity against Smooth Transition Models". *Biometrika,* Vol. 75, pp. 491-499.

Lyons, R.K. (2001). "The Microstructure Approach to Exchange Rates". *MIT Press: London.*

Maddala, G. S. and Kim, I. M. (1998). "Unit Roots Cointegration and Structural Change", *Cambridge University Press,* pp. 155-159, 198-210.

Mark, N.C. and Moh, Y.K. (2002). "Continuous-Time Market Dynamics, ARCH Effects, and the Forward Premium Anomaly," *University of Notre Dame and Tulane University.*

Maynard, A. and Phillips, P.C.B. (1998). “Rethinking an old Empirical Puzzle: Econometric Evidence on the Forward Discount Anomaly”. *Journal of Applied Econometrics,* Vol. 16, pp. 671-708.

McCallum, B.T. (1994). “A Reconsideration of the Uncovered Interest Rate Parity Relationship”. *Journal of Monetary Economics*. Vol. 33, pp. 105-132.

McCrae, M., Lin, Y.X., Pavlik, D. and Gulati, C. M. (2002). “Can Cointegration-based Forecasting Outperform Univariate Models? An Application to Asian Exchange Rates”. *Journal of Forecasting,* Vol. 21, pp. 355-380.

McMillan, D. G. (2004). “Non-Linear Error Correction: Evidence For UK Interest Rates”. *The Manchester School,* Vol. 72, no. 5, pp. 629-640.

McMillan, D. G. (2008). “Non-linear Cointegration and Adjustment: as Asymmetric Exponential Smooth-transition Model for US interest rates”. *Empir Econ,* Vol. 35, pp. 591-606.

Meese, R. (1989). “Empirical Assessment of Exchange Rate Risk Premiums”. In stone (ed.) *Financial risk: Theory, evidence and implications,* Kluwer, Boston, MA.

Messe, R.A. and Singleton, K.J. (1982). “On the Unit Roots and the Empirical Modeling of Exchange Rates”. *Journal of Finance,* Vol. 37, pp. 1029-1035.

Naka, A. and Whitney, G. (1995). “A Re-examination of the Unbiased Forward Rate Hypothesis”. *Journal of International Money and Finance,* Vol. 14, pp. 857-867.

Nath, P. (2003). “High Frequency Pairs Trading with U.S Treasury Securities: Risks and Rewards for Hedge Funds”, Working Paper, London Business School.

Nugroho, A. B. (2011). “Term Structure Examination of Indonesian Money Market: Some Efficiency Issue”. *The Asian journal of technology management,* Vol. 4, no. 2, pp. 99-108.

Pagan, A. and Ullah, A. (1988). “The Econometric Analysis of Models with Risk Terms”. *Journal of Applied Econometrics,* Vol. 3, pp. 87-105.

Pavabutra, P. and Prangwattananon, S. (2008). "Tick Size Change on the Stock Exchange of Thailand". *ECI Working paper series,* No. 2008-9.

Perlin, M. (2007). "Evaluation of Pairs Trading Strategy at the Brazilian Financial Market", MPRA Paper, No. 8308.

Pesaran, M. H. and Pesaran, B. (2003). "Working with Microfit 4.0 Interactive Econometric Analysis", *Oxford University Press,* pp.285-291.

Pesaran, M. H. and Timmermann, A. G. (1994). "A Generalization of the Non-parametric Henriksson-Merton Test of Market Timing", *Economics Letters,* Vol. 44, pp. 1-7.

Phengpis, C. (2006). "Market Efficiency and Cointegration of Spot Exchange Rates During Periods of Economic Turmoil: Another Look at European and Asian Currency Crises". *Journal of Economics and Business.* Vol. 58, pp. 323-342.

Pisit, L. (2008). "Thailand: the End of a Year of Political Troubles". Available: http://www.eastasiaforum.org/2008/12/28/thailand-the-end-of-a-year-of-political-troubles/ [1 July 2010].

Psaradakis, Z. and Spagnolo, F. (2005). "Forecasting Performance of Nonlinear Error Correction Models with Multiple Regimes", *Journal of Forecasting,* vol. 24, pp. 119-138

Psaradakis, Z., Sola, M. and Spagnolo, F. (2006). "Instrumental-Variables Estimation in Markov Switching Models with Endogenous Explanatory Variables: An Application to the Term Structure of Interest Rates". *Studies in Nonlinear Dynamics & Econometric.* Vol. 10, no. 2, pp. 1-29.

Roberds, W. and Whiteman, C.H. (1999). "Endogenous Term Premia and Anomalies in the Term Structure of Interest Rates: Explaining the Predictability Smile". *Journal of Monetary Economics,* Vol. 44(3), pp. 555-580.

Roll, R. and Yan, S. (2000). "An Explanation of the Forward Premium 'Puzzle'". *European Financial Management,* Vol. 6, pp. 121-148.

Ross, S. (1976) "The Arbitrage Theory of Capital Asset Pricing", *Journal of Economic Theory*, Vol. 13, pp. 341-360.

Sachsida, A., Ellery Jr., R. and Teixeria, J.R. (2001). "Uncovered Interest Rate Parity and the Peso Problem: the Brazilian Case". *Applied Economics Letters*, Vol. 8, pp. 179-181.

Sakoulis, G. and Zivot, E. (2005). "Time-Variation and Structural Change in the Forward Discount: Implications for the Forward Rate Unbiasedness Hypothesis". *Mimeo, Department of Economics, University of Washington.*

Sarno, L. (2005). "Towards a Solution to the Puzzles in Exchange Rate Economics: Where Do We Stand?" *Canadian Journal of Economics,* Vol. 38, pp. 673-708.

Sarno, L., Valente, G. and Leon, H. (2004). "Nonlinearity Deviation from UIP". *International Journal of Finance and Economics,* Vol. 9, pp. 15-23.

Schmidt, A. (2008), "Pairs Trading: A Cointegration Approach". University of Sydney Finance Thesis.

Sercu, P. and Wu, X., (2000). "Uncovered Interest Arbitrage and Transaction Costs: Errors-in-Variables versus Hysteresis Effects," *University of Leuven and City University of Hong Kong.*

Shen, C. H. (1998). "The Term Structure of Taiwan Money Market Rates and Rational Expectation". *International Economic Journal,* Vol. 12, no. 1, pp. 105-119.

Shivam, M. and Jayadev, M. (2005). "The Interest Rate Term Structure in Indian Money Market". *Indian Institute of Management,* Lucknow.

Shoesmith, G. L. (1992). "Non-cointegration and causality: Implications for VAR modeling". *International Journal of Forecasting,* Vol. 8, pp. 187-199.

Shoesmith, G.L. (1995a). "Long Term Forecasting of Noncointegrated and Cointegrated Regional and National Models". *Journal of Regional Science,* Vol. 35, pp. 43-64.

Shoesmith, G.L. (1995b). “Multiple Cointegrating Vector, Error Correction and Forecasting with Littermen’s Model”. *International Journal of Forecasting,* Vol. 11, pp. 557-567.

Siklos, P. and Wohar, M. (1997). “Cointegration and the Term Structure: A Multicounty Comparison”. *International Review of Economics and Finance,* Vol. 5, pp. 21-34.

Silva Lopes, A. C. and Monteiro, O. S. (2007). “The Expectations Hypothesis of the Term Structure: Some Empirical Evidence for Portugal”. *Munich Personal RePEc Archieve,* No. 3437

Spagnolo, F., Psardakis, Z. and Sola, M. (2005). “Testing the Unbiased Forward Exchange Rate Hypothesis Using a Markov Switching Model and Instrumental variables”. *Journal of Applied Econometrics,* Vol. 20, pp. 423-437.

Stekler, H. O. and Petrei, G. (2003). “Diagnostics for Evaluating the Value and Rationality of Economic Forecasts”. *International Journal of Forecasting,* Vol. 19, pp. 735-745.

Stock Exchange of Thailand. (2009). “Transaction by Investor Group, Primary Market VS. Secondary Market, (SET & mai)”. Available: http://www.set.or.th/en/market/files/200912_primary_secondary_market_en.pdf [1 July 2010].

Stock Exchange of Thailand. (2013). “Trading Units, Price Spread and Price Limits”. Available: http://www.set.or.th/en/products/trading/equity/tradingsystem_p5.html [29 January 2013]

Stock, J. H. (1987). “Asymptotic Properties of Least Squares Estimates of Cointegrating Vectors”. *Econometric,* Vol. 55: pp. 1035-1056.

Stock, J. H. and Watson, M. W. (1988). “Testing for Common Trends”. *Journal of the American Statistical Association,* Vol. 83 (404), pp. 1097-1107.

Stoll, H.R. (1978). “The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks”. *Journal of Finance, American Fiance Association*. Vol. 33(4), pp. 1153-1172.

Swanson N. R. and White, H. (1995). “A Model Selection Approach to Real-Time Macroeconomic Forecasting Using Linear Models and Artificial Neural Networks”. *Journal of Business & Economic Statistics,* Vol. 13, pp. 265-275.

Swanson N. R. and White, H. (1997). “Forecasting Economic Time Series Using Flexible Versus Fixed Specification and Linear Versus Nonlinear Economic models”. *International Journal of Forecasting,* Vol. 13, pp. 439-461.

Taylor, M.P. and Peel, D.A. (2000). “Non-linear Adjustment, Long-run Equilibrium and Exchange Rate Fundamentals’. *Journal of International Money and Finance,* Vol. 19, pp. 33-53.

Terasvirta, T. (1994). “Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models”. *Journal of the American Statistical association,* vol. 89, pp. 208-218.

Thomas, R. L. (1997). “Modern Econometrics an Introduction”, Manchester Metropolitan University, *Financial Times Prentice Hall,* pp. 424-436.

Thornton, D. L. (2003). “Tests of the Expectation HSypothesis: Resolving the Campbell-Shiller Paradox”. *Federal Reserve Bank of St. Louis.* Working paper 2003-033B.

Tinic, S.M. and West, R.R. (1972). “Competition and the Pricing of Dealer Service in the Over-the-Counter Stock Market”. *Journal of Financial and Quantitative Analysis.* Vol. 7, pp. 1707-1727.

Tong, W.H.S. (2001). “Cointegration, Efficiency and Forecasting in the Currency Market”. *Journal of Business Finance & Accounting,* Vol. 28, pp. 127-150

Vidyamurthy, G. (2004) “Pairs Trading, Quantitative Methods and Analysis”, *John Wiley & Sons,* Canada.

Villanueva, O.M. (2007). “Forecasting Currency Excess Returns: Can the Forward Bias be Exploited?” *Journal of Financial and Quantitative Analysis*, Vol. 42, pp. 963-990.

Villanueva, O.M. (2007). “Spot-Forward Cointegration, Structural Breaks and FX Market Unbiasedness”. *International Financial Markets, Institutions and Money*, Vol. 17, pp. 58-78.

Zivot, E. (1998). “Cointegration and Forward and Spot Exchange Rate Regressions”. *EconWPA*. Econometric 9812001.

APPENDIX

Appendix I: Thai Economic Data

Table I1: Gross domestic product (GDP) in Thailand

Year	Gross domestic product, constant prices	Percent Change
1980	4.601	
1981	5.91	28.45 %
1982	5.353	-9.42 %
1983	5.581	4.26 %
1984	5.76	3.21 %
1985	4.643	-19.39 %
1986	5.534	19.19 %
1987	9.519	72.01 %
1988	13.288	39.59 %
1989	12.194	-8.23 %
1990	11.623	-4.68 %
1991	8.112	-30.21 %
1992	8.083	-0.36 %
1993	8.251	2.08 %
1994	8.987	8.92 %
1995	9.237	2.78 %

1996	5.901	-36.12 %
1997	-1.371	-123.23 %
1998	-10.51	666.59 %
1999	4.448	-142.32 %
2000	4.75	6.79 %
2001	2.167	-54.38 %
2002	5.318	145.41 %
2003	7.14	34.26 %
2004	6.344	-11.15 %
2005	4.605	-27.41 %
2006	5.226	13.49 %
2007	4.926	-5.74 %
2008	2.592	-47.38 %
2009	-3.456	-233.33 %

Source: Index Mundi

Table I2: Inflation Rate in Thailand

Year	Inflation, average consumer prices	Percent Change
1980	19.7	
1981	12.7	-35.53 %
1982	5.3	-58.27 %
1983	3.7	-30.19 %
1984	0.9	-75.68 %
1985	2.4	166.67 %
1986	1.8	-25.00 %
1987	2.49	38.33 %
1988	3.8	52.61 %
1989	5.37	41.32 %
1990	-9.497	-276.85 %
1991	5.702	-160.04 %
1992	4.154	-27.15 %
1993	3.295	-20.68 %
1994	5.081	54.20 %
1995	5.773	13.62 %
1996	5.871	1.70 %
1997	5.583	-4.91 %

1998	8.08	44.73 %
1999	0.308	-96.19 %
2000	1.53	396.75 %
2001	1.627	6.34 %
2002	0.697	-57.16 %
2003	1.804	158.82 %
2004	2.759	52.94 %
2005	4.54	64.55 %
2006	4.637	2.14 %
2007	2.242	-51.65 %
2008	5.468	143.89 %
2009	-1.151	-121.05 %

Source: Index Mundi

Table I3: Stock Exchange of Thailand (SET) price index

Year	Index price
1999	477.33
2000	267.50
2001	305.51
2002	357.81
2003	773.40
2004	666.63
2005	714.27
2006	685.07
2007	870.12
2008	458.85

Source: Bank of Thailand

Figure I1: Thai GDP and % change

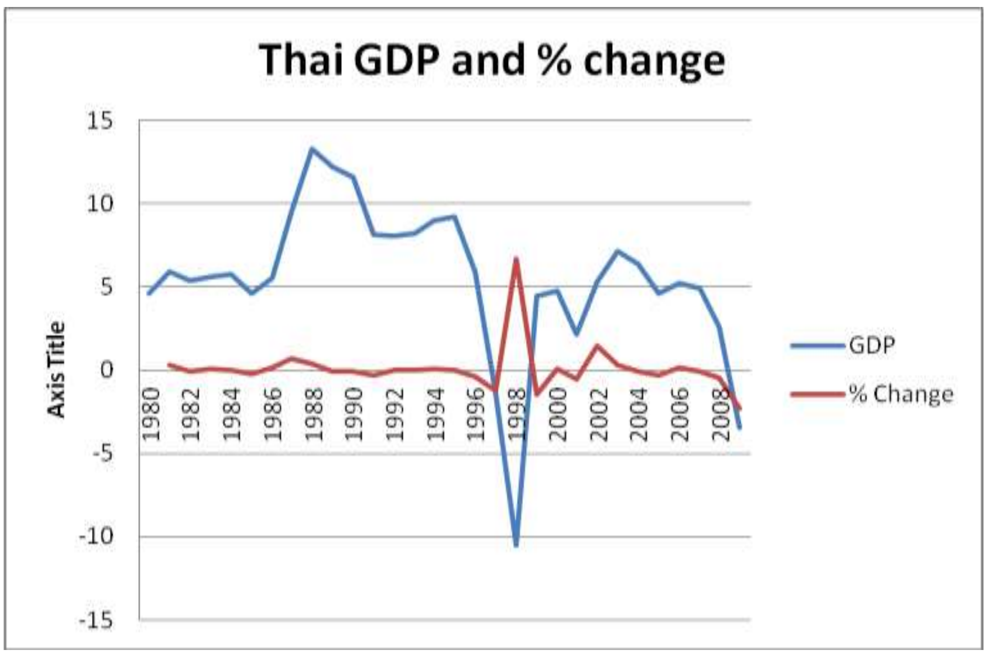


Figure I2: Thai Inflation and % change

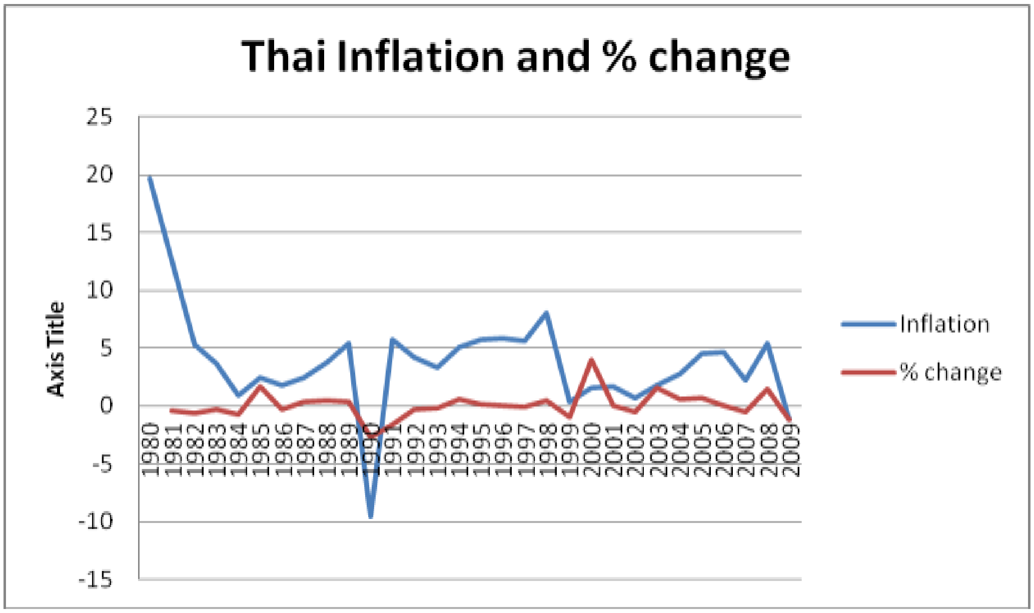
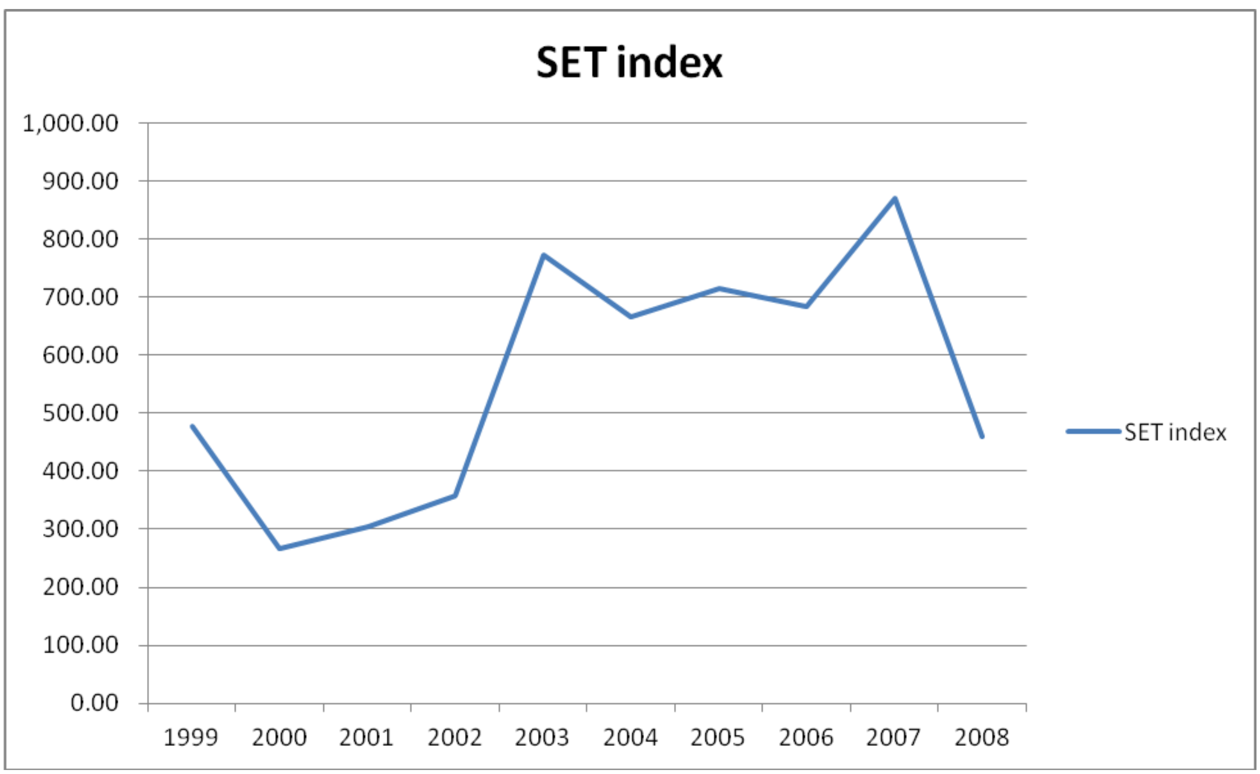


Figure I3: SET price index from 1999 to 2008



Appendix II: Stock Details

Table II1: Individual Stock detail that have been selected for cointegration test

Individual stock	Name of stock	Nature of the Business	Market Capital (in Million baht)
Resources sector			**1,854,114.86**
EGCO	Electricity generating public company limited	Power generating	43,038
LANNA	The lanna resources public company limited	Mining and distribution of Lignite	5,880
BANPU	Banpu public company limited	Mining for coal and other minerals and supplier of utilities	167,939
Financial sector			**1,430,196.12**
ACL	ACL Bank public company limited	Finance and securities business	17,941
ASP	Asia plus securities public company limited	Brokerage and securities trading	3,621
{Ayud}	Ayudhaya insurance public company limited	Non-life insurance such as fire, marine, accidents, automobile and miscellaneous insurance	4,124
BAY	Bank of Ayudhaya public company limited	Commercial bank	120,268
BBL	Bangkok bank public company limited	Commercial bank	239,559
KBANK	Kasikornbank public company limited	Commercial bank	219,581

Individual stock	Name of stock	Nature of the Business	Market Capital (in Million baht)
KK	Kiatnakin bank public company limited	Commercial bank	14,924
KTB	Krung Thai bank public company limited	Commercial bank	144,218
SCB	The Siam commercial bank public company limited	Commercial bank	279,869
TMB	TMB bank public company limited	Commercial bank	61,810
Property and construction sector			**897,513.85**
AMATA	Amata corporation public company limited	Investment, estate development, infrastructure facilities	9,069
CK	Ch. Karnchang public company limited	Contract construction business	11,402
CPN	Central Pattana public company limited	Developing real estate (Retail shops and offices)	43,794
AMATA	Amata corporation public company limited	Investment, estate development, infrastructure facilities	9,069
CK	Ch. Karnchang public company limited	Contract construction business	11,402
CPN	Central Pattana public company limited	Developing real estate (Retail shops and offices)	43,794
EMC	EMC public company limited	Construction contractor business	691
ITD	Italian-Thai development public company limited	Construction contractor business	12,329

Individual stock	Name of stock	Nature of the Business	Market Capital (in Million baht)
{KC}	K.C. Property public company limited	Estate development business (modern home)	761
LH	Land and Houses public company limited	Construction of high quality residential	55,142
LPN	L.P.N. Development public company limited	Real estate business, develop residential commercial and office building	12,691
{N-PARK}	Natural park public company limited	Real estate development	935
{PAE}	PAE public company limited	Construction, industrial service, communication and manpower	216
SCC	The Siam cement public company limited	Manufacturer and distributor of cement and refractory brick	319,200
SPALI	Supalai public company limited	Real estate development	15,448
STEC	Sino-Thai engineering and construction public company limited	General construction for civil and infrastructure, factory, marine work etc	8,303
{TSTH}	Tata steel public company limited	Manufacturing steel rods, rebars and finished steel products	13,478

Individual stock	Name of stock	Nature of the Business	Market Capital (in Million baht)
Services sector			
{AHC}	Aikchol hospital public company limited	Modern and well equipped private hospital	862
BGH	Bangkok dusit medical services public company limited	Private hospital specialized in cardiorasculan, lung, neurological, eye and genitourinary	36,738
BH	Bumrungrad hospital public company limited	Full service medical facility offering international standard medical care	23,488
BIGC	BIG C supercenter public company limited	Distributor of daily life consumer products at a lower price	45,478
{BJC}	Berli Jucker public company limited	Exporter, importer and distributor of cosmetics, confectionery and canned food products	13,737
ERAWAN	The erawan group public company limited	Office building, hotel, shopping center	4,489
MAKRO	Siam makro public company limited	Wholesale, retail, import and export of consumer products	26,759
ROBINS	Robinson department store public company limited	Department store	16,659
{SINGER}	Singer Thailand public company limited	Trading company such as sewing machines, refrigerators, television etc.	723

Individual stock	Name of stock	Nature of the Business	Market Capital (in Million baht)
{SPC}	Saha Pathanapibul public company limited	Wholesale distributor of consumer products such as detergent, vermicelli, toothpaste, shampoo, etc	8,278
Technology sector			**574,585.74**
{PT}	Premier technology public company limited	Research information	194
{MSC}	Metro systems corporation public company limited	Distributor of information technology products and services	928

Source: www.kimeng.co.th