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The Predictability of Stock Index Futures Markets in Taiwan

by

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Abstract

The thesis examines the predictability of stock index futures in Taiwan. The lead-lag relationships between the stock index and index futures, as well as across futures markets are first investigated. Empirical results confirm previous findings that there is an asymmetric lead-lag relation between cash and futures markets— the feedback from the futures markets into the cash market is much stronger than the reverse. On the other hand, the weak evidence that the spot index leads the futures diminishes as interval enlarges and the leadership becomes a unidirectional relation that only the futures leads the cash index. Although short-selling constraint is a reasonable hypothesis to conjecture the leadership relationship between the cash and futures, there is no evidence to support it from Taiwan markets.

Secondly, the mechanism of the index futures spread arbitrage is described and spreads between index futures in Taiwan can be constructed so as to result in risky arbitrage. The long-term relationships among index futures are detected by cointegration tests. The prices of related index futures in this study are found to be cointegrated and the spreads derived from the cointegration relationships are mean-reverting. The trading-rule simulations suggest that the average profit from spread arbitrage is statistically significant after transaction costs and the rates of return of spread arbitrage are very attractive.

The long memory properties of the spreads derived from the cointegration relationships is further investigated. Both spreads are revealed to be mean-reverting but non-stationary long memory process. Furthermore, there is strong evidence that Spread II is a double long memory process but Spread I lacks the property of long-range dependence in volatility.

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Chapter One: Introduction

The Efficient Market Hypothesis (EMH) is one of the most well-studied and controversial propositions in Finance. Even after several decades of research, economists have not yet reached a consensus about whether financial markets are efficient or not. One of reasons for this situation is that the EMH is not a well-defined and empirical refutable hypothesis. To make it operational, researchers must specify additional structure but then a test of the EMH becomes a test of several hypotheses too. A rejection of such a joint hypothesis tells us little about which aspect of the joint hypothesis is inconsistent with the data. A more informative way to measure the efficiency of a market is the relative efficiency of a market relative to other markets, e.g., futures vs. cash markets. An important aspect of this relationship is the nature of the lead-lag in the returns between equivalent securities traded in different markets or the predictive power of price movements in one market for those in the other. If a market reflects information faster than another one, then we can say the former leads the latter, or the latter lags the former. The lead-lag relation between price movements of index futures and the underlying cash market illustrates how fast one market reflects information relative to the other, and how well the two markets are linked.

Some issues regarding the lead-lag relation between markets deserve examination. First of all, the leadership relation between the cash and futures markets might change through time. The second issue to be examined is whether the reduction in transaction costs of futures contract will change the pattern of leadership. As suggested by the transaction costs hypothesis, the market with lower transaction costs will react more quickly to new information. The third is the effects of short-sales constraints on the lead-lag relationship between the spot index and index futures. Constraints on short-selling may hinder traders to reflect bad news in the stock market but futures do not subject to such restriction. As a result, the leadership would not be the same under good and bad news if the short-sale constraints are binding. The fourth issue is that, in the previous studies, various time intervals are chosen to investigate the leadership between the cash and futures markets. The lengths or patterns of leads and lags from the results of those studies are various for different intervals and markets. Prior work does not investigate a market with different time intervals. More complete understanding of the leadership may be recognised by doing this. As well as the lead-lag relationship between the cash and futures markets, there may also be leads and lags across futures. The differences of information adjustment for futures contracts may cause by differences in transaction costs or trading mechanisms, i.e., screen trading vs. open outcry.

Another way to see the predictability of index futures in Taiwan is to construct profitable futures spread trading positions. A futures spread position is constructed by taking a long position in one futures contract and a short position in another one simultaneously to exploit temporary disequilibrium between them. As far as the author is aware, there has been no study on intercommodity spread arbitrage between index futures with highly correlated but different underlying indices. If there are reasons to believe that two futures are virtually the same even though their underlying assets are not exactly the same, and if the stable relationship between them can be found out by modern statistical techniques, then spread arbitrage using these two futures contracts could be a profitable strategy. On the condition that two index futures are good substitutes for each other, they should be priced to the same fundamental value in efficient markets. If one of the index futures is mispriced, rational investors will take advantage of this mispricing by selling the relatively overpriced contract and simultaneously purchasing the relatively underpriced one to earn a profit and bring them in line. Consequently, their prices will revert to the fundamental value eventually. If two index futures are good substitutes for each other, there should be a long-term equilibrium and the spreads between them should be stationary. Therefore, cointegration tests are suitable to detect the long-term relationship. On the condition that the cointegration relationship is found out, trading strategies are designed to exploit the profits according to the mean-reverting property of the spreads between related futures.

The properties of long-range dependence in the spreads derived from the cointegration relationship are further examined. The spreads between index futures in Taiwan share the same property of mean-reverting with stationary series because any deviations in the spreads will revert to the long-term equilibrium eventually. However, the autocorrelation functions of the spreads are much more persistent than those of usual stock returns. The first-order autocorrelation is higher than 0.9 for both series and the autocorrelation coefficients of first five lags range from 0.69 to 0.95, indicating that both spread series tend to persist above or below zero, rather than fluctuate randomly around zero. In spite of this, they are not as persistent as the autocorrelations of an integrated series which remain persistently high at long lags. Such series having a slowly declining correlogram are argued to process long memory. The study on the long-range dependence properties of the index futures spreads concentrate on two parts: the first one is to investigate the long memory in spread levels, and the second part is to examine the volatility persistence of spreads. The results from the study may be used to improve the forecasting of the changes in the index futures spreads.

The thesis is organised as follows. In Chapter Two, the lead-lag relationships between stock index and index futures and across futures markets in Taiwan are investigated. The theory underlying the covariation of the stock index and index futures and the hypotheses that explain the lead-lag relationship between the spot index and futures markets are presented. In addition, prior empirical studies on the lead-lag relationship between the cash index and index futures, and the leadership across futures are reviewed. The primary tests are based on minutely intraday returns of the futures and cash index which are constructed for two sample periods. In addition, 5-, 15- and 30-minute intraday returns are also generated. Tests for unit roots and cointegration, and the regression models to examine the leadership between the stock index and futures markets are explained.

In Chapter Three, the cointegration approach is employed to construct spread arbitrage between stock index futures in Taiwan. The literature on futures spread trading is reviewed and the traditional method of index futures spread trading is discussed and evaluated. Moreover, the rationale of intercommodity index futures spread arbitrage is developed. Cointegration tests and error correction models are used to reveal the long-term relationship and the short-term dynamics between these index futures. In addition, simulation trading strategies are depicted and the simulation results are presented and discussed. Generally speaking, the cointegration relationships are strongly significant between Taiwanese index futures. The simulation results reveal that index futures arbitrage is profitable after transaction costs.

In Chapter Four, long memory and fractional dynamics in the spreads of index futures are examined. The concept of long memory is presented and literature on long memory in returns and in volatility is reviewed. Tests for unit roots and stationarity are applied to both spreads to determine their order of integration. Models for long memory in the conditional mean and in the conditional variance are estimated to find out the long-range dependence properties of these two spreads. The thesis concludes in Chapter Five with a summary.

Chapter Two: The Lead-Lag Relationships between the Stock Index and Index Futures and across Futures Markets in Taiwan

Abstract

This chapter investigates the lead-lag relationships between the stock index and index futures, as well as across futures markets in Taiwan. Empirical results confirm previous findings that there is an asymmetric lead-lag relation between cash and futures markets— the feedback from the futures markets into the cash market is much stronger than the reverse. Moreover, the weak evidence that the spot index leads the futures diminishes as interval enlarges and the leadership becomes a unidirectional relation that only the futures leads the cash index. Although short-selling constraint is a reasonable hypothesis to conjecture the leadership relationship between the cash and futures, there is no evidence to support it from Taiwan markets or any others. The results from Taiwan markets are basically consistent with the transaction costs hypothesis and the market maturation effects. Futures and stock markets become more closely integrated through time as futures have matured.

1. Introduction

The EMH is one of the most well-studied and controversial propositions in Finance. Even after several decades of research, economists have not yet reached a consensus about whether financial markets are efficient or not. One of reasons for this situation is that the EMH is not a well-defined and empirical refutable hypothesis (Lo and MacKinlay, 1999). To make it operational, researchers must specify additional structure but then a test of the EMH becomes a test of several hypotheses too. A rejection of such a joint hypothesis tells us little about which aspect of the joint hypothesis is inconsistent with the data. A more informative way to measure the efficiency of a market is the relative efficiency of a market relative to other markets, e.g., futures vs. cash markets. The temporal relationship between the stock index and the index futures has drew the attention of scholars, regulators, and market participants as a result of both the considerable volume of trading in these instruments and their role during periods of turmoil in financial markets. An important aspect of this relationship is the nature of the lead-lag in the returns between equivalent securities traded in different markets or the predictive power of price movements in one market for those in the other. The lead-lag relation between price movements of index futures and the underlying cash market illustrates how fast one market reflects information relative to the other, and how well the two markets are linked. With no market frictions, price changes must be unpredictable because they fully reflect all available information and new information must be incorporated into the prices of shares and their derivatives simultaneously, otherwise risk-free profits would be possible by arbitraging between markets. Since both the stock index and index futures reflect the same aggregate value of the underlying shares, index futures should neither lead nor lag the spot index. However, the existence of market frictions, e.g. transaction costs, taxes and regulations, reduces the efficiency of markets and information may be revealed quicker in one market than the others, i.e., prices in one market tend to lead or lag the other markets.

Several studies examine the lead-lag relationship between the cash and futures markets, e.g., Stoll and Whaley (1990), Chan (1992) and Abhyankar (1995; 1998). Their results suggest that index futures significantly lead the stock index although there is weak evidence that cash index have some predictive ability about futures. For instance, Chan (1992) finds that S&P 500 and Major Market Index (MMI) futures returns lead cash index by 10 to 15 minutes, but the feedback from the spot market into futures markets is shorter than that.

Some issues regarding the lead-lag relation between markets deserve examination. First of all, the leadership relation between the cash and futures markets might change through time. Stoll and Whaley (1990) state that futures and stock markets will become more closely integrated as the futures have matured. The futures markets based on the Taiwan stock market are newly established. There were no derivatives in Taiwan until 1997. The first index futures, coded TW, began trading on 9 January 1997 in the Singapore International Monetary Exchange (SIMEX)[1] and the second one, coded TX, began to trade on 21 July 1998 in the Taiwan Futures Exchange (TAIFEX). The trading

[1] The SIMEX has been acquired by the Singapore Exchange (SGX) and becomes the SGX Derivatives Trading Division (SGX-DT)

volume and liquidity of a futures contract are usually at a low level in the phase of its early life and gradually increase to higher level as the contract has matured. Since the TW began to trade early than the TX, the TW has the advantages of better liquidity and higher volume in the early stage of the TX. For example, in 1999 the average daily volume of the TX was only half as much as that of the TW in 1999 but the TX's volume increases to the same level as the TW's in 2001. Thus, the effects of market maturation in Taiwan markets can be discovered by comparing the different figures in two sub-periods.

The second issue to be examined is whether the reduction in transaction costs of futures contract will change the pattern of leadership. As suggested by the transaction costs hypothesis, the market with lower transaction costs will react more quickly to new information. As the futures transaction tax of the TX has been reduced from 0.05% to 0.025% one-sided on trading value since 1st may 2000, the reduction in futures transaction costs may cause a longer and stronger futures leadership.

The third is the effects of short-sales constraints on the lead-lag relationship between the spot index and index futures. Constraints on short-selling may hinder traders to reflect bad news in the stock market but futures do not subject to such restriction. As a result, bad news may be reflected in the futures market first, and then in the stock market later. Therefore, the leadership would not be the same under good and bad news if the short-sale constraints are binding. The restriction of short-sales on the Taiwan stock market, unlike the Uptick Rule in the U.S. or other countries, is that a share could not be short sold if its price is lower than the previous day's closing price. It is worthy to examine the lead-lag relationship under the unique restriction in Taiwan.

The fourth issue is that, in the previous studies, various time intervals are chosen to investigate the leadership between the cash and futures markets. The lengths or patterns of leads and lags from the results of those studies are various for different intervals and markets. Prior work does not investigate a market with different time intervals. More complete understanding of the leadership may be recognised by doing this. Hence, in addition to minutely data, five-, fifteen- and thirty-minute data are used in this study to explore the leads and lags relationship under different intervals.

As well as the lead-lag relationship between the cash and futures markets, there may also be leads and lags across futures. The differences of information adjustment for futures contracts may cause by differences in transaction costs or trading mechanisms, i.e., screen trading vs. open outcry. These two futures contracts in Taiwan happen to be traded by different trading mechanisms: the TX is a screen trading market and the TW is an open outcry market. Thus, the last issue is to examine leadership across futures contracts, rather than between the spot index and index futures.

The paper is organised as follows. In Section 2, the theory underlying the covariation of the stock index and index futures and the hypotheses that explain the lead-lag relationship between the spot index and futures markets are presented. In addition, prior empirical studies on the lead-lag relationship between the cash index and index futures, and the leadership across futures are reviewed. Data and methodology are described in Section 3. The features of the Taiwan stock market and the contract specifications of the futures based on the Taiwan stock market are depicted. The primary tests are based on minutely intraday returns of the futures and cash index which are constructed for two sample periods. In addition, 5-, 15- and 30-minute intraday returns are also generated. Tests for unit roots and cointegration, and the regression models to examine the leadership between the stock index and futures markets are explained. In Section 4, the empirical results of the lead-lag relationship between the Taiwan stock index and futures, as well as across futures markets are presented and discussed. This chapter concludes in Section 5.

2. Theory and Literature Review

In an informationally efficient market, price changes must be unpredictable because they fully reflect all available information and new information must be incorporated into the prices of shares and their derivatives, if exist, simultaneously, otherwise risk-free profits would be possible by arbitraging between markets. However, the existence of market frictions, e.g. transaction costs, taxes and regulations, reduces the efficiency of markets and information may be revealed quicker in one market than the others, i.e., prices in one market tend to lead or lag the other markets.

This chapter is organised as follows. The theory underlying the covariation of the stock index and index futures is described in Section 2.1. In Section 2.2, four hypotheses that explain the lead-lag relationship between the spot index and futures markets are presented. Previous empirical studies on the lead-lag relationship between the cash index and index futures, and the leadership across futures are reviewed in Section 2.3.

2.1 The theoretical relation between the stock index and index futures

The theoretical price of the futures can be derived from arbitrage pricing theory. In the absence of transaction costs and other market frictions[2], the theoretical relation between the price of an index futures contract and the price of the underlying index can be stated as:

$$F = (S - D)(1 + r) \tag{2.1}$$

where F is the market value[3] of the index futures, S is the market value of the underlying index, D is the present value of the expected dividend stream before expiration date of the futures contract, and r is the risk-free interest rate. This is the discrete-time version of the cost-of-carry model of futures pricing. Assuming the interest rate is continuously compounded, the continuous-time version can be expressed as:

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[2] Sutcliffe lists 27 assumptions on deriving his discrete time version of the formula for pricing stock index futures. Details see Sutcliffe (1997), pp. 67-68

[3] The market value is the price multiplied by the contract multiplier. For example, if the current price of the TX is 5,000 and the contract multiplier is NT$200, then the market value of a TX contract is NT$1,000,000

$$F_t = S_t e^{(r-d)(T-t)} \tag{2.2}$$

where F and S are the price of the index futures and the underlying index quoted at time t, respectively, T is the delivery date of the futures, e=2.7182818···, and d is the dividend yield rate on the underlying index. Thus, r-d= net cost of carrying the underlying shares in the index.

Equation (2.1) or (2.2) can be considered as the no-arbitrage condition between the spot index and the index futures and the market force driving the no-arbitrage condition is the endless search for a free-lunch. When, a riskless arbitrage profit can be earned by selling the futures contract, buying the stock index portfolio, financing the capital for purchasing shares with risk-free borrowings, and unwinding these positions at futures delivery date. The risk-free profit is equal to $F_t - S_t e^{(r-d)(T-t)}$. Alternatively, when $F_t < S_t e^{(r-d)(T-t)}$, an arbitrage profit can be made by buying the futures, short selling the index portfolio, investing the proceeds of the sale of stock at the riskless interest rate, and unwinding these positions at futures delivery date. The arbitrage profit equals $S_t e^{(r-d)(T-t)} - F_t$. Consequently, the no-arbitrage condition should be satisfied at every instant t during the futures contract life in perfect and efficient stock and futures markets.

The equation (2.2) can be restated in returns form:

$$R_{F,t} = R_{S,t} - (r-d) \tag{2.3}$$

where $R_{F,t} = Ln(F_t / F_{t-1})$ and $R_{S,t} = Ln(S_t / S_{t-1})$

If r and d are constant, the equation (2.3) implies that the contemporaneous rates of return of the futures and the index portfolio are perfectly positively correlated; the rates of return of the futures contract and of the underlying stock index are serially uncorrelated; and the noncontemporaneous rates of return of the futures and the index portfolio are uncorrelated (Stoll and Whaley, 1990).

2.2 Explanations on the lead-lag relationship

A number of empirical studies investigate the lead-lag relationship between the stock index and index futures markets. Sutcliffe (1997) states that trading futures has the advantages of a highly liquid market, low transactions costs, easily available short positions, low margins and rapid execution. Therefore, the futures price will respond first to general or market wide information. As indicated by Sutcliffe, the explanations on the lead-lag relationship can be divided into four hypotheses: the transaction costs hypothesis, the leverage hypothesis, the short-selling constraint hypothesis, and the information type hypothesis.

First of all, the transaction costs hypothesis suggests that the market with lowest overall transaction costs will react most quickly to new information because informed traders prefer to trade the security or contract with relative lower transaction costs. Since the net profit is the gross profit deducts transaction costs, it is reasonable for traders to trade in the market with relatively lower transaction costs. It is very expensive to launch positions in the TXI because traders have to purchase at least 500 individual shares[4], each subject to 0.285% of round-trip brokerage commissions, 0.3% of securities transaction tax, paid by the seller only, and 0.1%~0.67% of minimum price fluctuation[5]. On the other hand, the transactions costs involve in trading the TX and the TW are only 0.016% and 0.01% of brokerage commissions, 0.05% and 0% of futures transaction tax, and about 0.02% and 0.04% of bid-ask spreads[6], respectively. Therefore, the transaction costs for the TXI, the TX and the TW are about 0.7%, 0.086% and 0.05%, respectively. According to the transaction cost hypothesis, prices of both index futures will lead the cash index.

Secondly, the leverage hypothesis predicts that high-leverage securities or contracts are better in price discovery because traders can purchase more high-leverage instruments and expect higher return than low-leverage ones, given the same amount of capital available. Since investors have to pay 40~70% of margin on trading shares in Taiwan but only around 10% on trading futures, the leverage on trading futures are much higher than that on trading shares, and then the index futures should lead the spot index.

Thirdly, the short-selling constraint hypothesis states that short selling shares may be difficult or prohibited but futures do not subject to such restriction, therefore bad news

[4] There are 531 companies listed in the Taiwan Stock Exchange at the end of 2000.
[5] The minimum tick size depends on the current price levels. For example, for a stock quoted between NT$1 to 5, it ticks by NT$0.01 up or down. Details see Securities & Futures Markets, pp.38-39.
[6] The minimum tick size is 1 index point for the TX and 0.1 index point for the TW.

may be reflected in the futures market first, and then in the stock market later. The short sale is that a trader sells share but he or she does not own it. When an investor thinks that the price of a share is overpriced and will drop in the near future, he or she might short sells the share to make profit from the price declining. Diamond and Verrecchia (1987) show that prohibiting traders from short selling slows the price adjustment to private information, especially as regards private bad news. Given that there is no short-sale constraint in the futures market, futures are symmetric in reflecting good and bad news. Thus, the lead-lag relationship would not be the same under good and bad news if the short-sale constraints are binding.

Fourthly, different types of information may have opposite impacts on the lead-lag relationship. When public or private information is received, traders can choose to reflect this knowledge in the futures or stock markets. For industrial- or firm-specific information that affects the share prices of only a few companies, investors will probably choose to trade individual shares or their derivatives rather than index futures because the impact in the index will be much smaller than in the share prices of the affected companies. On the other hand, for macroeconomic or market-wide information that influences all shares, traders will prefer to use the futures market to exploit information rather than specific companies. As a result, the futures price will lead spot index price for market wide information, while the company-specific information will cause price movements in those companies and then result in a change in the index. This provides explanation that spot index leads index futures in some empirical studies.

In short, according to the implications of the hypotheses stated above, the futures market enjoys the advantages of low transaction costs, high leverage, absence of short-sales regulation, and being the instrument reflected marketwide information, and is to be the primary market for price discovery. On the contrary, the stock index probably behaves as the leading market only when firm specific information spreads over the market.

2.3 Empirical studies on the lead-lag relationship

Quite a lot of studies have investigated the intraday and daily lead-lag relationship between stock index and index futures market. Kwaller, Koch and Koch (1987) apply a simultaneous-equations model to examine the intraday price relationship between S&P 500 futures and the S&P 500 index using minute-to-minute data. The results suggest that futures price movements consistently lead index movements by twenty to forty-five minutes while movements in the index rarely affect futures beyond one minute. However, a critique of their study is that the lead of futures prices is spurious because constituent shares in the index did not necessarily trade at the same time. This is the nonsynchronous trading or nontrading effect which arises when time series are taken to be recorded at time intervals of one length when in fact they are recorded at time intervals of other, possibly irregular, lengths (Campbell, Lo, and MacKinlay, 1997). Since it is highly likely that some prices used in computing the index occurred a few minutes, or even few hours before hand, the reported index is a stale indicator and measures an average value of the 'true' index over the period. Due to the nonsynchronous effect, the index will exhibit significant positive autocorrelation, even if the price changes of the underlying shares are random.

The nonsynchronous trading effect is not the only cause of the autocorrelation in price changes. Transaction costs tend to induce noise that securities prices tend to fluctuate randomly between bid and ask prices in successive transactions. This bid-ask spread effect leads to negative autocorrelation in observed returns even though the true returns are serially independent (Roll, 1984; Ahn, Boudoukh, Richardson, and Whitelaw, 1999). Moreover, Sentana and Wadhwani (1992) conclude that the presence of positive feedback trading will induce negative autocorrelation in returns. To overcome the spurious autocorrelation of stock index returns, Stoll and Whaley (1990) fit an ARMA(p,q) model to the observed index returns series and the regression residuals are used as a proxy of the true but unobserved returns. They investigate the time series properties of 5-minute returns of stock index and stock index futures contracts and reveal that S&P 500 and MM index futures returns lead stock index returns by about five minutes on average, but occasionally as long as ten minutes or more, after the observed stock index returns have been purged of infrequent trading and bid/ask price effects. However, although futures returns tend to lead stock returns, the effect is not completely unidirectional. There is a weak positive predictive effect of lag stock index returns on current futures returns.

Chan (1992) investigates the intraday lead-lag relation between returns of the Major Market cash index and returns of the Major Market Index futures and S&P 500 futures. There is evidence that there is an asymmetric lead-lag relation between the MM cash index and the index futures; there is strong evidence that the futures leads the cash index and weak evidence that the cash index leads the futures.

Some studies examine the effect of the short-selling constraints on the leadership. Chan (1992) sorts observations by the sign and size of cash index returns and then the highest returns and the smallest returns quintiles are chosen to examine whether the lead-lag relation is different under good news and bad news. The smallest returns quintile is most likely to be subject to the short-sale constraints. The results indicate that there is no a stronger tendency for the futures to lead the cash index under bad news than under good news. Abhyankar (1995) stratifies the cash index and the futures returns according to Stephan and Whaley's (1990) method. His results also do not confirm the the short-selling constraint hypothesis. Neither market shows any consistent pattern in the predictive power of returns in bearish markets.

In the studies of the information release, Chan (1992) reveals that the futures leads the cash index to a greater degree when more stocks move together. Abhyankar (1995) and Frino, Walter and West (2000) also conclude that the lead of the futures market will be greater around macroeconomic information releases. On the other hand, investors may prefer to trade individual shares, instead of futures, while firm-specific information releases. Thus, the transmission of information may run from the cash to the futures market (Grunbichler, Longstaff, and Schwartz, 1994; Frino, Walter, and West, 2000).

Shyy, Vijayraghavan and Scott-Quinn (1996) argue that most of the lead-lag relation in the stock index and the index futures markets may primarily arises from nonsynchronous trading and stale price problems. They demonstrate that when the mid-quote points of bid/ask prices in France are used to represent the 'true' prices, instead of the last transaction prices, the leadership from futures to spot index disappears, and reverse causality from spot to futures becomes significant. The results suggest that previous studies showing futures leading cash may be primarily due to market nonsynchronous trading and stale price problems and differences in trading mechanisms used in cash or futures markets.

Since there is a substantial body of work on the lead-lag relationship between the stock index and index futures markets, a selective summary of previous research, sorted by time interval, is presented in Table 2.1. Firstly, the index futures generally lead the cash index with weak feedback from the stock index to the futures markets. Secondly, a longer time interval between observations would increase the lead length. For studies using intervals less than 15 minutes, the lead lengths are usually less than 30 minutes. However, when hourly or daily data are employed, the lead lengths could be up to one hour or even two days. Thirdly, even though studying the same market, different results can be derived by using different sample periods or time intervals. For example, the results of studies based on the S&P 500 index and index futures quite different. S&P 500 futures tend to lead the spot index about five minutes, but occasionally as long as 10 minutes in Stoll and Whaley's (1990) analysis; however, Pizzi, Economopoulos and O'Neill (1998) find that S&P500 futures lead the index by at least 20 minutes.

In addition to the leadership between the spot index and the index futures, there may also be leads and lags across futures. Kim, Szakmary and Schwarz (1999) argue that the key motivation for examining the leadership across futures is to study the flow of information in markets of similar microstructure. In particular, we will be able to bypass the relatively greater illiquidity and bid-ask problems of cash indices when focusing only on the futures.

Fleming, Ostdiek and Whaley (1996) introduce the trading cost hypothesis which predicts that the market with lowest overall trading cost will react most quickly to new information. Kim, Szakmary and Schwarz (1999) examine the lead-lag relationship among the S&P 500, NYSE Composite and MMI futures. They find that the S&P 500 exhibits price leadership over the other two futures by about five minutes. The result is consistent with the trading cost hypothesis.

Table 2.1 A summary on the studies on the lead-lag relationship between the spot index and index futures

Author	Index	Interval	Futures leads spot	Spot leads futures
Kawaller, Koch and Koch (1987)	S&P 500	1-min	20 to 45 min	
Pizzi, Economopoulos and O'Neill (1998)	S&P 500	1-min	20 min	3 to 4 min
Frino, Walter and West (2000)	All Ordinaries Index	1-min	18 min	5 min
Shyy, Vijayraghvan and Scott-Quinn (1996)	CAC 40	1-min		3 min
Stoll and Whaley (1990)	MMI and S&P 500	5-min	5 min	
Chan, Chan and Karolyi (1991)	S&P 500	5-min	5 min	
Chan (1992)	(1) MMI (2) S&P 500	5-min	15 min 10 min	5 min 5 min
Grünbichler, Longstaff and Schwartz (1994)	DAX index	5-min	15 min	5 min
Chung, Kang and Rhee (1994)	Nikkei Stock Average	5-min	20 min	15 min
Cheung and Ng (1990)	S&P 500	15-min	15 min	
Hodgson, Kendig and Tahir (1993)	All Ordinaries Index	15-min	30 min	15 min
Abhyankar (1995)	FTSE-100	Hourly	1 hour	
Ap Gwilym and Buckle (2001)	FTSE-100	Hourly	1 hour	
Tse (1995)	Nikkei Stock Average	Daily	2 days	
Östermark, Martikainen and Aaltonen (1995)	FOX	Daily	2 days	

Another possible explanation on the leadership across futures is they are traded by different trading mechanisms. Grünbichler, Longstaff and Schwartz (1994) assert that if futures contract is screen traded while the components shares of a stock index are floor traded, the futures leads over the spot index will tend to lengthen. The reason is electronic screen trading will lower the transaction costs and reduce the time required to physically process an order and execute the trade. They study the leadership between the Deutscher Aktienindex (DAX) index, whose stocks are floor-traded and the DAX index futures, which are screen-traded. After fitting an AR(3) to the index returns to remove autocorrelation, futures returns lead spot returns by 15 minutes, while spot returns lead futures returns by 5 minutes. In the USA, where both futures and shares are floor-traded, futures returns lead spot returns by less than 5 minutes. They argue that the longer leadership in Germany is consistent with their hypothesis that the price discovery process in the futures market speeds up by screen-based trading. However, Vila and Sandmann (1995) state that it is not clear which system is more transparent on an ex-ante basis, or which market is the preferring trading venue for informed traders. Informed traders may choose to trade on the computerised market due to the anonymity it offers. Still, they may choose to trade on the open outcry market because of the advantages of being close to the order flow or to avoid revealing information through the electronic limit order book. Vila and Sandmann (1995) use data for the Nikkei Stock Average futures contract, which is simultaneously being traded on the Singapore International Monetary Exchange (SIMEX), an open outcry market, and the Osaka Securities Exchange (OSE), a computerised market. The empirical evidence in their study is too weak to conclude that neither market presents a significant advantage in terms of informational efficiency.

3 Data and Methodology

This section is organised as follows. The features of the Taiwan stock market and the contract specifications of the futures based on the Taiwan stock market are depicted in Section 3.1. The data are described in Section 3.2. The primary tests are based on minutely intraday returns of the futures and cash index which are constructed for two sample periods. In addition, 5-, 15- and 30-minute intraday returns are also generated. In Section 3.3, tests for unit roots and cointegration, and the regression models to examine the leadership between the stock index and futures markets are explained.

3.1 Taiwan Stock and Futures Markets

The Taiwan Stock Exchange (TSE) was established in February 1962. The index used to measure market wide price movements is the TSE Capitalisation Weighted Stock Index (TXI) which consists of all shares listed in the TSE. There were 531 companies listed in the TSE and their total capitalisation was NT$ 81.9 billion in 2000. The formula to calculate the capitalisation weighted index is:

$$I_t = \left(\sum_{i=1}^{n} C_i P_{it} \Big/ \sum_{i=1}^{n} C_i P_{ib}\right) * 100 \qquad (2.4)$$

where C_i is the number of shares issued by the ith company, P_{ij} is the price of shares in the ith company at time j, b is the base date. The base date for the TXI is the end of 1966. Since it is a capitalisation weighted index, the shares with larger capitalisation have higher influence on the index. The largest capitalisation company is Taiwan Semiconductor Manufacturing whose weight is 18.04% of the total capitalisation in the TSE. Although there are more than 500 companies listed in the TSE the ten largest companies occupy more than 50% of the total capitalisation[7]. In addition to the overall index, the TSE also compiles 18 industrial group indices. The largest two industrial group indices are electronics and financials whose weights are 59.25% and 18.7%[8], respectively. Obviously, electronics manufacture and financial services are the most important industries in Taiwan.

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[7] The first ten largest companies are: Taiwan Semiconductor Manufacturing, United Micro Electronics, Chunghwa Telecom, Hou Hai Precision Industry, Asustek Computer Inc., Cathay Life Ins., Quanta Computer, CDB, Formosa Plastic and China Steel. Six of them belong to the electronics sector.

[8] Data source: TAIFEX, http://www.taifex.com.tw

Due to the government's regulation and the structure of investors, the features of the Taiwan stock market are quite different from other markets in the world. First of all, the daily price limits are 7%, in either direction. Although price limits are not uncommon in other stock markets, developed countries choose the circuit breakers[9], instead of price limits, to provide a cooling-off period if needed. Proponents of price limits claim that price limits can prevent investors from huge loses caused by violent price movements and allow investors to re-examine market information and to reformulate a new investment strategy. Opponents argue that price limits serve no purpose other than to delay a price change. The price will continue to move toward equilibrium in subsequent trading days. Chen (1993) finds that that price limits have no significant impact on reducing stock price volatility in Taiwan. Quite the reverse, price limits tend to slightly exacerbate price volatility.

Secondly, short selling on shares is subject to some constraints in Taiwan. Unrestricted short selling with full use of the proceeds is a crucial assumption underlying both arbitrage and equilibrium models of capital asset prices. However, not every country's stock market allows its listed shares to be short sold and the proceeds from short sales are typically not available for use by the traders. Short selling is banned in Norway, was a criminal offence in Hong Kong until 3 January 1994, and was banned in Australia until the mid-1980s. In the U.K. traders can sell shares they do not possess, but they are required to deliver these shares a few days later to the buyers. In order to meet this obligation the short sellers can roll over the short position by buying the shares to deliver and selling the shares for a new settlement period at the same time, or by borrowing shares[10]. Alternatively, short sellers can fail to deliver the shares on the due date without penalty (London Stock Exchange, 1994). In the U.S. the NYSE introduced the Uptick Rule on short-selling shares on 1 August 1990. If a stock is trading on an uptick or a zero-uptick, a short-sell order can execute at the last trade price or higher. If a stock is trading on a downtick or a zero-downtick, a short-sell order must execute at price higher than the last trade (Alexander and Pizzi, 1999). In Taiwan a stock could not

[9] The circuit breaker is a trading halt when the price movement reaches preset limits. The main difference between price limit and the circuit breaker is that for circuit breaker, any prices are possible after the period of trading halt, but trading at prices beyond the limits is prohibited in the case of price limit.

[10] Only market makers of London Stock Exchange and certain members of London International Financial Futures and Options Exchange (LIFFE) can borrow U.K. shares.

be short sold if its price is lower than the previous day's closing price[11]. In addition, institutional investors, including mutual funds, securities firms and foreign investors are prohibited to short sell shares. Moreover, if the closing price of a share has been lower than 10 New Taiwan Dollars (NT$) for two successive trading days, short-selling the share is prohibited until its closing price has been higher than NT$10 for six successive trading days.

Thirdly, the Taiwan stock market is the most volatile market in Asia. Titman and Wei (Titman and Wei, 1999) compare 6 Asian countries[12] from 1978 to 1991 and find that monthly standard deviations of the TSE are significantly higher than other markets. The causes of such a high volatile market may be: 1) 87% of shares are traded by individual investors, that means only 13% of shares are traded by institutional investors. In fact, there is about one brokerage account for every family on average. Individual investors are usually regarded as the main source of the noise traders. No wonder there is no shortage of noise traders in Taiwan (Titman and Wei, 1999). 2) Individual investors are partially encouraged by the low transaction costs. Since there is only securities transaction tax, no capital gain tax and the securities transaction tax is far lower than the capital gain tax, individual investors treat the securities market as a legal casino and enjoy the short-term gambling. Consequently, the low transaction costs and the participation of the individuals create an extraordinary volatile stock market and the highest stock turnover rate in the world (see Table 2.2).

Finally, Taiwan government prefers the stock market goes up rather than decline. Thus, the government often intervened when the market went down more than its expectation. The approaches to intervene includes: 1) moral persuasion on mutual funds, pension funds and securities firms, 2) regulations amendment to encourage securities purchasing (e.g. raise margin financing ratio on long positions and lower margin financing ratio on short-sales), 3) fiscal policies adjustment (e.g. reduce VAT on financial intermediaries), 4) monetary policies adjustment (e.g. reduce discount rate), and 5) direct intervention (use the 'National Security Fund' to purchase shares or futures).

[11] The constraint had been removed between 1 Jan 1994 and 3 Sep 1998.
[12] The six countries are Korea, Taiwan, Japan, Thailand, Hong Kong and Malaysia.

Table 2.2 Turnover rates in each stock exchange from 1989 to 2000 unit: %

	Taiwan	New York	Tokyo	Korea	London	HongKong	Thailand	Singapore
1989	590.14	52.00	73.10	111.85	51.30	49.00	57.17	31.00
1990	506.04	43.00	38.41	68.57	45.60	44.00	102.23	61.60
1991	321.90	47.00	28.38	82.38	43.70	35.00	88.40	12.00
1992	161.33	44.00	19.91	133.42	42.60	53.00	125.26	12.80
1993	252.42	53.00	25.86	186.55	80.50	61.00	66.19	26.20
1994	366.11	53.00	24.93	174.08	77.10	55.00	64.04	26.70
1995	227.84	59.00	26.77	105.11	77.60	38.00	43.06	17.80
1996	243.43	62.00	28.94	102.98	78.60	41.00	50.91	13.60
1997	407.32	65.71	32.93	145.56	44.03	90.92	49.56	56.28
1998	314.06	69.88	34.13	207.00	47.10	61.94	68.86	63.95
1999	288.62	74.62	49.37	344.98	56.71	50.60	78.14	75.16
2000	259.16	82.40	58.86	301.56	63.81	62.99	64.91	64.97

Data source: Taiwan Stock Exchange

There were no derivatives based on the Taiwan stock market until 1997. The first index futures, coded TW, began trading on 9 January 1997 in the SIMEX. The underlying index of TW is the MSCI Taiwan index[13] (TWI) which is a market capitalisation equity index of 89 securities listed on the TSE and represents approximately 60% of the underlying national market. The chosen list of stocks includes a representation sampling large, medium and small capitalization companies, taking into account the stock liquidity. The weights of the electronics and financials sectors are 60.88% and 18.15%[14], respectively, which are very close to the sector structure of the TSE.

The second index futures, coded TX, began trading on 21 July 1998 in the TAIFEX. Its underlying index is the Taiwan Stock Exchange Capitalisation Weighted Stock Index (TXI) which includes all shares listed on the TSE. Since the electronics and financials sectors are the largest two sectors in Taiwan, the TAIFEX has launched two sector index futures—the electronic index futures (TE) and the banking and insurance index futures (TF)—since 21 July 1999, based on their corresponding industrial group indices in the TSE. The contract specifications of the TW, TX, TE and TF are presented in Table 2.3.

[13] The index is compiled fully and independently by Morgan Stanley Capital International (MSCI).
[14] The weights are according to the market capitalisation on 12 Nov 2001. Data source: the MSCI, http://www.msci.com

Table 2.3 Contract specification of the TW, TX, TE and TF[15]

Ticker Symbol	TW	TX	TE	TF
Exchange	SGX	TAIFEX		
Underlying index	TWI	TXI	TSE Electronics Sector Index	TSE Banking & Insurance Sector Index
Contract months	2 nearest serial months and 4 quarterly months	Spot month, the next calendar month, and the next three quarterly months		
Denominated currency	U.S. dollar	New Taiwan (NT) dollar		
Minimum Price Fluctuation	0.1 index points =US$10	1 index point =NT$200	0.05 index point =NT$200	0.2 index point =NT$200
Contract size	TW points x US$100	TX points x NT$200	TE point x NT$4,000	TF point x NT$1,000
Trading mechanism	Dual system: Open outcry and Electronic Trading	Electronic Trading		
Trading hours (GMT+8)	Mon ~ Fri 8:45 am ~ 1:45 pm* 8.45 am - 2.45 pm** 4.00 pm - 7.00pm** *Open Outcry **Electronic Trading	Mon ~ Fri 08:45 am~1:45 pm		
Daily price limits	7% 10% and then 15%, in either direction, from the previous settlement price 10 minutes frozen between limits There shall be no price limits on the Last Trading Day for the expiring contract	±7% of previous day's settlement price		
Last trading day	The second last business day of the contract month	The third Wednesday of the contract month		
Settlement	Cash settlement. The official closing price of the index on the delivery day	Cash settlement. The opening price of the index on the next day of the delivery day		
Transaction costs	Commissions	1. Commissions 2. The futures transaction tax 0.025% one-sided on trading value 3. The TAIFEX fees NT$85 one-sided on trading and settlement per contract		
Position Limits	No limits	1. Individuals: 300 contracts 2. Institutional investors: 1,000 contracts 3. Institutional investors may apply for an exemption from the above limit on trading accounts for hedging purpose.		

Data sources: the SGX, http://www.sgx.com and the TAIFEX, http://www.taifex.com.tw

3.2 The data set

The data used in this study consist of one spot index, the TXI, and two index futures, the TX and the TW, obtained from three individual sources—the Securities and Futures

[15] TAIFEX launched another index futures on 9 Apr 2001, i.e. the mini-TX futures. Since the only difference between the TX and the mini-TX is the contract multiplier: NT$200 for the TX and NT$50 for the mini-TX, the mini-TX is not showed in this table.

Institute, the TAIFEX and the SGX-DT, respectively. Two six-month sample periods are chosen in this study, Period I is from 1st July to 31st December 1999, and Period II is from 1st April to 30th September 2001. There are 136 trading days in Period I. The trading hours for the TXI, the TX and the TW were 9:00 to 12:00, 9:00 to 12:15, and 8:45 to 12:45, respectively. The non-synchronous data, i.e. the futures samples before and after the trading hours of the TXI, are removed to ensure all three series can be observed at the same point in time. In addition, the opening price of the TXI is displayed at 9:01, so only the last transaction prices per minute between 9:01 and 12:00 are used as observations. If no price is observed within any 1-minute span, the last price in the previous one minute is recorded for this interval. Therefore, there are 180 prices in each trading day and 24480 observations in Period I altogether. In Period II there are 123 trading days[16]. As the trading hours of the TSE have been extended to 13:30 since 1st January 2001, the closing time of the TX and the TW has also been extended to 13:45. Again, non-synchronous data are eliminated. Thus, there are 270 observations from 9:01 to 13:30 in each day and 33210 prices in total in Period II. Further, before futures contracts expired, futures prices of the current month contract become less active than that of the next month contract in the last few trading days. Therefore, the prices of the current contract in last two trading days are replaced by that of next month contract for each contract to mitigate the infrequent trading problem.

There are two reasons to choose these two periods. The first one is that the transaction tax of futures trading on the TAIFEX has been reduced from 0.05% to 0.025% one-sided on trading value since 1st may 2000. Period I is the stage prior to the tax reduction and Period II is after the reduction. Hence, it is possible to test the transaction costs hypothesis by examining the differences in the temporal leadership in these two periods. The other one is that the TX was relatively immature, compared with the TW, in Period I because its trading volume was relatively low. The average daily volume of the TX and TW is 3716 and 8637 for the Period I, respectively. In contrast, both futures contacts are quite matured in the Period II. The average daily volume of the TX and TW is 13069 and 13464 for the Period II, respectively. Market maturation effects (Stoll and Whaley, 1990) predicts that as the index futures markets have matured, 1) there was a

[16] Although the TW traded on 21st September, the TXI and the TX did not. Also the TW did not trade on 27th October but the TXI and TX did. To synchronise the data, transaction data of these two trading days are deleted from period II.

strong tendency of index returns to lead futures returns early in the life of the futures market; 2) futures and stock markets will become more closely integrated through time; and 3) the estimated coefficients of the contemporaneous and lag one futures returns will grow larger through time. Therefore, the effects of tax reduction and market maturation can be examined by detecting the different figures in these two periods.

The 1-minute price observations are used to generate the 5-, 15- and 30-minute interval price series. All the price series are then employed to generate time series of instantaneous rate of return which is defined as $ln(P_t/P_{t-1})*100$, where the *ln* is natural logarithm, *P* is the last price of the cash index or futures in an interval. Overnight returns are not included because it is calculated over a longer period and would induce a severe heteroscedasticity problem (Ap Gwilym and Buckle, 2001).

3.3 Methodology

3.3.1 Tests for unit roots and cointegration

In order to test the lead-lag relationship between the spot and futures prices, the first step is to test the existence of a long-run stable relationship between them. To do this, they are first checked for stationarity. A series is called stationary if its mean and variance are constant and its covariance is independent of time[17]. On the other hand, if a series is expressed as a first order autoregressive or AR(1) process

$$Y_t = \theta Y_{t-1} + \varepsilon_t \quad (2.5)$$

with $\theta=1$, it is said to be integrated of order one, denoted $I(1)$ and is nonstationary[18] with a unit root, usually referred to as a random walk. The augmented Dickey-Fuller (ADF) test is believed to be a powerful test for unit roots:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (2.6)$$

where $\Delta Y_t = Y_t - Y_{t-1}$, and *n* is the number of lags and is selected to be large sufficient to remove autocorrelation in the residuals ε_t and ensure that ε_t are white noise. The null hypothesis of the ADF test is that the series Y_t follow a unit root $H_0: \beta=0$, against $H_1: \beta<0$. The rejection of H_0 implies that the series is stationary.

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[17] This is referred to as weak stationarity. A series is said to be strictly stationary if its properties of the entire distribution are unaffected by a change of time origin. Details see Verbeek (2000), pp. 226-229

[18] In fact, (2.5) describes a nonstationary process for any value of θ with $|\theta| \geq 1$.

If both spot index and index futures are $I(1)$ and follow unit roots, they are examined then to determine whether they are cointegrated[19]. The assumptions of the classical regression model require that all variables are stationary and the errors have a zero mean and finite variance. In the presence of nonstationary variables, there might be a spurious regression (Granger and Newbold, 1974). A spurious regression has a high R^2 and t-statistics that appear to be significant, but the results are without any economic meaning. The regression output looks good because the least-squares estimates are not consistent and the customary tests of statistical inference do not hold. Engle and Granger (1987) point out that a linear combination of two or more nonstationary series may be stationary. If such a stationary linear combination exists, the nonstationary series are said to be cointegrated, and there exists long-term equilibrium among them. If there is no strong statistical evidence to show the existence of such a relationship, the investigation comes to an end because the two time series are generated completely independently and can wander arbitrarily far from each other, and it is impossible for one to provide any information for predicting the other.

The adopted approach to test for cointegration in this study is Johansen's method described in Hamilton (1994). The starting point of the Johansen trace test is the Vector Autoregression (VAR) representation of a vector of nonstationary variables:

$$\Delta \boldsymbol{Y}_t = c + \boldsymbol{\Pi} \boldsymbol{Y}_{t-1} + \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{Y}_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim NID(0, \Sigma)$$

where $\boldsymbol{Y}_t$ is a vector of $I(1)$ variables and ε_t is NID(0, Σ). The coefficient matrix $\boldsymbol{\Pi}$ incorporates information about the cointegration relationship among the variables in $\boldsymbol{Y}_t$. The rank of the matrix $\boldsymbol{\Pi}$ represents the number of cointegration relationships present in $\boldsymbol{Y}_t$. The likelihood ratio test statistic for the hypothesis of at most r cointegration relationship and at least n-r common trends is given by

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

where T is the sample size and the $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$ are the eigenvalues of squared canonical correlation between two residual vectors from level and first-difference

[19] Many studies have found that spot and futures prices are I(1) and cointegrated. (Ghosh, 1993; Koutmos and Tucker, 1996; Shyy, Vijayraghavan, and Scott-Quinn, 1996).

regressions. The Johansen maximum eighenvalue test of the null hypothesis that there are exactly r cointegration relationships again r+1 is $\lambda_{max} = -T\ln(1-\hat{\lambda}_{r+1})$.

3.3.2 The models for examining lead-lag relationship

The direction of leads and lags[20] can be tested to examine the discovery role of futures prices. The lead-lag relationship can be examined through Granger's causality test, which is designed to examine whether two series move one after the other or contemporaneously. If past values of the variable S improve predictions of the current value of valuable F, relative to predictions made using just the past values of F, then S 'Granger causes' F, or S leads F. There are four possibilities: (1) S causes F but F does not cause S; (2) F causes S but S does not cause F; (3) S causes F and F causes S; (4) S does not cause F and F does not cause S. In the first two cases, the relation between S and F can be expressed as S leads F and F leads S, respectively. In the third case, there is a feedback relationship or bidirectional causality between S and F. And, S and F are independent in the last case.

There are at least 3 basic ways to model the lead-lag relationship between two variables. The first one is the simultaneous equation model (SEM), specified as follows:

$$\begin{aligned} S_t &= \gamma_1 + \sum_{k=1}^{n} \alpha_{1k} S_{t-k} + \sum_{k=0}^{n} \beta_{1k} F_{t-k} + \varepsilon_{1t} \\ F_t &= \gamma_2 + \sum_{k=0}^{n} \alpha_{2k} S_{t-k} + \sum_{k=1}^{n} \beta_{2k} F_{t-k} + \varepsilon_{2t} \end{aligned} \tag{2.7}$$

The SEM is the model which Granger (1969) expresses his causal relations and is adopted by Kawaller, Koch and Koch (1987), Min and Najand (1999) and other studies. In (2.7) α_{1k} and β_{2k} are the coefficients whether S and F are predictable by their own past prices. If any β_{1k} is significant, the past value of F has explanatory power on the current S. Other the other hand, S lead F if any α_{2k} is significant.

The second model is the error correction model (ECM) which can be specified as follows:

[20] Using the terms "lead" and "lag" does not necessarily mean that price movement in one market causes price movement in the other one. The more appropriate way to interpret it is that one market reacts to information faster than the other market, which lags and then catches up (Chan, 1992).

$$\Delta S_t = \alpha_1 + \alpha_S \hat{e}_{t-1} + \sum_{i=1}^{n} \alpha_{11}(i) \Delta S_{t-i} + \sum_{i=1}^{n} \alpha_{12}(i) \Delta F_{t-i} + \varepsilon_{St}$$
$$\Delta F_t = \alpha_2 + \alpha_F \hat{e}_{t-1} + \sum_{i=1}^{n} \alpha_{21}(i) \Delta S_{t-i} + \sum_{i=1}^{n} \alpha_{22}(i) \Delta F_{t-i} + \varepsilon_{Ft} \quad (2.8)$$

where $\Delta S_t = S_t - S_{t-1}$, $\Delta F_t = F_t - F_{t-1}$, $\hat{e}_{t-1} = S_{t-1} - \delta F_{t-1}$ is an error correction term. The error correction term represents the previous period's deviation from long-term equilibrium. The coefficients of the error correction term α_S and α_F have the interpretation of speed of adjustment parameters. The greater the coefficients are, the greater the response of F_t to the previous period's deviation from long-term equilibrium. An additional condition for the existence of Granger causality is that the speed of adjustment coefficient be equal to zero. However, the coefficients must not be zero at the same time. If both α_S and α_F are equal to zero, the long-term equilibrium relationship does not appear and the model is not one of error correction or cointegration (Enders, 1995). In the ECM, we can find that ΔS_t or ΔF_t (or both) must be Granger caused by $\hat{e}_{t-1}$ which is itself a function of ΔS_t, ΔF_t. Thus, either ΔS_t is Granger caused by ΔF_{t-1} or ΔF_t by ΔS_{t-1}. The ECM method has been adopted by Shyy, Vijayraghavan, and Scott-Quinn (1996), Pizzi, Economopoulos, and O'Neill (1998) and Chu, Hsieh and Tse (1999).

Finally, the third method to model the causality relation is expressed as a single equation form with lead and lag coefficients:

$$S_t = \alpha + \sum_{k=-n}^{+n} \beta_k F_{t+k} + \varepsilon_t \quad (2.9)$$

The coefficients with negative subscripts ($\beta_{-1}, \beta_{-2}, \ldots, \beta_{-n}$) are lag coefficients, and those with positive subscripts ($\beta_{+1}, \beta_{+2}, \ldots, \beta_{+n}$) are lead coefficients. If the lag coefficients are significant, the spot index is predictable by the past value of the index futures. On the other hand, if the lead coefficients are significant, the spot index leads futures. (2.9) can be considered as the reduced form of (2.7) but the endogenous variables' own lags are eliminated.

All the three models are suitable for price levels data but only (2.9) is appropriate to be employed when the variables are returns. Firstly, since all the autocorrelation in return series of the spot and futures are removed by fitting an ARMA(p,q), the past returns has not ability to predict its own current value of course. Thus, it is not essential to include the endogenous variables' own lags in the equations. Secondly, all of the studies with dummy variables employ return series into (2.9) to investigate the effects of bad news or information types, for example, Chan (1992), Abhyankar (1995), and Frino, Walter and West (2000). Moreover, overnight price gaps will occur when price levels are observed. The overnight price gaps in price levels arise from overnight information and futures contracts rolling when the new contract replaces the expired contract. It is better to exclude overnight price jumps because they are calculated over a longer period and would induce a severe heteroscedasticity problem. Exclusion of overnight returns removes the necessity for any adjustment when a switch to the next futures contract occurs at the expiry date. Since overnight returns can be easily removed in returns series but there is no way to exclude overnight price jumps in price levels, returns series provides a better measure than price levels.

Thus, when returns series are employed as the variables for regression, (2.9) can be expressed as follows:

$$R_{S,t} = a + \sum_{k=-n}^{+n} b_k R_{F,t+k} + \varepsilon_t \qquad (2.10)$$

where $R_{S,t}$ and $R_{F,t}$ are the minutely spot index and index futures returns at time t, respectively, and n is the number of leads and lags used. The returns series are not used for regressing directly. They are fitted with ARMA(p,q) models first to purge spurious autocorrelations arose from market microstructure and then the serially uncorrelated return innovations are extracted and employed as variables in the regression. The t-statistics reported in this study are based on the White's (1980) heteroscedasticity-consistent estimate of the covariance matrix[21]. Furthermore, chi-square (χ^2) tests that the lag coefficients ($b_{-1}, b_{-2} \ldots b_{-n}$) and the lead coefficients ($b_{+1}, b_{+2} \ldots b_{+n}$) are jointly zero provide tests of the hypotheses that the futures does not lead the spot and the spot does not lead the futures, respectively.

[21] Many authors adopt Hansen's (1982) heteroscedasticity and autocorrelation consistent estimate of the covariance matrix, e.g. Chan (1992), Abhyankar (1995 and 1998) and Ap Gwilym and Buckle (2001). Grünbichler, Longstaff and Eduardo (1994) state that the White's (1980) heteroscedasticity-consistent estimate of the covariance matrix is virtually the same as the Hansen's (1982) variance-covariance matrix when the return innovations are serially uncorrelated.

3.3.4 Dummy coefficients on bad news

To examine the effects of the short-sales constraints on the lead-lag relationship, observations are sorted by the sign of the spot index returns. However, since the short-sales constraints on the Taiwan stock market is totally different from that on the NYSE, Chan's (1992) methodology of sorting data is unsuitable in this study. Given that a stock could not be short sold if its price is low than the previous day's closing price, shares are quite unlikely subject to the constraints if good news dominates the stock market but most of the shares could not be short sold if bad news overshadows the trading pits. Therefore, observations are divided into two groups according to the sign, i.e. positive or negative, of the daily spot index returns. When the daily spot return is negative, all the intraday returns in that day are assigned to bad news group, which is most likely to be subject to short-sales constraints. On the other hand, when the daily spot return is positive, all the intraday returns in that day are assigned to good news group, which is least likely to be subject to short-sales constraints. After stratification, a dummy variable is created and its value is set to one if returns belong to bad news group and zero if good news group. The equation with a dummy is specified as follows:

$$R_{S,t} = a + d_t a' + \sum_{k=-n}^{+n} b_k R_{F,t+k} + \sum_{k=-n}^{+n} b'_k d_t R_{F,t+k} + \varepsilon_t \qquad (2.11)$$

where d_t is the dummy variable, a' is the dummy intercept and b'_k are the dummy slope coefficients. If the short-sales constraints are binding, the spot index lags futures longer, and the dummy slope lag coefficients will be significantly positive. Again, the t-statistics are based on the White's (1980) heteroscedasticity-consistent estimate of the covariance matrix.

4. Empirical results

The empirical results of the lead-lag relationship between the Taiwan stock index and index futures, as well as across futures markets are presented and discussed in this section. In Section 4.1, the cash index and futures prices are showed to be nonstationary and cointegrated with each other. Descriptive statistics, including serial correlations, of minutely returns of the spot index and futures are provided in Section 4.2. Regression results of the lead-lag behaviour between the cash and futures markets in minutely returns are showed in Section 4.3, and the lead-lag patterns in different periods are discuss in Section 4.4. In Section 4.5, a dummy variable is introduced to investigate the effects of short-sales constraints on the leadership. In Section 4.6, empirical results of the leadership patterns in longer time intervals, including 5-, 15- and 30-minute, are presented and compared. Empirical findings of the lead-lag relationship across futures returns, as well as the changes in the leadership patterns in different intervals are provided in Section 4.7.

4.1 Tests for unit roots and cointegration

The stock index and index futures series are first checked whether each series is a nonstationary process. The ADF unit root test statistics are reported in Table 2.4. It is assumed that there is a constant and a linear time trend in the data generation process. Further, 10 lagged first difference terms are added to the test regression to remove any serial correlation in the residuals. Tests for the presence of a unit root in the levels of each series fail to reject the null hypothesis of a unit root at the 1% critical value[22]. Therefore, the cash index and futures prices in both periods are nonstationary $I(1)$ processes. In contrast, the null hypothesis is rejected for the first-order differences of each series at the 1% significance level. Thus, the differences of prices series are stationary $I(0)$ processes.

[22] The critical values are available in MacKinnon (1991).

Table 2.4 ADF unit root tests on the TXI, TX and TW in both periods

	TXI		TX		TW	
Period	I	II	I	II	I	H
Levels						
ADF	-2.0549	-1.9825	-1.8366	-1.9587	-2.3151	-1.6843
Differences						
ADF	-50.4469	-56.7794	-51.4460	-56.1797	-49.3442	-55.8734

Note: 1% critical value: -3.9641

Table 2.5 Johansen cointegration tests

Period I				Period II			
Regressand	TXI	TX	TW	Regressand	TXI	TX	TW
TXI	---	84.8222	57.3274	TXI	---	111.6986	38.0840
TX	---	---	75.8890	TX	---	---	48.0725
TW	---	---	---	TW	---	---	---

Note: 1 % critical value: 30.45

The nonstationarity in price levels raises the possibility of spurious regressions and therefore required a cointegration test. The results of Johansen cointegration tests are presented in Table 2.5. The intercept and linear trends are assumed in the data and 2 lags are included according to the Akaike information criterion (AIC). Since there are only two variables involved in the lead-lag relationship, the cointegration test is performed in pairs, i.e. TXI and TX, TXI and TW, and TX and TW. So only the trace tests are reported. The null hypothesis of no cointegration is rejected at 1% significance level and the estimated rank is equal to 1for all pairs. Therefore, the three Taiwan stock related instruments are cointegrated with each other and form a cointegrated system.

4.2 Descriptive statistics

Table 2.6 shows summary statistics on the minutely spot index (TXI) and index futures (TX and TW) returns. First of all, the autocorrelation pattern is not stable. The first-order autocorrelation of the index return is 0.246 and -0.130 for Period I and II, respectively. However, the autocorrelation of the index return at the first lag is positive in most studies (see Stoll and Whaley 1990, Chan 1992 and Abhyankar 1995) because of infrequent trading effect which leads to positive autocorrelation into returns. The negative autocorrelation at the first lag in the TXI for the Period II may be induced by bid-ask spreads in the large capitalisation shares. Although Chan (1992) argues that bid-ask spreads in the individual shares are likely to be cancelled out in the index returns as a result of diversification, Stoll and Whaley (1990) and Ap Gwilym and Buckle (2001) suggest that when there are only a small number of stocks making up the index, there will be some negative serial correlation induced in the index return. In Taiwan while the index is comprised of more than 500 stocks, the 10 largest companies have more than half of the total capitalisation. Therefore, the situation is similar to what they suggest. Since a limited number of shares have more influence on the index than others, if their bid-ask spreads do not cancel out each other, negative serial correlation still will be introduced in the index.

Table 2.6 Summary statistics for the TXI, TX and TW minutely returns for the Period I (July to Dec, 1999) and Period II (April to September, 2001)

	TXI		TX		TW	
Period	I	II	I	II	I	II
Obs	24344	33087	24344	33087	24344	33087
Mean	-0.001115	-0.000891	-0.000660	-0.000939	-0.000781	-0.001073
s.d.	0.072221	0.076811	0.097445	0.079199	0.107518	0.091031
Skewness	0.067340	0.199856	-1.412820	0.306919	-0.035603	0.044613
Kurtosis	24.91206	4.188325	90.63140	10.03488	27.62989	7.362327
$\rho(r_t, r_{t-k})$, k=						
1	**0.246***	**-0.130***	**-0.050***	**0.146***	**0.051***	**0.074***
2	**0.315***	**0.217***	**0.068***	**0.059***	**0.055***	**0.032***
3	**0.183***	**0.113***	**0.042***	0.005	**0.031***	-0.005
4	**0.070***	**0.070***	0.016	**-0.023***	-0.001	**-0.023***
5	-0.004	**0.039***	-0.009	-0.011	**-0.038***	-0.009
6	**-0.064***	**-0.019***	**-0.016***	**-0.022***	**-0.026***	**-0.027***
7	**-0.083***	-0.016	**-0.046***	**-0.021***	**-0.030***	-0.016
8	**-0.105***	**-0.047***	**-0.022***	-0.013	**-0.040***	0.001
9	**-0.101***	**-0.043***	**-0.034***	-0.009	-0.021	-0.010
10	**-0.083***	**-0.039***	**-0.047***	-0.014	-0.020	-0.004

*Significant level at 0.001

Secondly, the sample size for the Period I and II are enormous 24344 and 33087, respectively. As Chan (1992) point out, for large number of observations lower significance may be required. Thus, all tests for the minutely data use 0.1 percent level of significance as the rejection criterion, instead of conventional levels of significance. Even though, most of the serial correlations of the cash index for both periods and of the futures for the Period I are significant at the 0.001 level. Stoll and Whaley (1990) indicate that due to the large samples, very small autocorrelations can be statistically significant under the null hypothesis of zero serial correlation, albeit other specific null hypotheses also may be rejected. In the interpretation of the autocorrelation results and the regression results to follow, significance is evaluated in economic terms.

Thirdly, the autocorrelations of the TXI at the first three lags are reasonably large (greater than 0.100) and significant at the 0.1 percent level. As mention above, the positive serial correlation in the index return is a result of infrequent trading effects in the individual shares. On the other hand, the serial autocorrelations of futures returns are relatively small. The only autocorrelation greater than 0.100 is the first-order autocorrelation of the TX for Period II. The difference in the serial correlations between spot index returns and futures returns may due to nonsynchronous trading of component shares within the TXI. It may also be due to slow dissemination of market-wide information in the stock market. Some shares response to market-wide information faster than others. Moreover, the negative autocorrelation at the first lag of the TX in 1999 may result from the bid-ask spreads because the liquidity and trading volume is relatively lower in the period.

4.3 Lead-lag relationship

The lead-lag relationship between the spot index and index futures markets is examined by (2.10) and reproduced here:

$$R_{S,t} = a + \sum_{k=-12}^{12} b_k R_{F,t+k} + \varepsilon_t \qquad (2.12)$$

where $R_{S,t}$ are 1-minute spot index returns (TXI) and $R_{F,t}$ are futures returns of either the TX or TW, at time t. The fitting of an ARMA(3,3)[23] model is used to purge the spurious autocorrelation arising from infrequently trading effect and bid-ask spreads in cash returns and the residuals are used as a proxy of the true but unobserved returns. Table 2.7 presents evidence on the lead-lag relationship between the raw futures returns and spot returns innovations from an ARMA(3,3) model. All the previous studies on the leadership follow Stoll and Whaley's (1990) way that only the cash index returns are fitted with an ARMA(p,q) model. Futures raw returns are used in regression directly[24]. However, from Table 2.6 it is clear that both futures return series do show some autocorrelation. Therefore, it is necessary to report the evidence using futures return innovations if the results are different from the former. The results of regressing the TXI return innovations from an ARMA(3,3) on futures return innovations from an ARMA(3,3) are showed in Table 2.8.

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[23] A number of different ARMA(p,q) models were estimated; however, the AIC was minimised for an ARMA(3,3) specification. The same specification was identified using the Schwartz Criteria.

[24] Abhyankar (1995) re-runs the regressions using futures return innovations from an AR model. The results are virtually the same, so he does not report this results in his study.

Table 2.7 Regression of one-minute TXI ARMA(3,3) returns on lags and leads of one-minute TX or TW futures raw returns

	I (July~ December, 1999)				II (April~ September, 2001)			
	TX		TW		TX		TW	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
b_{-12}	0.0066	1.6030	0.0010	0.1976	0.0131	2.6532	0.0107	2.4961
b_{-11}	**0.0153***	3.5156	0.0057	1.2579	**0.0228***	4.6325	**0.0150***	3.3749
b_{-10}	**0.0255***	6.2781	**0.0140***	3.3703	0.0107	2.1895	0.0118	2.7735
b_{-9}	**0.0166***	3.9774	**0.0148***	3.5050	0.0066	1.3046	0.0060	1.3822
b_{-8}	0.0111	2.5382	0.0107	2.5249	0.0130	2.5525	0.0096	2.2169
b_{-7}	**0.0220***	4.9492	0.0137	3.1219	**0.0171***	3.3743	**0.0174***	4.0307
b_{-6}	**0.0184***	4.0188	0.0163	3.2085	**0.0203***	4.0761	**0.0215***	5.0010
b_{-5}	**0.0198***	4.3704	**0.0200***	3.7147	**0.0492***	9.8875	**0.0445***	10.0259
b_{-4}	**0.0176***	3.7648	**0.0329***	6.4709	**0.0645***	12.6002	**0.0585***	13.1109
b_{-3}	**0.0435***	8.0318	**0.0358***	6.9951	**0.0970***	18.3741	**0.0756***	16.6492
b_{-2}	**0.0593***	10.7149	**0.0344***	6.6589	**0.0853***	15.7502	**0.0547***	11.8913
b_{-1}	**0.0849***	16.1676	**0.1604***	19.5558	**0.0909***	16.5949	**0.1622***	34.4915
b_0	**0.2030***	23.0943	**0.1482***	17.2846	**0.2659***	41.7825	**0.1796***	35.1916
b_{+1}	**0.1299***	16.6273	0.0342	3.1417	**0.0622***	10.5177	**0.0293***	5.9338
b_{+2}	**0.0513***	9.2764	0.0035	0.2795	0.0028	0.5206	**0.0156***	3.3794
b_{+3}	0.0090	1.4217	-0.0165	-1.4790	**-0.0187***	-3.5264	-0.0018	-0.4107
b_{+4}	-0.0179	-2.8984	-0.0006	-0.0617	**-0.0210***	-4.0601	-0.0067	-1.4639
b_{+5}	**-0.0221***	-4.2091	-0.0010	-0.1826	-0.0048	-0.9211	-0.0112	-2.4628
b_{+6}	-0.0145	-2.5002	-0.0041	-0.8134	-0.0095	-1.7973	-0.0009	-0.2043
b_{+7}	-0.0060	-1.2390	-0.0027	-0.5270	-0.0101	-2.0282	-0.0071	-1.6696
b_{+8}	-0.0067	-1.3027	-0.0045	-0.9428	-0.0071	-1.4036	0.0024	0.5655
b_{+9}	-0.0015	-0.3207	-0.0031	-0.7036	-0.0087	-1.6715	-0.0056	-1.2699
b_{+10}	0.0025	0.5365	0.0009	0.2047	-0.0010	-0.1942	-0.0094	-2.1579
b_{+11}	0.0108	2.1784	-0.0070	-1.5677	0.0030	0.5871	-0.0014	-0.3225
b_{+12}	-0.0004	-0.1012	0.0056	1.1941	-0.0015	-0.3020	0.0012	0.2761
χ^2_{lag}	**609.60***	p=0.000	**700.21***	p=0.000	**1573.3***	p=0.000	**2140.9***	p=0.000
χ^2_{lead}	**456.31***	p=0.000	**41.95***	p=0.000	**171.17***	p=0.000	**71.10***	p=0.000
$\bar{R}^2$	0.1625	---	0.1544	---	0.1565	---	0.1304	---

Notes: *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. $\chi^2_{lag}/\chi^2_{lead}$ is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero. *Significant level at 0.001.

Firstly, there is significant evidence that there is a lead-lag relation between the spot index and the index futures, regardless of whether the TX or TW are used. Secondly, the lead length of futures in Table 2.8 is shorter than that in Table 2.7. That means, using raw futures returns may generate spurious lead or lag evidence. Even though serial correlations are removed from cash and futures returns, the lead-lag evidence is still significant. Thus, the lead-lag relation is not well explained by nonsynchronous trading and bid-ask spread effects. Thirdly, the leadership is bidirectional. The χ^2_{lag} and χ^2_{lead} statistics reject that the lag and lead coefficients are jointly zero for both periods.

Table 2.8 Regression of one-minute TXI ARMA(3,3) returns on lags and leads of one-minute TX or TW futures ARMA(3,3) returns

	I (July~ December, 1999)				II (April~ September, 2001)			
	TX		TW		TX		TW	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
b_{-12}	-0.0011	-0.2627	-0.0036	-0.6974	0.0106	2.1543	0.0089	2.0656
b_{-11}	0.0028	0.6413	-0.0017	-0.3851	**0.0174***	3.5597	0.0119	2.6813
b_{-10}	0.0104	2.5599	0.0040	0.9496	0.0038	0.7811	0.0072	1.7102
b_{-9}	0.0011	0.2602	0.0032	0.7580	-0.0005	-0.1072	0.0008	0.1795
b_{-8}	-0.0043	-0.9902	-0.0007	-0.1662	0.0064	1.2567	0.0041	0.9496
b_{-7}	0.0098	2.2124	0.0043	1.0019	0.0128	2.5510	0.0124	2.8671
b_{-6}	0.0112	2.4761	0.0111	2.1876	**0.0223***	4.5414	**0.0186***	4.3444
b_{-5}	**0.0210***	4.6905	**0.0207***	3.8443	**0.0571***	11.582	**0.0440***	9.9285
b_{-4}	**0.0253***	5.4887	**0.0403***	8.0967	**0.0800***	15.811	**0.0613***	13.770
b_{-3}	**0.0574***	10.7229	**0.0502***	9.6192	**0.1170***	22.430	**0.0835***	18.3887
b_{-2}	**0.0784***	14.1946	**0.0507***	9.8404	**0.1150***	21.3040	**0.0720***	15.6496
b_{-1}	**0.0882***	17.0957	**0.1693***	20.9219	**0.1328***	24.5493	**0.1762***	37.6442
b_0	**0.2013***	23.4115	**0.1502***	17.9503	**0.2754***	43.5626	**0.1826***	35.8051
b_{+1}	**0.1275***	16.4842	**0.0341***	3.3150	**0.0619***	10.5639	**0.0307***	6.2610
b_{+2}	**0.0484***	8.7167	0.0032	0.2558	-0.0005	-0.0891	**0.0156***	3.3878
b_{+3}	0.0074	1.1699	-0.0164	-1.5043	**-0.0216***	-4.1525	-0.0024	-0.5318
b_{+4}	-0.0185	-2.9920	-0.0008	-0.0818	**-0.0221***	-4.3271	-0.0072	-1.5919
b_{+5}	**-0.0223***	-4.2339	-0.0013	-0.2515	-0.0068	-1.3153	-0.0113	-2.4896
b_{+6}	-0.0149	-2.5847	-0.0045	-0.8930	-0.0116	-2.2034	-0.0012	-0.2707
b_{+7}	-0.0055	-1.1511	-0.0031	-0.6125	-0.0116	-2.3527	-0.0071	-1.6704
b_{+8}	-0.0060	-1.1586	-0.0048	-1.0124	-0.0083	-1.6603	0.0018	0.4153
b_{+9}	-0.0008	-0.1767	-0.0032	-0.7274	-0.0087	-1.6910	-0.0062	-1.4240
b_{+10}	0.0017	0.3660	0.0009	0.2204	-0.0007	-0.1309	-0.0094	-2.1754
b_{+11}	0.0107	2.1392	-0.0067	-1.4949	0.0028	0.5552	-0.0013	-0.3047
b_{+12}	-0.0006	-0.1416	0.0057	1.2024	-0.0015	-0.3055	0.0011	0.2698
χ_{lag}	**730.32***	p=0.000	**734.52***	p=0.000	**1952.8***	p=0.000	**2336.2***	p=0.000
χ_{lead}	**457.81***	p=0.000	**42.46***	p=0.000	**171.32***	p=0.000	**70.91***	p=0.000
$\bar{R}^2$	0.1625	---	0.1546	---	0.1565	---	0.1304	---

Notes: *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. χ_{lag}/χ_{lead} is the χ statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.001.

Hence, while the futures lead the spot, the spot also leads the futures. Finally, the lead-lag relation is asymmetric—the feedback from the futures markets into the cash market is stronger than the reverse. While the futures lead the cash up to 11 minutes, the spot only leads the futures up to 5 lags. However, most of the significant coefficients are positive but the TX's lead coefficients b_{+5} in 1999 and b_{+3} and b_{+4} in 2001 are negative. Many authors ignore the negative coefficients or limit the significant coefficients to be positive, e.g., Chan (1992), Abhyankar (1995, 1998) and Min and Najand (1999). Although Stoll and Whaley (1990) do not find any significantly negative coefficient in their study, they describe that a phenomenon, for the futures prices to overshoot their equilibrium values and then fall back into alignment with respect to the stock index level, would be indicated if the coefficients of the lead futures returns were significantly large negative values. On the premise that the positive coefficients exist in the leadership when a market 'under-reacts' to information relatively to another market, it could be reasonably inferred that the negative coefficients exist when a market 'overreacts' to information relatively to another market. Therefore, the TX's negative coefficients, though rather small, illustrate that the futures (TX) overshoots to information and then go back to its equilibrium level so the spot predicts the futures in opposite direction.

4.4 Transaction costs hypothesis and market maturation effects

The transaction costs hypothesis predicts that the market with lowest overall transaction costs will react most quickly to new information. From the hypothesis it can be inferred that when the transaction costs of one market have been further reduced, the lead length from this market to another one will be longer or the lead coefficients will be more significant. Moreover, as the index futures markets have matured, futures and stock markets will become more closely integrated through time, so the R^2, the estimated coefficients of the contemporaneous and lag one futures returns will grow larger through time. This is the market maturation effects (Stoll and Whaley, 1990).

In table 2.8 the lead length of the futures markets in Period II is longer than in Period I. The lead length of TX expands from 5 to 11 minutes, and that of the TW rises from 5 to 6 minutes. In addition, all the estimated coefficients of the lag one to lag five (b_{-1}, b_{-2} ... b_{-5}) futures returns in Period II are larger than in Period I. For instance, b_{-1} of the TX has grown from 0.0882 to 0.1328, and b_{-1} of the TW has enlarged from 0.1693 to 0.1762 for Period I and II, respectively. On the contrary, the estimated first lead coefficient (b_{+1}) of the TX has shrunk from 0.1275 to 0.0619 and that of the TW has reduced from 0.0341 to 0.0307. As the transaction tax of the TX has been trimmed down since 1st may 2000 and both futures markets are more matured than even, the leadership of futures markets has become more significant, on the other hand, the leadership of the cash market has faded away. The lead negative coefficients of the TX, which indicate the overreaction, have shifted from b_{+5} to b_{+3} and b_{+2}. As the futures matured, the futures market's speed of adjustment to information improves. Consequently, the time required to correct overreaction is reduced though the overreaction of the TX still exists. The results mentioned above are consistent with transaction costs hypothesis and the market maturation effects.

The contemporaneous relationship between the cash and futures markets can not be overlooked while investigating on leads and lags. The contemporaneous coefficients between the TXI and the TX and between the TXI and the TW are 0.2013 and 0.1502, respectively, for Period I and 0.2754 and 0.1826, respectively, for Period II. Futures and stock markets become more closely integrated through time as the index futures markets have matured. The contemporaneous coefficients between the TXI and the TX are greater than those between the TXI and the TW for both periods because the TXI is the underlying index of the TX but not that of the TW. The correlation coefficient (ρ) between the TXI and TX is 0.9894 and 0.9983, and the ρ between the TXI and TW is 0.9283 and 0.9868 for Period I and II, respectively[25]. It is clear that the ρ between the TXI and TX is higher than the ρ between the TXI and TW. Most of the contemporaneous coefficients are considerably greater than any other lead or lag coefficients, however, b_0, which is 0.1502, of the TW in 1999 is smaller than b_{-1}, 0.1693. It indicates that the dominate relation in the first period was the TW leads the cash index. However, although the contemporaneous coefficients increases through time, the $\bar{R}^2$ get smaller. The $\bar{R}^2$ of the TX reduces from 0.1625 to 0.1565 and of the TW shrinks from 0.1546 to 0.1304. It is inconsistent with Stoll and Whaley's (1990) market maturation effects.

4.5 The effects of short-sales constraints on the leadership

The effects of short-sales constraints on the lead-lag relationship between the spot index and index futures markets is examined by (2.11) and reproduced here:

$$R_{S,t} = a + d_t a' + \sum_{k=-12}^{+12} b_k R_{F,t+k} + \sum_{k=-12}^{+12} b'_k d_t R_{F,t+k} + \varepsilon_t \qquad (2.13)$$

where $R_{S,t}$ are cash index returns, $R_{F,t}$ are futures returns of either the TX or TW, at time t, d_t is the dummy variable, d_t=1 if the daily spot return<0 and d_t=0 otherwise, a' is the dummy intercept and b'_k are the dummy slope coefficients. If the short-sales constraints

[25] The data of minutely price levels are used for measuring ρ.

are binding, the spot index lags futures longer, and the dummy slope lag coefficients will be significantly positive. Results based on (2.13) are reported in Table 2.9. None of the dummy slope coefficients (b'_k) are significant at 0.1% level in any regression. The χ'_{lag}/χ'_{lead} is the χ statistic that tests whether the dummy slope lag/lead coefficients are jointly zero. They are not significant for both periods. The results do not indicate that short-sales constraints have any effect on the lead-lag relationship between cash and futures returns. There is no stronger tendency for the futures to lead the spot index under bad news than under good news.

Table 2.9 Regression of one-minute TXI ARMA(3,3) returns on lags and leads of one-minute TX or TW futures ARMA(3,3) returns, with dummy slope coefficients for observations from bad news group

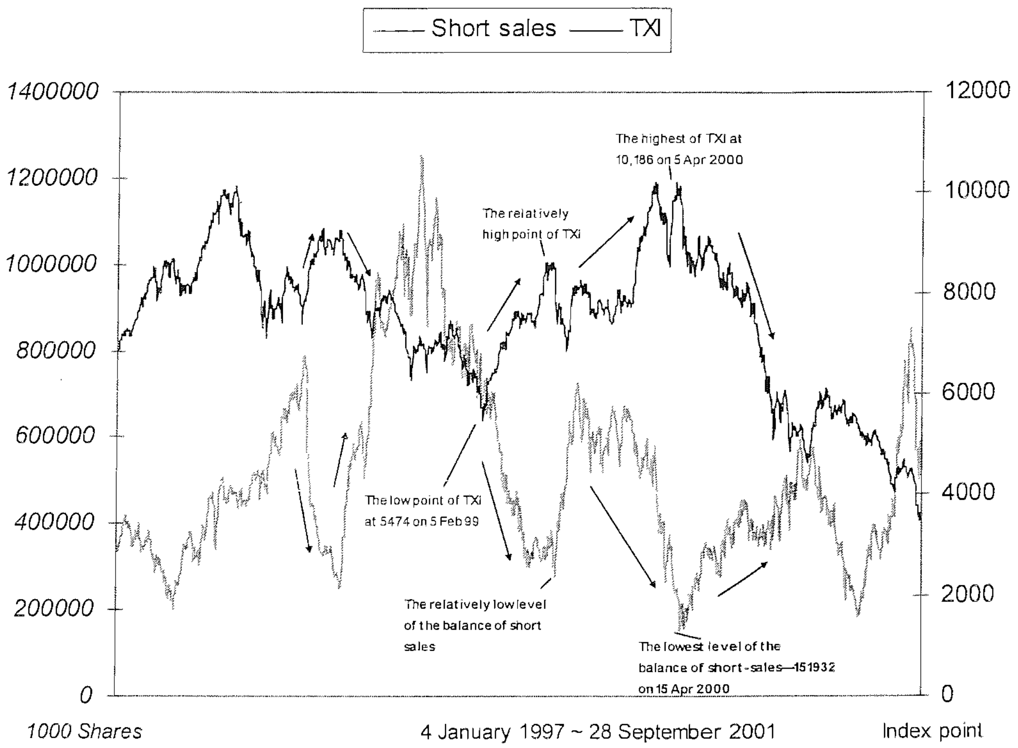
	I (July~ December, 1999)				II (April~ September, 2001)			
	TX		TW		TX		TW	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
b'_{-12}	0.0057	0.6714	-0.0119	-1.2349	-0.0004	-0.0373	-0.0101	-1.1500
b'_{-11}	-0.0008	-0.0892	-0.0064	-0.7465	-0.0083	-0.8360	0.0169	1.8747
b'_{-10}	0.0137	1.6871	0.0229	2.7381	0.0020	0.1977	-0.0047	-0.5404
b'_{-9}	-0.0064	-0.7535	-0.0012	-0.1467	0.0017	0.1709	0.0083	0.9243
b'_{-8}	-0.0016	-0.1803	-0.0044	-0.5235	0.0198	1.9563	0.0169	1.9137
b'_{-7}	-0.0075	-0.8547	-0.0020	-0.2308	0.0186	1.8181	0.0105	1.1820
b'_{-6}	-0.0005	-0.0585	0.0054	0.5574	0.0119	1.1450	0.0203	2.0531
b'_{-5}	0.0064	0.7041	0.0177	1.7395	0.0155	1.5590	0.0100	1.1051
b'_{-4}	0.0161	1.7120	-0.0183	-1.8725	-0.0183	-1.8129	0.0059	0.6468
b'_{-3}	0.0291	2.7965	0.0112	1.1247	-0.0090	-0.8466	-0.0262	-2.8199
b'_{-2}	0.0050	0.4602	-0.0041	-0.4134	-0.0213	-2.1081	-0.0251	-2.0531
b'_{-1}	-0.0122	-1.1880	-0.0208	-1.4376	-0.0192	-1.9065	-0.0209	-2.1463
b'_0	-0.0155	-0.9212	-0.0256	-1.6477	-0.0046	-0.3657	-0.0215	-2.2661
b'_{+1}	-0.0200	-1.4015	0.0141	0.7717	0.0236	2.0197	-0.0042	-0.4311
b'_{+2}	0.0009	0.0770	-0.0025	-0.1170	0.0171	1.5795	0.0186	1.9996
b'_{+3}	0.0014	0.1122	0.0158	0.8279	0.0193	1.8102	0.0080	0.8881
b'_{+4}	0.0369	2.9121	0.0298	1.7856	0.0233	2.2386	0.0100	1.0843
b'_{+5}	0.0145	1.3870	0.0011	0.0967	-0.0006	-0.0568	0.0056	0.6161
b'_{+6}	-0.0194	-1.6742	0.0049	0.5090	-0.0176	-1.6665	-0.0116	-1.2656
b'_{+7}	-0.0216	-2.1527	-0.0013	-0.1255	-0.0123	-1.2306	-0.0012	-0.1357
b'_{+8}	-0.0125	-1.2130	0.0007	0.0751	-0.0051	-0.5093	0.0011	0.1235
b'_{+9}	0.0126	1.3628	-0.0098	-1.1307	-0.0084	-0.8160	-0.0117	-1.3080
b'_{+10}	-0.0034	-0.3594	-0.0139	-1.6336	0.0115	1.1272	-0.0027	-0.3069
b'_{+11}	0.0055	0.5370	-0.0028	-0.3146	0.0038	0.3738	0.0071	0.7998
b'_{+12}	0.0025	0.2788	-0.0065	-0.6671	0.0021	0.2149	0.0107	1.2482
$\chi^2{}'_{lag}$	17.13	p=0.144	21.26	p=0.046	24.64	p=0.021	34.38	p=0.011
$\chi^2{}'_{lead}$	24.04	p=0.020	14.69	p=0.259	21.95	p=0.038	12.73	p=0.389
$\bar{R}^2$	0.16418	---	0.15642	---	0.15857	---	0.13259	---

Notes: *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. $\chi^2{}_{lag}/\chi^2{}_{lead}$ is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.001.

The reason may be short selling shares is not an important approach for informed traders to reflect information. First, the volume of short-sales is very small relatively to the total trading volume in Taiwan. The short selling volume-to-total trading volume ratio is only 3.3% and 3.49% in 1999 and 2000, respectively. Short-selling has trivial impact on the behaviour of the stock market. Second, Institutional investors, usually regarded as informed traders, are prohibited from short selling shares. Therefore, they sell current positions in their well-diversified portfolios, instead of short selling, to reflect bad news. Third, since institutional investors are not involved in the short sales, it is reasonable to infer that most of the short sold shares are done by individual investors, who are the main source of the noise traders. Noise traders are the speculators who follow simple 'rule of thumb' or 'trends' or waves of investor sentiment rather than act on the basis of fundamentals (Cuthbertson, 1996). If all investors are rational and trade shares based on fundamentals, short-selling a share will only occur when its price is overshooting. Thus, the balance of short-sales should go up as the stock index flies and decline as the index drops. On the contrary, if noise traders, especially positive feedback traders who buy shares when prices are high and sell when prices are low, dominate the majority of the short-sales trading, the balance of short-sales will go up as the stock market is falling because positive feedback traders believe that the market will drop further, and the balance of short-sales will decrease as the market is rising because they believe that it will get higher.

Figure 2.1 shows the chart of the daily closing price of the TXI and the daily balance of short-sales between 4 January 1997 and 28 September 2001. The balance of short-sales is measured by the left X-axis and the TXI by the right X-axis. It seems that there is an inverse relationship between these two series. When the TXI is rising in the bull market, the balance of short-sales keeps going down in that period. For example, when the TXI soared up from the lowest level 5474 points on 5 February 1999 to its peak over 8,000 points between 16 June and 13 July 1999, the balance of short-sales kept dropping to its bottom around 300,000 thousand shares and reached the lowest amount on 17 July. In addition, when the TXI reached the 10-year highest point—10,186 points on 5 April 2000, the balance of short-sales reached the lowest level—151932 thousand shares after 9 trading days on 15 April. In addition, the correlation coefficient between these two variables is -0.1815. That means there is a negative relationship between the TXI and the balance of short-sales. Therefore, it may be inferred that short-selling may be most done by noise traders and then the trading of short-sales provides no 'correct' information on the stock market. That is why the futures returns do not lead cash returns longer under the short-sales constraints. Although short-selling constraint is a reasonable hypothesis to conjecture the lead-lag relationship between the stock index and index futures, there is no evidence to support it from Taiwan markets or any other markets.

Figure 2.1 The chart of the daily closing price of the TXI and the daily balance of short-sales



4.6 The leadership patterns in longer time intervals

In the previous studies various time intervals are chosen to investigate the leadership between the cash and futures markets. The lengths or patterns of leads and lags from those studies are various for different intervals and markets. More complete understanding of the leadership may be recognised by examining the same market with some different intervals. Hence, in addition to minutely data, five-, fifteen- and thirty-minute data are generated and used in this study to explore the leads and lags relationship under different intervals.

Table 2.10 Summary statistics for TXI, TX and TW 5-minute returns for each period

	TXI		TX		TW	
Period	I	II	I	II	I	II
Obs	4896	6642	4896	6642	4896	6642
Mean	-0.005545	-0.004439	-0.003281	-0.004676	-0.003883	-0.005344
s.d.	0.222848	0.185392	0.219604	0.198436	0.257665	0.215720
Skewness	-0.301039	0.509959	-0.599576	0.509983	-0.203797	0.230007
Kurtosis	8.806918	7.365944	14.019582	7.579272	11.837173	6.331966
$\rho(r_t, r_{t-k})$, k=						
1	**0.095***	**0.150***	0.000	0.011	-0.042	-0.026
2	**-0.199***	**-0.152***	**-0.140***	**-0.063***	**-0.055***	-0.031
3	-0.043	-0.036	0.029	0.023	**0.049***	0.035
4	**0.054***	**0.078***	**0.091***	**0.058***	0.046	0.034
5	0.015	0.038	0.035	0.014	**0.049***	-0.012
6	-0.013	0.007	-0.032	-0.021	-0.016	0.005
7	0.021	0.001	-0.006	0.008	0.013	0.015
8	0.040	0.027	**0.067***	0.020	0.047	0.007
9	0.032	0.004	-0.006	0.009	-0.007	0.019
10	-0.017	-0.016	-0.030	-0.021	-0.011	-0.018

*Significant level at 0.001

Table 2.11 Summary statistics for TXI, TX and TW 15-minute returns for each period

	TXI		TX		TW	
Period	I	II	I	II	I	II
Obs	1632	2214	1632	2214	1632	2214
Mean	-0.016635	-0.013317	-0.009842	-0.014028	-0.011648	-0.016031
s.d.	0.388941	0.343416	0.361774	0.338260	0.422404	0.367462
Skewness	-0.489631	0.419238	-1.025297	0.414207	-0.451692	0.281339
Kurtosis	8.283582	4.814234	13.38977	6.148294	7.839420	5.312293
$\rho(r_t, r_{t-k})$, k=						
1	**-0.100***	-0.022	0.021	0.046	**0.087***	0.018
2	0.034	0.043	0.038	0.007	0.051	0.020
3	**0.068***	0.005	0.024	-0.001	0.005	-0.003
4	-0.045	0.021	-0.019	0.026	0.027	0.004
5	0.037	-0.009	0.026	0.025	0.001	0.028
6	**0.076***	0.041	0.062	0.031	0.039	0.049
7	0.000	0.016	0.040	0.032	0.038	0.010
8	0.031	0.018	0.011	0.022	-0.006	0.012
9	0.025	-0.009	**0.075***	0.014	0.037	0.016
10	0.017	0.047	-0.003	0.042	0.046	0.049

*Significant level at 0.01

Summary statistics on the five-, fifteen- and thirty-minute spot index (TXI) and index futures (TX and TW) returns are provided in Table 2.10, 2.11 and 2.12, respectively. First of all, the serial correlations of 5- to 30-minute returns are not as significant as those of 1-minute returns. The biggest autocorrelation in 1-minute TXI returns is 0.217 but only 0.199 in absolute value in 5-minute returns. As the time interval enlarges, the number of the significant autocorrelation reduces. No serial correlation is found in the 30-minute futures returns. Secondly, the autocorrelation pattern is not constant and cannot be completely explained by the infrequent trading and the bid-ask spreads effects.

In the case of the spot index returns, there are a positive and a negative significant autocorrelations at the first lag for minutely returns, 2 positive ones for 5-minute returns, 1 negative significant autocorrelation for 15-minute returns and none for 30-minute returns. The infrequent trading and the bid-ask spreads effects cannot explain the changes in the autocorrelation in different time interval data. The changes in autocorrelation seem to arise from the aggregation, but not simple summation, of autocorrelations from shorter interval. For instance, the summation of the first five lags autocorrelations of the TXI in the minutely returns are positive in 2001, so the first autocorrelation in the 5-minute returns becomes positive. Furthermore, all the autocorrelations at the second lag in the 5-minute returns are negative. They seem to be the result of the aggregation of all the serial correlations at the sixth to tenth lags, which are all negative, in the minutely returns. In additional to the nonsynchronous and bid-ask spreads effect, another possible explanation of autocorrelation in stock index and futures is the existence of noise traders. Cuthbertson (1996) demonstrates that in the presence of feedback traders, over short horizons, returns are positively serially correlated: positive returns are followed by further positive returns and negative returns by further negative returns. Over long horizons, returns are negatively serially correlated. Hence, returns are serially correlated and predictable. Since about 87% of shares are traded by individuals, it is reasonable to infer that noise traders have important influence on the behaviour of the Taiwan stock market and generate autocorrelations in price returns.

Table 2.12 Summary statistics for TXI, TX and TW 30-minute returns for each period

	TXI		TX		TW	
Period	I	II	I	II	I	II
Observations	816	1107	816	1107	816	1107
Mean	-0.033270	-0.026634	-0.019684	-0.028055	-0.023295	-0.032062
s.d.	0.529590	0.477728	0.535913	0.478961	0.639905	0.516183
Skewness	-0.780288	0.637724	-0.900350	0.380893	-0.752133	0.145365
Kurtosis	13.01280	6.419707	13.43458	6.571953	12.01269	5.592139
$\rho(r_t, r_{t-k})$, k=						
1	0.003	0.049	0.019	0.077	0.047	0.049
2	-0.019	0.022	0.004	0.013	0.052	0.006
3	**0.118***	0.024	0.088	0.043	0.030	0.066
4	0.049	0.045	0.068	0.057	0.014	0.040
5	0.029	0.016	0.028	0.024	0.067	0.033
6	-0.007	0.009	-0.049	-0.001	-0.056	-0.002
7	-0.060	-0.006	-0.049	0.018	-0.021	-0.006
8	-0.024	-0.001	0.010	-0.044	-0.019	-0.007
9	-0.029	**-0.125***	-0.044	-0.106	-0.055	-0.093
10	0.035	0.019	0.077	-0.048	-0.007	-0.027

*Significant level at 0.01

(2.12) is employed again to explore the lead-lag relationship between cash index and index futures under different time intervals. Again, all the cash index and futures return series are purged by fitting an ARMA(p,q) model and the residuals from the model are used as a proxy of the true returns. Since the pattern of autocorrelation is not the same for each series, a number of different ARMA(p,q) models were estimated for each returns[26]. If the results from return innovations and raw returns are the same, the latter is used in regressions rather than the former. The results of the lead-lag relationship between the spot index and index futures returns using 5-, 15- and 30-minute returns are presented in Table 2.13, 2.14 and 2.15, respectively.

Table 2.13 Regression of 5-minute TXI returns on lags and leads of 5-minute TX or TW futures returns

	I (July~ December, 1999)				II (April~ September, 2001)			
	TX		TW		TX		TW	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
b_{-5}	0.0170	1.4113	-0.0282	-1.5698	0.0103	0.9692	0.0055	0.5587
b_{-4}	0.0120	1.0976	-0.0106	-0.5621	0.0069	0.6718	-0.0066	-0.6948
b_{-3}	-0.0219	-1.8145	0.0087	0.5747	0.0141	1.3300	0.0128	1.2953
b_{-2}	-0.0282	-2.0877	-0.0093	-0.5922	0.0102	0.9524	0.0084	0.8099
b_{-1}	**0.2454***	16.3603	**0.3201***	18.1662	**0.3353***	29.7355	**0.2912***	27.1203
b_0	**0.6844***	36.5567	**0.4457***	21.6929	**0.5162***	37.7325	**0.4347***	34.5631
b_{+1}	-0.0242	-1.3716	-0.0175	-1.1814	**-0.0719***	-6.7189	-0.0231	-2.2782
b_{+2}	-0.0116	-0.9025	-0.0046	-0.2991	-0.0021	-0.2150	-0.0094	-1.0275
b_{+3}	0.0123	0.8856	0.0154	1.0348	0.0057	0.5128	0.0118	1.1400
b_{+4}	-0.0157	-1.0390	0.0033	0.2585	-0.0069	-0.6983	0.0096	0.9153
b_{+5}	0.0056	0.3274	-0.0012	-0.0890	0.0108	1.0748	0.0057	0.5824
χ^2_{lag}	**289.87***	p=0.000	**388.64***	p=0.000	**892.31***	p=0.000	**751.88***	p=0.000
χ^2_{lead}	5.74	p=0.332	3.19	p=0.670	**48.09***	p=0.000	8.76	p=0.119
$\bar{R}^2$	0.53557	---	0.41426	---	0.47172	---	0.39446	---

Notes: the TXI is purged by fitting an AR(2) model, and the TX by ARMA(2,2) for Period I, and both the TXI and TX by ARMA(2,2) and the TW by ARMA(1,2) for Period II. t-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. $\chi^2_{lag}/\chi^2_{lead}$ is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.001.

[26] The specific ARMA(p,q) model with minimised AIC for each series is showed in the notes under Table 2.13, 2.14 and 2.15.

Table 2.14 Regression of 15-minute TXI returns on lags and leads of 15-minute TX or TW futures returns

	I (July~ December, 1999)				II (April~ September, 2001)			
	TX		TW		TX		TW	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
b_{-5}	0.0291	1.0689	0.0118	0.4809	-0.0018	-0.1102	0.0124	0.8339
b_{-4}	-0.0299	-1.3795	-0.0471	-1.8055	0.0000	0.0002	0.0072	0.4943
b_{-3}	0.0187	0.7971	0.0037	0.1588	0.0270	1.4035	0.0263	1.6375
b_{-2}	-0.0183	-0.9126	-0.0406	-1.3939	0.0390	2.1371	0.0165	1.0610
b_{-1}	**0.0883***	4.9400	**0.1013***	3.4995	**0.1325***	7.6447	**0.1046***	6.5270
b_0	**0.8872***	37.596	**0.6747***	22.879	**0.7864***	38.193	**0.6895***	38.745
b_{+1}	-0.0051	-0.2022	0.0115	0.5376	-0.0142	-0.8358	0.0204	1.3030
b_{+2}	0.0111	0.6913	0.0341	1.5388	-0.0074	-0.4451	-0.0098	-0.6423
b_{+3}	0.0343	2.1564	0.0179	0.8665	-0.0084	-0.4540	-0.0012	-0.0772
b_{+4}	0.0014	0.0883	-0.0033	-0.1837	0.0021	0.12718	-0.0099	-0.6733
b_{+5}	-0.0008	-0.0475	-0.0031	-0.1684	-0.0382	-2.3830	-0.0264	-1.7612
χ^2_{lag}	**29.02***	p=0.000	**28.93***	p=0.000	**66.77***	p=0.000	**47.99***	p=0.000
χ^2_{lead}	4.98	p=0.419	3.74	p=0.587	7.13	p=0.211	5.34	p=0.376
$\bar{R}^2$	0.70222	---	0.55579	---	0.61756	---	0.55934	---

Notes: the TXI is purged by fitting an ARMA(1,2) model, the TX by ARMA(1,1) and the TW by AR(1) for Period I, and the TXI by ARMA(1,1) and TX by AR(1) for Period II. *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. $\chi^2_{lag}/\chi^2_{lead}$ is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.01.

Table 2.15 Regression of 30-minute TXI returns on lags and leads of 30-minute TX or TW futures returns

	I (July~ December, 1999)				II (April~ September, 2001)			
	TX		TW		TX		TW	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	Coef	*t*-stat
b_{-5}	0.0093	0.4015	0.0120	0.3922	0.0038	0.1661	0.0103	0.5324
b_{-4}	-0.0044	-0.1725	0.0020	0.0707	0.0062	0.3258	0.0000	0.0019
b_{-3}	0.0432	1.4090	-0.0059	-0.1907	0.0192	0.8691	-0.0045	-0.2137
b_{-2}	-0.0283	-1.4957	0.0018	0.0685	-0.0006	-0.0297	0.0120	0.6679
b_{-1}	0.0060	0.2694	-0.0389	-0.8673	**0.0973***	4.9415	**0.0988***	5.5184
b_0	**0.8597***	27.3641	**0.6675***	16.3127	**0.8249***	30.5343	**0.7414***	29.5272
b_{+1}	0.0248	1.2837	0.0602	1.7427	-0.0457	-2.2553	-0.0163	-0.9218
b_{+2}	0.0018	0.1013	-0.0175	-0.7698	0.0093	0.4734	0.0058	0.3136
b_{+3}	0.0036	0.2002	0.0174	0.8624	-0.0234	-1.3975	-0.0300	-1.8551
b_{+4}	0.0004	0.0166	0.0093	0.4667	0.0065	0.3216	0.0097	0.5122
b_{+5}	0.0031	0.1404	-0.0174	-0.8065	-0.0146	-0.7713	-0.0277	-1.5847
χ^2_{lag}	4.78	p=0.443	1.00	p=0.963	**26.54***	p=0.000	**32.64***	p=0.000
χ^2_{lead}	2.05	p=0.842	3.18	p=0.672	7.95	p=0.159	6.83	p=0.233
$\bar{R}^2$	0.76859	---	0.66555	---	0.69687	---	0.65153	---

Notes: the TXI is purged by fitting an AR(3) model for Period I. *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. $\chi^2_{lag}/\chi^2_{lead}$ is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.01.

First of all, the lead-lag relation between the cash and futures markets exists in all time interval data, regardless of whether the TX or TW are used. Secondly, the lead-lag relation is asymmetric—the feedback from the futures markets into the cash market is much stronger than the reverse. The evidence of futures lead the cash index can be found in all time interval data, but the evidence of the spot leads futures only can be found in 5-minute returns. However, the only significant coefficient (b_{+1}) is negative so the spot leads futures only when futures overreact to information. As interval enlarges, there is no evidence that the cash leads futures and the leadership becomes a unidirectional relation that only futures lead the spot index. Thirdly, although the same data are used to generated different interval returns, the results of lead-lag relationship, which are presented in Table 2.16, are not the same under different intervals. Futures lead the cash up to 11 lags in minutely returns but only 1 lag in 5-, 15- and 30-minute returns, i.e., the length of futures lead the cash is 11, 5, 15, 30 minutes in 1-, 5-, 15- and 30-minute returns. Futures seem to lead the cash 30 minutes using 30-minute returns. However, while comparing the size of the futures first lag coefficient (b_{-1}) with the size of the contemporaneous coefficient (b_0), the b_{-1} in 30-minute returns are not so meaningful relative to the b_{-1} in shorter interval returns. For instance, the b_{-1}-to-b_0 ratio of the TW in minutely returns for Period II is 0.9650 which means the b_{-1} is equivalent to the b_0. But, the ratio drops to 0.6699, 0.1517 and 0.1333 in 5-, 15- and 30-minute returns. It is clear that the meaningfulness of the b_{-1} falls quickly as the interval broadens from 1 minute to 30 minutes. Therefore, when investigating a meaningful lead-lag relationship, it had better no choose interval longer than 15 minutes if the study will be used in further application, e.g. exploiting abnormal returns from the leadership.

Table 2.16 Summary results of the lead-lag relationship between the spot index and futures under different intervals

	Futures lead the spot index				The spot index leads futures			
Interval	1-min	5-min	15-min	30-min	1-min	5-min	15-min	30-min
Lag	11	1	1	1	5	1	---	---
Length	11 min	5 min	15 min	30 min	5 min	5 min	---	---

The levels of the regression coefficients cannot be compared meaningfully since different purging ARMA(p,q) models are used for each instrument in each period. However, the t-ratios (levels of significance) can be compared (Stoll and Whaley, 1990). The significant level of the contemporaneous coefficient becomes stronger through time, indicating that the relation between returns in the stock index and futures markets has grown tighter, and firmer in longer interval except in 30-minute returns. There seems to be a ceiling on the contemporaneous coefficients between the spot index and futures.

4.7 The lead-lag relationship across futures

In Table 2.8 TW's first lag coefficients are greater than TX's in both periods so the TW seems to reflect information faster than the TX. This provides a motivation for examining the lead-lag relationship across futures. The structural differences between the TX and TW can be understood from the following aspects. First, the volume of the TW is higher than the volume of the TX. As mention before, the average daily volume of the TX and TW is 3716 and 8637 for the Period I, respectively. The average daily volume of the TX was only half as much as the TW's volume in 1999. Since the TW was the first index futures based on the Taiwan stock, most of investors were used to trade it for the purpose of hedging, speculation and arbitrage. However, as the growth of futures trading in Taiwan and the transaction tax of the TX has been reduced in 2000, their trading volumes are equivalent, although the TX's volume is still higher, for the second period. The average daily volume of the TX and TW in the period is 13069 and 13464, respectively. Second, as mentioned in Section 2.2, the overall transaction costs of the TX and TW were about 0.086% and 0.05% in 1999. In addition, since TW has higher trading volume and then higher liquidity, the bid-ask spreads in the TW should be narrower than the TX, and the difference in transaction costs should be greater expected. Therefore, the TW had the advantage of lower trading costs for Period I but the advantage will be diminished for Period II. As predicted by the transaction costs hypothesis, the TW will reflect information faster than the TX, and then lead the TX.

Moreover, these two futures contracts are traded by different trading mechanisms: the TX is a screen trading market and the TW is an open outcry market[27]. According to Grünbichler, Longstaff and Schwartz (1994), screen trading will lower the transaction costs and reduce the time required to physically process an order and execute the trade, the TX could be the primary market for price discovery. It is contradictory to the prediction of the transaction costs hypothesis.

The lead-lag relationship across futures is investigated by (2.10) again and reproduced here:

[27] Although electronic trading is also available in the main trading hours (8:45am~ 1:45pm), more 97% of transactions of the TW are occurred in the open-outcry pit.

$$R_{TX,t} = a + \sum_{k=-5}^{+5} b_k R_{TW,t+k} + \varepsilon_t \quad (2.14)$$

where the $R_{TX,t}$ are returns of the TX and $R_{TW,t}$ are returns of the TW, at time t. If the lag coefficients (b_{-1}, b_{-2}...b_{-5}) are significant, the TW is the leading market. In contrast, if the lead coefficients (b_{+1}, b_{+2}...b_{+5}) are significant, the TX leads the TW. Since the lengths of leads and lags from raw returns are the virtually same with those from ARMA(p,q) innovations, all variables used in regressions are raw returns. The results of the lead-lag relationship across futures are presented in Table 2.17 and 2.18.

Table 2.17 Regression of 1- or 5-minute TX future raw returns on lags and leads of 1- or 5-minute TW futures raw returns

	1 min				**5min**			
	I		**II**		**I**		**II**	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
b_{-5}	0.0171	1.8797	-0.0075	-1.3301	0.0022	0.2514	0.0094	1.0847
b_{-4}	**0.0337***	3.5909	-0.0084	-1.6228	0.0257	2.9237	0.0125	1.4872
b_{-3}	**0.0606***	7.6327	0.0087	1.6165	-0.0060	-0.6803	-0.0048	-0.5337
b_{-2}	**0.1246***	13.4774	**0.0627***	10.9316	**-0.0652***	-7.4169	-0.0166	-1.9087
b_{-1}	**0.2190***	20.4500	**0.2588***	46.8046	**0.1755***	19.9301	**0.0584***	6.2702
b_0	**0.1706***	14.1568	**0.3476***	57.5154	**0.5620***	63.7264	**0.7477***	73.8895
b_{+1}	**0.0782***	9.3617	**0.1515***	27.1069	**0.0510***	5.7904	**0.0823***	9.8374
b_{+2}	**0.0473***	4.6675	**0.0404***	7.2383	-0.0271	-3.0756	-0.0122	-1.4043
b_{+3}	0.0280	1.8365	0.0078	1.5252	0.0244	2.7808	0.0087	1.0358
b_{+4}	0.0128	1.2493	0.0063	1.2440	0.0175	1.9884	0.0263	3.1639
b_{+5}	0.0105	1.4490	0.0124	2.4068	-0.0024	-0.2689	0.0040	0.4678
χ^2_{lag}	548.86	p=0.000	2305.07	p=0.000	489.31	p=0.000	45.80	p=0.000
χ^2_{lead}	110.69	p=0.000	807.36	p=0.000	57.40	p=0.000	112.32	p=0.000
$\bar{R}^2$	0.1517	---	0.3243	---	0.4890	---	0.6715	---

Notes: : *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. χ^2_{lag}/ χ^2_{lead} is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.001.

Table 2.18 Regression of 15- or 30-minute TX future raw returns on lags and leads of 15- or 30-minute TW futures raw returns

	15 min				30 min			
	I		II		I		II	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
b_{-5}	0.0249	1.7355	-0.0015	-0.1412	0.0221	0.8165	0.0025	0.1798
b_{-4}	-0.0098	-0.6324	0.0192	1.6710	-0.0381	-1.7982	-0.0027	-0.1902
b_{-3}	0.0104	0.6367	0.0106	0.9292	-0.0506	-2.3703	0.0259	1.4634
b_{-2}	-0.0205	-0.9615	-0.0115	-1.0534	0.0252	0.7270	-0.0236	-1.6739
b_{-1}	0.0219	0.8038	0.0252	2.1408	0.0875	1.0855	0.0237	1.5416
b_0	**0.6870** *	23.6202	**0.8270***	63.8266	**1.0363***	39.8577	**1.0001***	52.992
b_{+1}	0.0280	1.2837	**0.0518***	4.9162	-0.0091	-0.2083	-0.0133	-0.9664
b_{+2}	0.0140	0.6428	0.0100	0.9437	0.0571	2.0898	0.0109	0.7854
b_{+3}	-0.0044	-0.2134	-0.0021	-0.2025	-0.0126	-0.5462	0.0127	0.9121
b_{+4}	-0.0099	-0.5899	-0.0072	-0.6846	-0.0297	-1.0393	-0.0102	-0.6808
b_{+5}	0.0041	0.2786	-0.0020	-0.1850	0.0380	1.1364	0.0069	0.4837
χ^2_{lag}	7.44	0.190	7.82	p=0.166	13.48	p=0.019	7.84	p=0.165
χ^2_{lead}	2.31	0.805	26.13	p=0.000	7.36	p=0.195	2.86	p=0.721
$\bar{R}^2$	0.6536	---	0.8106	---	0.7557	---	0.8637	---

Notes: : *t*-statistics are based on standard errors adjusted for heteroscedasticity using White's (1980) correction. $\chi^2_{lag}/\chi^2_{lead}$ is the χ^2 statistic that tests whether the lag/lead coefficients are jointly zero.
*Significant level at 0.01.

First of all, there is substantial evidence that there is a lead-lag relationship across futures contracts and the leadership is bidirectional. While the TW leads the TX, the TX also leads the TW. Secondly, the leadership is asymmetric for the first period but relatively symmetric for the second period. In 1999 the TW leads the TX four lags but the TX only leads the TW two lags for minutely returns, and the TW leads the TX two lags but the TX only leads the TW one lag for 5-minute returns in 2001. However, the lengths of lead in both directions become the same for 1- and 5-minute returns. The findings are consistent with the transaction costs hypothesis that the TW has the advantage of lower trading costs for Period I but the advantage is diminished for Period II due to tax reduction and liquidity improvement of the TX. However, the results do not confirm Grünbichler, Longstaff and Schwartz's (1994) assertion that screen trading instrument could be the primary market for price discovery. Even though the TW's advantage in trading costs is weakened in the second period, the lead lengths of the TX are not longer lead lengths than those of the TW. The only possible evidence that consists with Grünbichler, Longstaff and Schwartz's (1994) declaration is from 15-minute returns in Table 2.8. The b_{+1} in 2001 is the only significant lead or lag coefficient for 15-minute returns. That means that the TX leads the TW 15 minutes. In spite of this, the lead-lag relation should not be overemphasized since it is trivial compared with the contemporaneous relationship which is much stronger than the leadership. Thirdly, as the TX is relatively immature in 1999, the first lag coefficient (b_{-1}) in minutely returns for the first period is greater than the contemporaneous coefficient. The similar situation can be found in Table 2.8 that the b_0 between the TXI and TW is smaller than the b_{-1} in minutely returns for Period I. Therefore, the TW was the leading market and strongly led the TX and TXI in 1999, but the advantage disappeared in 2001. Finally, none of the lead or lag coefficient for 30-minute returns is significant and the contemporaneous coefficients, which are 1.0363 and 1.0001 for Period I and II, respectively, are very close to 1. According to the Wald coefficient test, the null hypothesis of the coefficient equals to one cannot be rejected[28]. Thus, the lead-lag relationship completely disappears and these two futures contracts are perfectly, contemporaneously correlated for 30-minute returns.

The contemporaneous relationship becomes stronger as the interval enlarged. The b_0, for example, increases from 0.3476 in minutely returns, 0.7477 in 5-minute returns, and 0.8270 in 15-minute returns to 1.0001 in 30-minute returns. The dominant relation is contemporaneous, instead of lead-lag, for intervals greater than 5 minutes. In addition, the $\bar{R}^2$ also grow as the interval widened, suggesting that the correlation between the two markets is higher in larger interval. Moreover, the contemporaneous relationship also grows to be tighter through time. The magnitudes of the b_0 and $\bar{R}^2$ in 1999 are larger than in 2001 for all intervals, indicating that the two markets have become more closely integrated as markets matured.

[28] The χ statistics are 1.9524 and 0.0000 for Period I and II, respectively.

5. Conclusion

In this chapter the lead-lag relations between the intraday cash index and index futures returns, as well as across futures returns over two sample periods, July through December 1999 and April through September 2001, are investigated. Empirical results confirm previous findings that there is an asymmetric lead-lag relation between cash and futures markets— the feedback from the futures markets into the cash market is much stronger than the reverse. Moreover, the weak evidence that the spot index leads the futures diminishes as interval enlarges and the leadership becomes a unidirectional relation that only the futures leads the cash index.

Significant coefficients are not necessarily limited to be positive. The negative futures lead coefficients found on Taiwan markets illustrate that the futures overreact to information and then go back to its equilibrium values with respect to the stock index level. Therefore, the spot returns predict the futures returns in opposite direction.

There is no evidence that the spot index lags futures longer under the short-sales constraints. This may indicate that short selling is not a main approach for informed traders to reflect information. Most of informed traders sell their long positions in portfolios to reflect bad news, instead of short sell shares. Furthermore, the trading of short-sales contains no 'correct' information on the stock market. There seems to be an inverse relationship between these the balance of short-sales and the index prices. When the stock index is rising in the bull market, the balance of short-sales keeps going down, and vice versa. Although short-selling constraint is a reasonable hypothesis to conjecture the lead-lag relationship between the stock index and index futures, there is no evidence to support it from Taiwan markets or any others.

The results from Taiwan markets are basically consistent with the transaction costs hypothesis and the market maturation effects. The leadership of futures markets becomes more significant in Period II, on the other hand, the leadership of the cash market fades away. The stronger contemporaneous coefficients confirm that futures and stock markets become more closely integrated through time as the index futures markets have matured. However, the $\bar{R}^2$ in the second period is smaller than in the first period. It is inconsistent with Stoll and Whaley's (1990) market maturation effects.

The results of lead-lag relationship are not the same under different intervals. Futures returns can lead the cash returns as long as 30 minutes in 30-minute returns data or as short as 5 minutes in 5-minutes returns. However, as the interval widens, the meaningfulness of lag or lead coefficients drops compared with contemporaneous coefficients. Therefore, the lead-lag relationship between the cash and futures markets should not be overemphasized when the contemporaneous relationship is much stronger than the lead-lag relationship.

The evidence of the lead-lag relationship across futures is bidirectional in short intervals. The leadership is asymmetric for the first period but relatively symmetric for the second period. The findings are consistent with the transaction costs hypothesis that the TW had the advantage of lower trading costs for Period I but the advantage is diminished for Period II, but do not confirm Grünbichler, Longstaff and Schwartz's (1994) assertion that screen trading instrument could be the primary market for price discovery. The only possible evidence that consists with Grünbichler, Longstaff and Schwartz's (1994) declaration is from 15-minute returns. In spite of this, the lead-lag relation should not be overemphasized since it is trivial compared with the contemporaneous relationship which is much stronger than the leadership. None of the lead or lag coefficient for 30-minute returns is significant and the contemporaneous coefficients. Thus, the lead-lag relationship completely disappears and these two futures contracts are perfectly, contemporaneously correlated for 30-minute returns.

Chapter Three: Spread Arbitrage between Stock Index Futures in Taiwan: A Cointegration Approach

Abstract

As far as the author is aware, there has been no study on intercommodity spread arbitrage between index futures with highly correlated but different underlying indices. If there are reasons to believe that two futures are virtually the same even though their underlying assets are not exactly the same, and if the stable relationship between them can be found out by modern statistical techniques, then spread arbitrage using these two futures contracts could be a profitable strategy. In this chapter the traditional method of spread trading is evaluated, and the rationale of the index futures spread arbitrage is explained. The empirical results show that the spreads between index futures in Taiwan can be constructed that result in risky arbitrage, and index futures spread arbitrage is profitable by simulation trading.

1. Introduction

The simplest approach to futures trading is to establish either a long or short position; that is, to buy in anticipation of a price increase, or sell in anticipation of a decline. In addition to straight long or short position, another way to trade futures is to construct a spread position. A futures spread position is constructed by taking a long position in one futures contract and a short position in another one simultaneously to exploit temporary disequilibrium between them. Generally speaking, trading spreads is less risky than trading straight positions because both contracts tend to move in the same direction, so most of the market risk is offset by opposite positions. A subset of futures spreads is the intercommodity spreads which are constructed from futures contracts on linked commodities. Some of the studies on intercommodity spreads included: crude oil crack spread (Girma and Paulson, 1999), soybean crush spread (Simon, 1999), energy spark spread (Emery and Liu, 2002), gold-silver spread (Wahab, Cohn, and Lashgari, 1994), and municipal-treasury spreads (Arak, Fischer, Goodman, and Daryanani, 1987).

However, only a few studies have been done on spread trading between index futures contracts. Board and Sutcliffe (1996) reported the only paper on the intermarket spread trading using the Nikkei 225 index futures prices in Osaka, Singapore and Chicago. Since the futures contracts in their study contracts share the underlying index, spreads between them can be constructed that result in a risky arbitrage. Billingsley and Chance (1988) presented the first study on intercommodity spread trading between index futures by investigating spreads between S&P 500 and NYSE futures. Their results showed that stock index futures spreads were efficiently priced. Brenner, Subrahmanyam and Uno (1989) examined the behaviour of Japanese futures markets and found significant departures between the actual prices of the contracts and their theoretical prices. The results suggested that spread trading between the Nikkei Stock Average and the Osaka Stock Futures 50 is profitable. Butterworth and Holmes (1999) simulated intercommodity spread trading between FTSE 100 and FTSE Mid 250 futures contracts from March 1994 to September 1996. However, their simulation trading reported a substantial loss after transaction costs.

As far as the author is aware, there has been no study on intercommodity spread arbitrage between index futures with highly correlated but different underlying indices. If there are reasons to believe that two futures are virtually the same even though their underlying assets are not exactly the same, and if the stable relationship between them can be found out by modern statistical techniques, then spread arbitrage using these two futures contracts could be a profitable strategy.

The purposes of this chapter are 1) to explain the rationale of the index futures spread arbitrage, 2) to demonstrate that spreads between index futures in Taiwan can be constructed that result in risky arbitrage, and 3) to show that index futures spread arbitrage is profitable by simulation trading. If two index futures are good substitutes for each other, they should be priced to the similar fundamental value in efficient markets. If one of the index futures is mispriced, rational investors will take advantage of this mispricing by selling the relatively overpriced contract and simultaneously purchasing the relatively underpriced one to earn a profit and bring them in line. Consequently, their prices will revert to the fundamental value eventually. If two index futures are good substitutes for each other, there should be a long-term equilibrium and the spreads between them should be stationary. Therefore, cointegration tests are suitable to detect the long-term relationship. If the cointegration relationship is found out, trading strategies are designed to exploit the profits according to the mean-reverting property of the spreads between related futures.

The paper is organised as follows. In Section 2, the literature on futures spread trading is reviewed and the traditional method of index futures spread trading is discussed and evaluated. Moreover, the rationale of intercommodity index futures spread arbitrage is developed. Data and methodology are described in Section 3. All tests are based on daily prices. The contract specifications of the four index futures based on the Taiwan stock market are depicted. Cointegration tests and error correction models are used to reveal the long-term relationship and the short-term dynamics between these index futures. The empirical results based on the methodology described in Section 3 are reported in Section 4. In addition, simulation trading strategies are depicted and the simulation results are presented and discussed. Generally speaking, the cointegration relationships are strongly significant between Taiwanese index futures. The simulation results reveal that index futures arbitrage is profitable after transaction costs. This chapter concludes in Section 5 with a summary.

2. Literature Review and the Rationale of Spread Arbitrage between Index Futures

2.1 Literature review

A futures spread position is constructed by purchasing a long position in a futures contract and selling a short position in another one simultaneously to exploit the temporary disequilibrium between them. A spread trader anticipates making a profit from correctly predicting the relative price movements between two futures contracts. In general, trading spread is less risky than trading straight positions because both contracts tend to move in the same direction, so most of the market risk is offset by opposite positions. Futures spreads can be divided into three varieties: *intermonth*, *intermarket* and *intercommodity*. *Intermonth* or *calendar* spread consists of offsetting positions in two or more maturities of the same futures contract. For example, a spreader buys a March and sells a June FTSE-100 futures. Such spreads represent speculation on the basis which is the difference between the futures price and the cash price. *Intermarket* spread is made up of offsetting positions in different futures markets but the same commodity, usually in the same delivery month. An intermarket spread, for instance, can be constructed between the Nikkei 225 index futures in Osaka and Singapore. As the two futures have the same delivery date, they must both have the same value of the underlying index at delivery. In fact, such spread trading results in spread arbitrage (Board and Sutcliffe, 1996). *Intercommodity* spread involves different commodities, whether in the same delivery month or not. Not all such combinations can be considered as spreads. There must be a reasonable linkage in the prices of the two commodities, and the linkage must be direct for a spread to be a recognised spread. Recognised intercommodity spreads include corn versus wheat, soybeans versus end products (oil and meal), gold versus silver, T-bills versus T-bonds, and lumber versus plywood. The common thread running through such spreads is that each set of long and short positions are affected by the same factors of supply and demand (Herbst, 1992, p.31).

The literature on intercommodity spreading trading is not extensive owing to the complexity of the intercommodity spread relationships. Intercommodity futures spreads are often constructed through a production process. Refiners and processors use these spreads to deal with operating risk, while arbitrageurs use them to get profits when the commodity prices falls outside the no-arbitrage conditions implied by the production process. Girma and Paulson (1999) investigated the petroleum crack spread among crude oil, unleaded gasoline and heating oil futures and found the spreads among these three futures are stationary. This suggests that the crack spreads will not deviate without bounds and will revert to the normal levels. The moving average and the corresponding standard deviation were used as a basis for trading strategies to identify risk arbitrage opportunities in crack spreads. The average profits were statistically significant. Simon (1999) studied the soybean crush spread among soybean, soybean meal and soybean oil traded at the Chicago Board of Trade from 1985 to 1995. The long-run equilibrium of the soybean crush spread was characterised by strong seasonality and by a persistent uptrend in soy meal and soy oil prices relative to soybean prices. Simulations based on 5-day moving average demonstrated that the soybean crush spread arbitrage is profitable. Emery and Liu (2002) analyzed the relationship between electricity futures prices and natural-gas futures prices. The spark spread is defined as the gross-generation profit margin earned by buying natural gas and burning it to produce electricity. There was a statistically significant tendency for the spark spread to revert to the long-term equilibrium. Simulations results showed that spark spread arbitrage is profitable in both in-sample and out-of-sample tests.

Other studies on spread trading or arbitrage included: gold-silver spread (Wahab, Cohn, and Lashgari, 1994), wheat (Booth, Brockman, and Tse, 1998), gold and T-bill spreads (Monroe and Cohn, 1986), municipal-treasury spreads (Arak, Fischer, Goodman, and Daryanani, 1987), treasury futures spreads (Park and Switzer, 1996), and government bonds (D'amato and Pistoresi, 2001). However, little research has been done on the spread trading between index futures contracts. The only research examining *intermarket* spread trading (arbitrage) between index futures was reported by Board and Sutcliffe (1996). As mentioned above their study focused on two futures contracts with the same underlying index. The first study on *intercommodity* spread trading between index futures was presented by Billingsley and Chance (1988). They investigated spreads between S&P 500 and NYSE futures. While the results showed that futures prices significantly deviated from theoretical prices, most were well within transaction cost boundaries. This implied that stock index futures spreads were efficiently priced. Brenner, Subrahmanyam and Uno (1989) examined the behaviour of the Nikkei Stock

Average (NSA) on the Singapore International Monetary Exchange (SIMEX) and the Osaka Stock Futures 50 (OSA 50) on the Osaka Securities Exchange (OSE) from 1987 to 1988. They found significant departures between the actual prices of the contracts and their theoretical prices. This suggested spread trading between the NSA and the OSF 50 is profitable. Butterworth and Holmes (1999) adopted the same method proposed by Brenner, Subrahmanyam and Uno (1989) to simulate intercommodity spread trading between FTSE 100 and FTSE Mid 250 futures contracts from March 1994 to September 1996. However, their results were unsatisfied. 166 spread trading opportunities were found in the sample period but the simulation yielded £15983 loss, or £96 per trade in average, after transaction costs.

As far as the author is aware, there has been no documented empirical or theoretical work on intercommodity spread arbitrage between index futures with different underlying indices. If there are reasons to believe that two futures are virtually the same even though their underlying assets are not exactly identical, and if the stable relationship between them can be discovered by modern statistical techniques, then spread arbitrage using these two futures contracts could be a profitable strategy. The rationale of intercommodity spread arbitrage between index futures will be introduced in Section 2.3.

2.2 The traditional method of the index futures spread trading and its faults

The method of index futures spread trading, adopted by Billingsley and Chance (1988), Brenner, Subrahmanyam and Uno (1989) and Butterworth and Holmes (1999), was based on the relative deviations of futures prices from their theoretical prices[29]. According to the cost-of-carry model, the theoretical price of an index futures can be defined as:

$$FP_{i,t} = S_{i,t}e^{(r_i - d_i)(T_i - t)}$$

where FP_t is the fair price of the index futures, S_t is the cash index at time t, i is the individual futures contract, r is the risk-free interest rate, d is the dividend yield rate, and, therefore, r - d is the net cost of carrying the underlying shares in the index.

[29] In fact, Board and Sutcliffe's (1996) study was also based on the same method but they consider futures denominated in different currencies in their model.

However, the fair price is determined on the assumption that markets are frictionless, that is, there are no taxes or transaction costs and all market participants have the same access to the risk-free interest rate. In the presence of market friction, the futures price is usually deviated from the fair price implied by the cost-of-carry model. The mispricing of futures price from its fair price can be normalised as follows:

$$M_{i,t} = \frac{F_{i,t} - FP_{i,t}}{FP_{i,t}}$$

where the M_t is the normalised mispricing and F_t is the actual futures price.
If two related futures have a common expiry date, futures pricing in both contracts will converge towards their fair prices eventually. So, the mispricing and the spread mispricing differential (M_{1t} - M_{2t}) at expiration are zero and the future direction of the spread mispricing series is known with certainty. When the mispricing differential of two linked futures is greater than transaction costs, i.e., $M_{1t} - M_{2t} > TC$, a spread position is initiated, i.e. a long position in the underpriced contract with a simultaneous short position in the overpriced one, to make profit from the convergence of futures prices to their fair prices.

The defect of the traditional method is the relative market movements in the underlying indices may be unpredictable. The futures spread ($F_{1,t} - F_{2,t}$) can be decomposed into two parts: the mispricing differential $[(F_{1,t} - FP_{1,t}) - (F_{2,t} - FP_{2,t})]$ plus the fair prices differential ($FP_{1,t} - FP_{2,t}$). The traditional method only takes account of mispricing differentials $[(F_{1,t} - FP_{1,t}) - (F_{2,t} - FP_{2,t})]$ but ignores the possible effects of changes in fair prices differential ($FP_{1,t} - FP_{2,t}$) on futures spreads. Assuming the interest rate, the dividend yield rate and time to expiration are known in advanced, the only variables in the fair prices differential are the underlying cash indices according to the cost-of-carry model. If the two index futures share the same underlying index ($S_1 = S_2$) and delivery day, e.g. Nikkei 225 in the study of Board and Sutcliffe (1996), there is no fair prices differential ($FP_{1,t} = FP_{2,t}$ or $FP_{1,t} - FP_{2,t} = 0$) at any time and therefore the futures spread is equal to the mispricing differential which will become zero at futures' expiration by definition. In this case, there is no risk of relative market movements and the traditional method could be a profitable strategy as long as the mispricing differential is bigger than transaction costs. On the other hand, if their underlying assets are not the same ($S_1 \neq S_2$), and the relative movements of S_1 and S_2 may be unstable, the futures spreads may shrink back if $FP_{1,t}$ - $FP_{2,t}$ is convergent, or extend further if $FP_{1,t}$ - $FP_{2,t}$ is divergent, during the lifetime of the futures contracts. In this situation, the spread trader, who employs the traditional method, is subject to the uncertainty caused by unexpected relative market movements. If the underlying indices keep moving away from each other, then futures spread trading may involve substantial loses, instead of profits as anticipated. The divergence of the price movements of the cash indices is the reason why Butterworth and Holmes's (1999) simulation was profitless after transaction costs. Such a spread trading is risky and represents speculation on the spread, rather than arbitrage.

2.3 The rationale of intercommodity index futures spread arbitrage

One of the fundamental concepts in finance is the EMH. Market efficiency has been defined by Jensen (1978) as "a market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t." The basic theoretical case for the EMH rests on three assumptions. First of all, investors are assumed to be rational and therefore to evaluate securities rationally. When investors are rational, they evaluate each security for its fundamental value: the net present value of its future cash flows, discounted using their risk characteristics. When investors find out changes in the fundamental values of securities, they quickly respond to the new information by bidding up prices when the news is good and bidding them down when the news is bad. Consequently, security prices incorporate all the available information almost immediately and prices adjust to new levels corresponding to the new net present values of cash flows. Secondly, to the degree that some investors are not rational, their trades are random and therefore cancel each other out without affecting prices. Third, even though investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices. Assume that a share is overpriced in a market relative to its fundamental value owing to correlated purchases by irrational investors. Being aware of this overpricing, rational investors, or arbitrageurs, would sell or even sell short this pricey security and simultaneously purchase other essentially similar securities to hedge their risks. If such substitute securities are available and arbitrageurs are able to trade them, they can earn a profit, since they are short expensive securities and long the same, or very similar, but cheaper securities. In point of fact, if arbitrage is quick and effective enough, the price of a security can never get far away from its fundamental value, and indeed arbitrageurs themselves are unable to earn much of an abnormal return. A similar argument applies to an undervalued security. Arbitrage plays a critical role in the analysis of securities markets, because its effect is to bring prices to fundamental values and to keep markets efficient even when some investors are not fully rational and their demands are correlated, as long as securities have close substitutes.

A necessary condition for arbitrage is the availability of an exact or close substitute for a security. Without a substitute, even though the rational investors observe the mispriced securities, they cannot bring the security prices in line with their fundamental values. Shleifer (2000) defines that an exact substitute for a given security is another security, or portfolio of securities, with identical cash flows in all states of the world; a close substitute is a security or portfolio with very similar cash flows in all states of the world, and therefore with similar risk characteristics to those of a given security (Shleifer, 2000, p.8-9). Therefore, the searching for a substitute is a primary task for an arbitrageur. It may require sophisticated computation to identify an exact or close substitute to a given security or portfolio, but not to a market portfolio. An index futures is an exact substitute for its underlying cash index because the price of the index futures is principally determined by the price of the corresponding cash index. In the case of index arbitrage, when the mispricing between the spot index and index futures is greater than a certain degree, arbitrageurs will sell the relatively overpriced instrument and simultaneously buy the relatively underpriced one to earn a profit and bring these two securities in line.

The underlying cash index is not the only substitute for an index future. There are three possibilities that an index futures could be a substitute for another. First of all, if two or more futures share the same index but are traded in different markets or denominated in different currencies, they are close substitutes for each other. For example, the Nikkei 225 index futures traded in Osaka, Singapore and Chicago have the same final settlement value of the index even though their denominated currencies are not the same. Spreads between such index futures can be constructed that result in a risky arbitrage. Since these futures share the same underlying index, arbitrage opportunities can be easily recognised on the screen. Given the much lower costs of trading futures rather than the basket of shares in the index, it is likely that the prices of two index futures will be kept in line through spread arbitrage, rather than by trading the underlying shares (Board and Sutcliffe, 1996).

Secondly, it is possible that two index futures have different underlying assets but these cash indices virtually represent the same market. In this case, these futures could be good substitutes for each other. For instance, the underlying index of the MSCI Taiwan Index Futures (TW) is the MSCI Taiwan Index which includes a representation sampling large, medium and small capitalisation companies, taking into account the stock liquidity. On the other hand, the underlying index of the Taiwan Stock Index futures (TX) is the Taiwan Stock Exchange Capitalisation Weighted Stock Index which includes all shares listed on the Taiwan Stock Exchange. Although the underlying indices of TW and TX are not identical, they both represent the national market and therefore they can be considered as the same. In portfolio management, it is not necessary to purchase all shares in the market to track the index and to eliminate the unsystematic risk. Several studies[30] have shown that it is possible to get most of the benefits of diversification with a portfolio consisting of only a certain number of stocks. Further spreading of the portfolio's assets does not obtain the benefit of risk reduction but involve high transaction costs. Therefore, although the MSCI Taiwan Index only consists of 90 shares, it is a well-diversified portfolio and could resemble the market portfolio. The MSCI states that to construct an MSCI Country Index, every listed security in the market is identified, and data on its price, outstanding shares, significant owners, free float, and monthly trading volume are collected. The securities are then organised by industry group, and stocks are selected, targeting 60% coverage of market capitalisation. Selection criteria include: size, long- and short-term volume, cross-ownership and float. By targeting 60% of each industry group, the MSCI index captures 60% of the total country market capitalisation while maintaining the overall risk structure of the market — because industry, more than any other single factor, is a key characteristic of a portfolio or a market[31]. Although The MSCI Taiwan Index is compiled to represent the national market by certain rigid criteria, it is not guaranteed that the performance and risk structure of the compiled index will align with the

[30] Evans and Archer (1968) concluded that approximately ten shares will make a diversified portfolio; however, Statman (1987) showed that at least thirty stocks are needed for a well-diversified portfolio.
[31] Information source: http://www.msci.com/methodology/index.html

national market. For that reason, the MSCI Equity Indices are quarterly rebalanced to maintain with the objective of reflecting, on a timely basis, the evolution of the underlying equity markets[32]. The quarterly rebalancing is an important mechanism to align the MSCI Taiwan Index with the national market. Consequently, The MSCI Taiwan index keeps tracking the performance of the Taiwan stock market in the long-run. Hence, TX and TW may be good substitutes for arbitrage activities albeit their underlying indices are measured in different scales.

Finally, if the combination of two or more index futures' underlying assets is approximately equal to another futures' underlying index, then these futures may be each other's close substitute for spread arbitrage. In addition to TX, there are two more index futures traded in Taiwan Futures Exchange, i.e. the electronics sector index futures (TE) and the banking & insurance sector index futures (TF). The shares in electronics and financials sectors represent about 80% of the total country market capitalisation, so in a well-diversified portfolio most of the shares should be from electronics or financials sectors. Thus, when investors holding well-diversified portfolio in the stock market need futures to eliminate systematic risk, the difference between TX and the combination of TE and TF is trivial. What matters is which one may produce better outcome for traders. Hedgers would choose relatively overpriced futures to hedge share long positions to increase their profits. So, the relatively overpriced contract(s) will be bidden down. Index arbitrageurs would initiate long (short) position on the underpriced (overpriced) futures relative to the cash index to cover their corresponding positions in the stock market. Hence, the futures with a relatively low price will be bidden up and those with a relatively high price will be bidden down. Also, speculators would choose cheaper instrument to establish long position or expensive one for short position. Consequently, market force from all kinds of traders narrows the relative price differential between these three futures contracts and brings them into line.

If two or more futures are good substitutes for each other, short-term deviations from their fundamental value are temporary and market forces will push them toward the fundamental value. Whether there exists a long-term relationship between futures can be detected by cointegration test. If the linear combination of integrated variables is

[32] MSCI Methodology Book: MSCI Enhanced Methodology (2002), p. 17

stationary, such variables are said to be cointegrated. This implied that there is an equilibrium relationship among them and their stochastic trends must be linked. On the other hand, if the linear combination of nonstationary variables is still nonstationary, there is no long-term equilibrium among them, so they can wander arbitrarily far from each other (Enders, 1995, p.355-359). Therefore, if two or more futures are good substitutes for each other in the arbitrage activities, they should be cointegrated. The spreads, derived from the residuals in the cointegrated relationship, between these futures should be mean reverting and then any short-term deviations will return to the long-term equilibrium value. Consequently, the cointegration approach is employed to identify whether an intercommodity spread can be constructed as a risky arbitrage or merely a risky speculation. If two or more index futures prices are cointegrated, trading the spread between them is equivalent to spread arbitrage. On the other hand, if they are not cointegrated, trading the spread is actually speculating the spread. As the cointegration relationship between index futures prices is discovered, it is possible to develop spread trading strategies to make profits.

3. Data and Methodology

3.1 Data

The variables used in this study are daily closing prices of the four index futures contracts based on the Taiwan stock market. The first one is the MSCI Taiwan Index Futures (TW) traded in the Singapore Exchange (SGX-DX). The underlying cash index of TW is the MSCI Taiwan Index which includes a representation sampling large, medium and small capitalisation companies, taking into account the stock liquidity. In September 1997, the index captured 62.93% of the total country market capitalisation and 77 stocks were chosen to compile the index. The inclusion weight of the MSCI Taiwan Index has increased to 80% of the total country market capitalisation and selected shares have grown to 90 since November 2000. The second index futures is TX traded in the Taiwan Futures Exchange (TAIFEX). The underlying index of TX is Taiwan Stock Exchange Capitalisation Weighted Stock Index (TXI) which includes all shares listed on the Taiwan Stock Exchange (TSE). The last two index futures are TE and TF which are traded in the TAIFEX as well. Their underlying assets are the TSE Electronics Sector Index and the TSE Banking & Insurance Sector Index, respectively. Daily closing data of TW have been collected from the SGX-DT and those of TX, TE and TF from the TAIFEX. The contract specifications of these futures are showed in Table 3.1. The sample period was from the first trading day of TE and TF, which was 21 July 1999, to 30 April 2002. The period contained 713 observations. However, a problem of daily closing data is that the futures contracts in the TAIFEX and in the SGX-DX were not closed at the same time. The three contracts trading in the TAIFEX were closed at 12:15 pm before 31 December 2000 and at 1:45 pm after 1 January 2001. On the other hand, the closing time of TW has been changed several times. It was closed at 12:15 pm before 4 Apr 2000; at 1:15 pm between 5 April and 25 June; and at 12:45 pm from 26 June to 31 December 2000. The closing time has been extended to 1:45 pm since Jan 1 2001 which is the same with contracts in the TAIFEX. For the purpose of synchronisation, the last transaction prices of TW occurring before the end of 12:15 pm are substituted for the actual closing prices for the period from 5 April 2000 to 31 December 2000. Moreover, in order to get the cointegration coefficients for the spread ratios, data used for regression are the series of the market value of the futures contract, instead of the price levels. The market value is equal to the price multiplied by the contract multiplier and the exchange rate when applicable.

Table 3.1 Contract specifications of the four index futures in Taiwan markets

Futures contract	TW	TX	TE	TF
Exchange	SGX-DT	TAIFEX		
Underlying Index	MSCI Taiwan Index	TXI	TSE Electronics Sector Index	TSE Banking & Insurance Sector Index
Constituents	90 selected shares listed in the TSE	All shares listed in the TSE (500+)	190 electronics sector shares	48 banking & insurance sector shares
Capitalisation Weight	80%	100%	62.4%	16.2%
Denominated currency	U.S. Dollar	New Taiwan Dollar		
Minimum Price Fluctuation	0.1 index points =US$10	1 index point =NT$200	0.05 index point =NT$200	0.2 index point =NT$200
Contract size	TW points × US$100	TX points × NT$200	TE point × NT$4,000	TF point × NT$1,000

3.2 Methodology

Cointegration tests are employed to find out the long-term relationships between index futures prices in Taiwan. If these index futures are found to be cointegrated, then the spreads derived from the cointegrating vectors are stationary. This suggests that the spreads will not deviate without bounds and will revert to the equilibrium level in the long-run. In contrast, if the futures prices are not cointegrated, then the spreads can meander without limits and trading these spreads may be quite risky and not profitable. Therefore, when the cointegration relationships between index futures prices are found, it is possible to set up trading strategies by using statistical tools such as the standard deviation for determining extremes.

The necessary conditions for index futures prices to be cointegrated are: 1) each series must be nonstationary at price level, and 2) they have the same order of integration. Therefore, the test for cointegration requires first testing for unit roots in each series and then determining whether they are cointegrated. A series is called stationary if its mean and variance are constant and its covariance is independent of time[33]. On the other hand, if a series is expressed as a first order autoregressive or AR(1) process:

$$Y_t = \theta Y_{t-1} + \varepsilon_t \tag{3.1}$$

with $\theta = 1$, it is said to be integrated of order one, denoted $I(1)$ and is nonstationary[34] with a unit root, usually referred to as a random walk. The augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) is used to test for unit roots:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta Y_{t-i} + \varepsilon_t \tag{3.2}$$

where Y is the futures prices series, $\Delta Y_t = Y_t - Y_{t-1}$, and n is the number of lags selected to be large sufficient to remove autocorrelation in the residuals ε_t and ensure that ε_t are white noise. The null hypothesis of the ADF test is that the series Y_t follow a unit root H_0: $\beta = 0$, against H_1: $\beta < 0$. The rejection of H_0 implies that the series is stationary.

If all index futures are $I(1)$ and follow unit roots, they are examined then to determine whether they are cointegrated. In general, linear combinations of $I(1)$ variables will also be $I(1)$, but if they happen to be $I(0)$, the variables are said to be cointegrated, and there exists a representation of an error correction model (ECM) among the cointegrated variables (Engle and Granger, 1987). The cointegration among index futures prices implied that there exists long-term equilibrium among them, and any short-term deviations have tendency to move toward the long-term equilibrium through the error correction mechanism (Granger, 1986). The main idea behind cointegration is a specification of models that include beliefs about the movements of variables relative to each other in the long-run. Thus, a common stochastic trend(s) in a system of index futures prices can be interpreted to mean that the stochastic trend in one index futures price is related to the stochastic trend in some other index futures price. There exists more than one method of conducting cointegration tests. The long-run relationship tests in this paper are conducted by means of the method developed by Johansen (1988) and Johansen and Juselius (1990). This procedure provides more robust results when there are more than two variables (Gonzalo, 1994) and when the number of observations is greater than 100 (Hargreaves, 1994). The Johansen maximum likelihood approach sets up a vector autoregression (VAR) representation of a vector of nonstationary variables:

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[33] This is referred to as weak stationarity. A series is said to be strictly stationary if its properties of the entire distribution are unaffected by a change of time origin. Details see Verbeek (2000), pp. 226-229

[34] In fact, (3.1) describes a nonstationary process for any value of θ with $|\theta| \geq 1$.

$$\Delta Y_t = c + \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim NID(0, \Sigma) \tag{3.3}$$

where Y_t is an $n \times 1$ vector of $I(1)$ variables, Γ is an $n \times n$ coefficient matrix, and c is an $n \times 1$ constant vector, and ε_t is an $n \times 1$ vector of white noises with zero mean and finite variance. The coefficient matrix Π incorporates information about the cointegration relationship among the variables in Y_t. The information on the coefficient matrix between the levels of the series Π is decomposed as $\Pi = \alpha\beta'$ where the relevant elements of the α matrix are the speed of adjustment coefficients and the β matrix contains the cointegrating vectors. The Π matrix must have reduced rank of r, $r < n$, when the system is cointegrated. If there exists no long-run equilibrium among the variables in Y_t, then Π will be the null matrix and have zero rank and (3.3) reduces to a standard first differenced VAR. If Π has full column rank, then all variables are stationary prior to differencing. The likelihood ratio trace test statistic for the hypothesis of at most r cointegration relationship and at least $n - r$ common trends is given by

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

where T is the sample size and the $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$ are the eigenvalues of squared canonical correlation between two residual vectors from level and first-difference regressions. The Johansen maximum eigenvalue test of the null hypothesis that there are exactly r cointegration relationships against $r + 1$ is

$$\lambda_{\max} = -T \ln(1 - \hat{\lambda}_{r+1}).$$

Cointegration also implies that the transitory components of the series can be given a dynamic error-correction representation, i.e., a constrained error-correction model can be applied that captures the short-run dynamic adjustment of cointegrated variables (Engle and Granger 1987). In an ECM, the short-term dynamics of the variables in the system are influenced by the deviation from equilibrium. In the present context the following representation is implied:

$$\Delta Y_t = c + \alpha \hat{e}_{t-1} + A(L)\Delta Y_t + u_t \tag{3.4}$$

where c is an $n \times 1$ vector of constant terms, α is a matrix of speed of adjustment coefficients, $\hat{e}_{t-1}$ is the error-correction term from the cointegration relationship, and $A(L)$ is a matrix of finite order lag polynomials.

The third term on the right-hand side of (3.4) represents the short-term dynamics between the left-hand side index futures and the other futures. The disequilibrium adjustment of each variable towards its long-run equilibrium value is then captured by the lagged error-correction term, ε_{t-1}, with the coefficient on this term in each individual equation depending on the speed of adjustment of the variable towards its long-run equilibrium value. At least one of the speed of adjustment coefficients must be nonzero. If all elements in the matrix $\boldsymbol{\alpha}$ are equal to zero, the long-term equilibrium relationship does not appear and the model is not one of the error correction or cointegration (Enders, 1995, p.367).

If the cointegration relationship can be found between futures prices, the normalised cointegrating coefficients are used to generate spreads between these futures prices. The formula to calculate spreads can be expressed as follows:

$$Spread_t = \beta_1 F_{1,t} - c - \sum_{i=2}^{n} \beta_i F_{i,t} \qquad (3.5)$$

where F_i are futures prices, β_i are the normalised cointegrating coefficients and $\beta_1 = 1$. The spreads computed by (3.5) are used for the trading simulation of the index futures spread arbitrage. Negative spread represents that F_1 is underpriced relative to the other futures. In contrast, positive spread signifies that F_1 is overpriced compared with the other contract(s). In both cases, spread arbitrage is constructed by purchasing the relatively underpriced futures and selling the relatively overpriced one(s). The spread ratio in the trading strategies is the ratio of the normalised cointegrating coefficients, 1: β_2 in the case of two variables or 1: β_2: β_3 in the case of three variables. However, most of the estimated coefficients are not integers but futures only can be traded in unities. Therefore, the coefficients are adjusted to round numbers. If the spread is zero or near zero, that means these futures are in equilibrium so the arbitrage opportunities do not exist. If the spread is much different from zero, then these futures are in disequilibrium and it is possible to earn a profit by trading spread. Details of the trading rules will be outlined in Section 4.2.

4. Empirical Results

4.1 Unit root tests, cointegration tests and the error correction models

Since the prerequisite of cointegration is that all variables must be nonstationary at price levels and have the same order of integration, the ADF tests are employed to check the orders of integration for the price series of index futures first. The results of unit root tests are presented in Table 4.1. The number of lagged terms is chosen according to the Akaike information criterion (AIC) to remove any serial correlation in the residuals. It is assumed that there is a constant and a linear time trend in the data generation process[35]. Tests for the presence of a unit root in the levels of each series fail to reject the null hypothesis of a unit root at the 1% critical value. Therefore, all index futures in Taiwan are nonstationary $I(1)$ processes. On the contrary, the null hypothesis of a unit root is rejected for the first-order differences of each series at the 1% significance level. Thus, the differences of prices series are stationary $I(0)$ processes.

Table 3.2 ADF unit root tests

Variable	TX	TW	TE	TF
Level				
ADF	-1.58	-1.78	-1.75	-2.30
First difference				
ADF	-13.91**	-19.25**	-17.90**	-14.50**
Lag	2	1	1	2

Notes: The critical values are available in MacKinnon (1991).
** Significant at 0.01

As indicated by the rationale in Section two the four futures contacts in Taiwan are arranged into two groups, TX and TW (Group I), and TX, TE and TF (Group II), to test the cointegration relationship between index futures prices in each group[36]. Panel A and B of Table 3.3 demonstrate the results of cointegration tests for Group I and II, respectively, and the normalised cointegrating vectors are showed in Panel C. The trace

[35] Removing the constant and/or a trend term does not change the results qualitatively.
[36] Another way to examine the cointegration relationships is testing the cointegration relationships among these four futures contacts, and then imposing restrictions on the cointegrating vectors to see whether the restrictions are binding. The results are reported in Appendix A.

tests in Panel A reject the null hypothesis of no cointegration ($r = 0$) at 1% significance level but fails to reject the other null hypothesis that there is at most one cointegrating vector ($r \leq 1$). The maximum eigenvalue tests produce similar results. The null hypothesis of $r = 0$ is rejected at 1% significance level in favour of the alternative $r = 1$. The other null hypotheses of $r = 1$ versus $r = 2$ is not rejected. Therefore, TX and TW are cointegrated with one cointegrating vector. In Panel B the trace statistics reveal that the null hypothesis of $r = 0$ is rejected at 1% significance level but the other null hypotheses, $r \leq 1$ and $r \leq 2$, are not rejected. The maximum eigenvalue tests confirm the results from the trace tests. The null hypothesis of $r = 0$ is rejected at 1% significance level in favour of the alternative $r = 1$. All other null hypotheses, $r = 1$ versus $r = 2$ and $r = 2$ versus $r = 3$ are not rejected. Consequently, the result suggests that there is a cointegrating vector among TX, TE and TF.

Table 3.3 Johansen cointegration tests

Panel A: Group I (TX and TW)							
		Critical Values				Critical Values	
H_0	Trace	5 %	1 %	H_0	Max-Eigenvalue	5 %	1 %
$r = 0$	**39.18****	19.96	24.60	$r = 0$	**36.73****	15.67	20.20
$r \leq 1$	2.45	9.24	12.97	$r = 1$	2.45	9.24	12.97
Panel B: Group II (TX, TE and TF)							
		Critical Values				Critical Values	
H_0	Trace	5 %	1 %	H_0	Max-Eigenvalue	5 %	1 %
$r = 0$	**44.51****	34.91	41.07	$r = 0$	**32.38****	22.00	26.81
$r \leq 1$	12.13	19.96	24.60	$r = 1$	9.97	15.67	20.20
$r \leq 2$	2.16	9.24	12.97	$r = 2$	2.16	9.24	12.97

Panel C: Normalised cointegrating vector				
Group I	TX	C	TW	
Coefficient	1.000000	464671.9	-1.852167	
Group II	TX	C	TE	TF
Coefficient	1.000000	117791.3	-0.632680	-0.713472

Note: ** Significant at 0.01

However, when there are three or more variables in a cointegration system with one cointegrating vector, it would be better to examine the significance of cointegrating coefficients further. When two variables are cointegrated, adding any third $I(1)$ variable in the system can still form a cointegration relationship. Since rank of the cointegrating matrix (**Π**) is reduced in a system with two cointegrated variables, if any third $I(1)$

variable is put into the system, the rank of the cointegrating matrix is still reduced and these three variables are showed to be cointegrated according to the trace and the maximum eigenvalue tests, although the third variable might be not cointegrated with the other two. Therefore, when the cointegration test involves three or more variables and the test results reveal that there is a cointegrating vector, the cointegration relationship should be further examined by testing the significance of the cointegrating coefficients. If one of the coefficients is not significantly different from zero, then the cointegration relationship should be re-estimated after dropping the insignificant variable. The method to do this is to impose zero restrictions on the cointegrating coefficients individually and test whether the restrictions are binding. The tests that $\beta_i=0$ entail one restriction on one cointegrating vector; hence, the likelihood ratio (LR) test[37] has a χ^2 distribution with one degree of freedom in a large sample. Table 3.4 reports the restricted log-likelihood functions, the LRs and the *p*-values. It is clear that all the LRs are significant at the 1% level, therefore the null hypotheses that $\beta_i = 0$ are rejected and TX, TE and TF are indeed formed a cointegrated system. The existence of one cointegrating vector implies that there are two common trends (unit roots) that drive the movement of futures prices of Group II over time. In other words, in Group II there is one direction where the variance is finite (i.e. stable) and two directions in which the variance is infinite (since the variance of a unit root is infinite). Since the index futures in each Group are cointegrated, they are good substitutes for each other in the arbitrage activities and then it is possible to perform futures spread arbitrage using these cointegrated futures contracts.

Table 3.4 Likelihood ratio tests of zero restrictions on cointegrating coefficients

H_0	$\ln LR$	$\lambda \xrightarrow{d} \chi^2(1)$	*p*-value
$\beta_{TX}=0$	-10909.953	19.634**	0.0000
$\beta_{TE}=0$	-10909.994	19.716**	0.0000
$\beta_{TF}=0$	-10912.067	23.862**	0.0000

Notes: The unrestricted log-likelihood is -10900.136.

** Significant at 0.01

[37] The LR test statistic $\lambda = -2(\ln L_R - \ln L_U)$, where $\ln L_R$ and $\ln L_U$ denote the restricted and the unrestricted log-likelihood function, respectively.

Since the cointegration relationship can be found in Group I and II, there must exist a representation of an ECM which reveals both long and short run dynamics among futures markets among the cointegrated variables. The equation forms of the ECM for Group I and II are illustrated in (3.6) and (3.7), respectively.

$$\Delta TX_t = c_1 + \alpha_{TX}\hat{e}_{t-1} + \sum_{i=1}^{k} b_{1,i}\Delta TX_{t-1} + \sum_{i=1}^{k} b_{2,i}\Delta TW_{t-1} + u_{1,t} \quad (3.6\text{ a})$$

$$\Delta TW_t = c_2 + \alpha_{TW}\hat{e}_{t-1} + \sum_{i=1}^{k} b_{1,i}\Delta TX_{t-1} + \sum_{i=1}^{k} b_{2,i}\Delta TW_{t-1} + u_{2,t} \quad (3.6\text{ b})$$

$$\Delta TX_t = c_1 + \alpha_{TX}\hat{e}_{t-1} + \sum_{i=1}^{k} b_{1,i}\Delta TX_{t-1} + \sum_{i=1}^{k} b_{2,i}\Delta TE_{t-1} + \sum_{i=1}^{k} b_{3,i}\Delta TF_{t-1} + u_{1,t} \quad (3.7\text{ a})$$

$$\Delta TE_t = c_2 + \alpha_{TE}\hat{e}_{t-1} + \sum_{i=1}^{k} b_{1,i}\Delta TX_{t-1} + \sum_{i=1}^{k} b_{2,i}\Delta TE_{t-1} + \sum_{i=1}^{k} b_{3,i}\Delta TF_{t-1} + u_{2,t} \quad (3.7\text{ b})$$

$$\Delta TF_t = c_3 + \alpha_{TF}\hat{e}_{t-1} + \sum_{i=1}^{k} b_{1,i}\Delta TX_{t-1} + \sum_{i=1}^{k} b_{2,i}\Delta TE_{t-1} + \sum_{i=1}^{k} b_{3,i}\Delta TF_{t-1} + u_{3,t} \quad (3.7\text{ c})$$

where α is the speed of adjustment coefficient, $\alpha_{TX} \leq 0$, α_{TW}, α_{TE} and $\alpha_{TF} \geq 0$, $\hat{e}_{t-1}$ denotes the lagged error-correction term from (3.3), and b_1, b_2 and b_3 represent the short-run dynamics among markets.

Panel A and B of Table 3.5 present the results of the ECM of Group I and II, respectively. In Panel A while the speed of adjustment coefficient (α) of TW is not significant, the coefficient of TX is significant at the 5% level. That means in Group I only TX responds to the previous period's deviation from equilibrium. Furthermore, as indicated by TX's α, the half-life[38] of the response of TX price to a random shock is 18 days, suggesting a slow adjustment process. Moreover, the short-run feedback relationships only exist between the changes in the price levels and their own lagged terms; the cross-market terms are insignificant. So, the source of causality running from TW to TX is only generated by the cointegration relationship in the daily price levels. In Panel B the speed of adjustment coefficients of TE and TF are significant at the 5% level but the coefficient of TX is insignificant, suggesting TX does not respond to the previous period deviation from equilibrium but TE and TF do in Group II. The half-lives of TE and TF are 7 and 10 days, respectively, indicating the adjustment process in

[38] The half-life is defined as $\ln(2)/\ln(1+\alpha)$ (Madhavan and Smidt, 1993) which represent the expected number of days required for a deviation returned to the long-term equilibrium by 50 percent.

Group II is faster than in Group I. Concerning the short-run dynamics among markets, all the lagged terms in (3.7 a) and (3.7 c) are insignificant; the only two significant coefficients are $b_{1,1}$ and $b_{3,1}$ in Equation (3.7 b), that means there exist unidirectional lead-lag relationships from TX and TF to TE.

Table 3.5 Estimated coefficients of the error correction models

Panel A

		α	$b_{1,1}$	$b_{2,1}$
ΔTX_t	coef	**-0.0391***	**-0.1699***	0.1531
	std	0.0190	0.0971	0.1209
	t-stat	-2.0630	-1.7506	1.2655
ΔTW_t	coef	0.0022	0.0549	**-0.1741***
	std	0.0152	0.0777	0.0969
	t-stat	0.1420	0.7062	-1.7966

Panel B

		α	$b_{1,1}$	$b_{1,2}$	$b_{2,1}$	$b_{2,2}$	$b_{3,1}$	$b_{3,2}$
ΔTX_t	coef	0.0348	-0.1052	-0.0657	0.1339	0.0418	-0.1429	0.1589
	std	0.0480	0.1392	0.1437	0.0883	0.0904	0.0953	0.09719
	t-stat	0.7240	-0.7551	-0.4569	1.5145	0.4623	-1.5002	1.6351
ΔTE_t	coef	**0.1090***	**0.3217***	0.0399	-0.0704	-0.0400	**-0.4216****	0.1670
	std	0.0601	0.1742	0.1797	0.1105	0.1130	0.1191	0.1215
	t-stat	1.8146	1.8471	0.2223	-0.6366	-0.3544	-3.5393	1.3740
ΔTF_t	coef	**0.0694***	-0.0262	-0.0462	0.0428	0.0579	-0.0566	0.0539
	std	0.0339	0.0983	0.1014	0.0624	0.0638	0.0672	0.0686
	t-stat	2.0460	-0.2669	-0.4559	0.6868	0.9081	-0.8425	0.7861

Notes: The lag length is chosen by the AIC.
* and ** represent significance at 0.05 and 0.01 levels, respectively.

Since TX and TW, and TX, TE and TF are cointegrated, the index futures spreads for arbitrage simulations can be generated by (3.5) using the normalised cointegrating vectors in Panel C of Table 3.3. Therefore, Spread I, i.e. TX against TW, is equal to TX – 464671.9 – 1.852167*TW, and Spread II, i.e. TX against TE and TF, equals TX – 117791.3 – 0.63268*TE – 0.713472*TF. The descriptive statistics of Spread I and Spread II are summarised in Table 3.6. Spread I is slightly negatively skewed, and a little platykurtic (flat) relative to the normal, but the assumption of a normal distribution cannot be rejected at the 5% significant level according to Jarque-Bera statistics. On the other hand, Spread II is negatively skewed too, but its distribution is leptokurtic (peaked) relative to the normal and the hypothesis of a normal distribution is rejected at the 1% level. Since Spread I and II are derived from the residuals of cointegrated futures prices, they should be stationary by definition. The results of the ADF tests on these two series confirm that they are $I(0)$ processes as the null hypothesis of a unit root is rejected at the 1% critical value for both spreads.

Table 3.6 Descriptive statistics of index futures spreads

	Spread I		**Spread II**	
Variables	TX against TW		TX against TE and TF	
Observations	713		713	
Mean	4805.76		842.95	
Maximum	178926.10		94536.52	
Minimum	-137497.10		-83420.18	
Std. Dev.	58442.56		23474.19	
Skewness	-0.18		-0.13	
Kurtosis	2.83		3.65	
Jarque-Bera	4.58		14.51**	
Probability	0.10		0.00	
ADF	-3.39**		-5.11**	
Autocorrelations	levels	first differences	levels	first differences
1	0.95	-0.26	0.90	-0.21
2	0.92	0.02	0.84	0.04
3	0.89	0.00	0.78	-0.08
4	0.86	-0.03	0.73	-0.02
5	0.83	0.04	0.69	0.00

Notes: The lag length of Spread I and Spread II chosen by the AIC is 1 in the ADF tests.
The ADF tests are performed based on the assumption that there is no intercept and time trend.
** denotes significance at 0.01 levels.

The series of the spreads levels are highly autocorrelated. The first-order autocorrelation is higher than 0.9 for both series and the autocorrelation coefficients of all five lags range from 0.69 to 0.95, indicating that both spread series tend to persist above or below zero, rather than fluctuate randomly around zero. This confirms the results from the half-lives that the adjustment process toward equilibrium is slow. The autocorrelation behaviour of the first differences is close to zero, except for the first lag which is negative. This suggests that when the spread deviates from zero, it is elastically pulled toward long-term equilibrium by the action of those traders who perceive that transacting in one market is cheaper. The deviations of the Spread I and II from the cointegrating relationships are showed in Figure 1 and 2, respectively.

Figure 3.1 Spread I–TX against TW

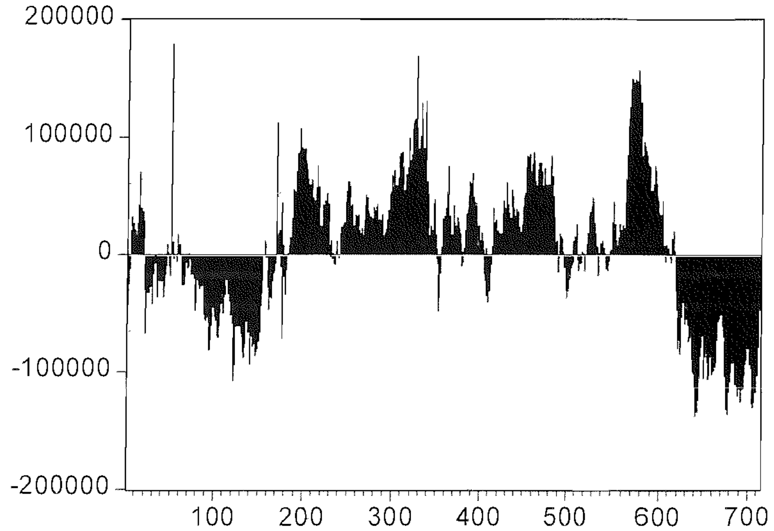
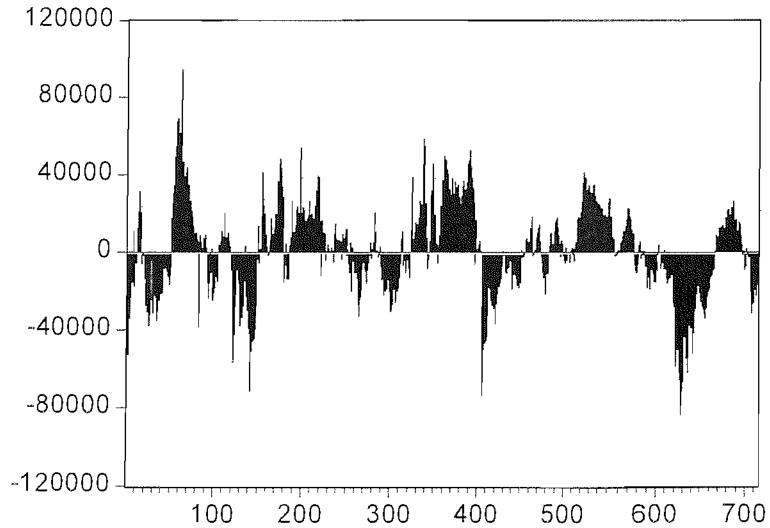


Figure 3.2 Spread II–TX against TE and TF



4.2 Trading strategies

The significance for traders of the mean-reverting tendencies of the index futures spread is assessed by simulating trading rules that exploit these tendencies. The simulations are performed in-sample and thus provide information as to whether the degree of mean reversion during the sample period could have been the basis for successful index futures spread arbitrage strategies. Since daily data are used for simulation, trades occur only at the daily closing prices. Therefore, the effects of bid-ask spreads are not considered in this study. Besides, all purchases and sales are in the first near-by contract, assuming there is no rollover and only the near-by contract exists in the markets.

Since the spread tends to revert toward its long-term equilibrium level (LE), traders should buy the spread when it is below the LE to profit from a tendency to rise toward the LE. In contrast, when the spread is higher than the LE, traders should sell the spread to profit from a tendency to drop toward the LE. In long spread, TX is bought and TW or TE&TF is sold. In short spread, TX is sold and TW or TE&TF is bought. These positions are closed by executing offsetting trades when the spread returns to its equilibrium value. In addition, these positions are closed if any futures is expired even though the spread has not reverted to the LE yet and the transaction might still be not profitable. New spread position is reopened the following day when the new first near-by contract starts trading if trading rules are satisfied.

The following trading rules based on combinations of the above principles and assumptions are simulated.

Buy spread if:
Spread is less than the LE by $\varphi\sigma$
Close long spread position if:
(1) Spread is greater than or equal to the LE or
(2) Any contract is expired

Sell spread if:
Spread is greater than the LE by $\varphi\sigma$
Close short spread position if:
(1) Spread is less than or equal to the LE or
(2) Any contract is expired

where σ is sample standard deviation, φ= 0.75, 1 and 1.25, and $\varphi\sigma$ are filters set to exclude noises and unprofitable fluctuations. Only abnormal spreads which deviate away from the LE than $\varphi\sigma$ are considered.

The spread ratio in the simulation trading is derived from the ratio of normalised cointegrating coefficients which have been showed in Panel C of Table 3.3. The estimated coefficients are not integers but futures only can be traded in unities. Hence, the coefficients are rounded off to the nearby and smallest integers. Therefore, 1 TX against 2 TW contracts for Spread I, and 3 TX against 2 TE and 2 TF contracts for Spread II are the spread ratios used in the simulation.

There are two costs of implementing this trading scheme. The first cost is the commission paid to a broker. The commission is NTD 800 per contract per side for futures contracts trading in the TAIFEX and 0.1% of the contract market value per contract per side for contracts in the SGX-DT. The second cost is futures transaction tax. The futures transaction tax only levies upon trades in the TAIFEX, not in the SGX-DT. The tax rate is 0.05% per trade per side before 30th April 2000 and has been reduced to 0.025% afterward. Since the daily data are used for simulation, the implicit transaction costs arisen from the bid-ask spreads are not considered here.

4.3 Simulation results

The simulation results of index futures spread arbitrage are presented in Table 3.7. The main feature to note in these results is that spread arbitrage is profitable. First, all the average profits using different filters are significantly greater than zero at the 5% level for every type of positions. Second, the majority of trades are profitable. The percentage of winning trades ranges from 64% to 100%. Third, for the overall positions the average profit increases but the total profit drops as φ becomes bigger; meanwhile, as the number of trades drops with larger φ, the percentage of winning rate does not necessarily go up as φ becomes bigger. The results indicate that the filter not only rules out noises but also profitable opportunities.

Table 3.7 Simulation results of spread arbitrage before transaction costs

	Spread I (1 TX against 2 TW)			**Spread II** (3 TX against 2 TE & 2 TF)		
Entry condition φ=	**0.75**	**1**	**1.25**	**0.75**	**1**	**1.25**
Long Spread						
Number of trades	22	17	12	19	14	8
Average duration	7.50	7.29	8.17	9.53	10.21	10.75
% of winning trades	63.64%	70.59%	75.00%	94.74%	93.33%	100.00%
Maximum profit	186,856.40	91,149.38	60,655.52	140,600.00	189,200.00	189,200.00
Minimum profit	-59,419.12	-59,419.12	-25,086.18	-132,800.00	-120,200.00	30,600.00
Total profit	556,111.60	395,702.68	274,020.04	1,164,800.00	1,108,400.00	845,000.00
Average profit	25,277.80	23,276.63	22,835.00	61,305.26	79,171.43	105,625.00
Standard deviation	52,908.69	40,030.85	28,753.90	58,952.88	73,039.37	52,396.45
t-statistic	2.2409	2.3975	2.7510	4.5328	4.0558	5.7018
Probability	0.0360	0.0291	0.0189	0.0003	0.0014	0.0007
Short Spread						
Number of trades	30	23	17	22	17	16
Average duration	7.37	7.61	7.29	9.5	9.29	10.31
% of winning trades	73.33%	69.57%	70.59%	68.18%	70.59%	75.00%
Maximum profit	183,043.20	183,043.20	183,043.20	221,800.00	221,800.00	221,800.00
Minimum profit	-58,229.28	-58,229.28	-47,347.40	-97,800.00	-84,000.00	-88,400.00
Total profit	988,152.90	813,129.62	688,283.28	1,057,800.00	1,069,200.00	1,245,000.00
Average profit	32,938.43	35,353.46	40,487.25	48,081.82	62,894.12	77,812.50
Standard deviation	57,145.84	61,969.50	61,163.87	81,162.31	88,218.06	85,296.86
t-statistic	3.1570	2.7360	2.7293	2.7787	2.9395	3.6490
Probability	0.0037	0.0121	0.0149	0.0113	0.0096	0.0024
Overall positions						
Number of trades	52	40	29	41	31	24
Average duration	7.42	7.48	7.66	9.51	9.71	10.46
% of winning trades	69.23%	70.00%	72.41%	80.49%	80.65%	80.33%
Maximum profit	186,856.40	183,043.20	183,043.20	221,800.00	221,800.00	221,800.00
Minimum profit	-59,419.12	-59,419.12	-47,347.40	-132,800.00	-120,200.00	-88,400.00
Total profit	1,544,264.48	1,208,832.30	962,303.32	2,222,600.00	2,177,600.00	2,090,000.00
Average profit	29,697.39	30,220.81	33,182.87	54,209.76	70,245.16	87,083.33
Standard deviation	54,992.79	53,481.36	50,406.53	71,181.88	80,809.38	75,893.68
t-statistic	3.8942	3.5738	3.5451	4.8764	4.8399	5.6213
Probability	0.0003	0.0010	0.0014	0.0000	0.0000	0.0000

Notes: The t-statistic tests the null hypothesis that the average profits per trade are equal to zero, and the probability is computed from the t-distribution with n-1 degrees of freedom.

Table 3.8 Simulation results of spread arbitrage after transaction costs

	Spread I (1 TX against 2 TW)			Spread II (3 TX against 2 TE & 2 TF)		
Entry condition φ=	**0.75**	**1**	**1.25**	**0.75**	**1**	**1.25**
Long Spread						
Maximum profit	173,443.30	76,699.36	51,173.71	120,080.00	166,701.20	166,701.20
Minimum profit	-69,072.81	-69,072.81	-35,057.37	-147,237.00	-134,690.50	14,067.15
Total profit	306,255.30	202,874.49	142,013.63	817,782.00	850,927.00	694,827.05
Average profit	13,920.70	11,933.79	11,834.47	43,041.16	60,780.50	86,853.38
Standard deviation	52,320.71	39,271.30	28,712.46	58,089.39	71,722.58	50,523.25
t-statistic	1.2480	1.2529	1.4278	3.2297	3.1708	4.8623
Probability	0.2258	0.2282	0.1811	0.0046	0.0074	0.0018
Short Spread						
Maximum profit	171,702.30	171,702.30	171,702.30	199,186.50	199,186.50	199,186.50
Minimum profit	-67,560.02	-65,110.67	-57,710.60	-120,810.00	-106,176.00	-103,001.40
Total profit	698,479.60	592,031.21	523,641.11	673,414.00	777,752.95	975,611.30
Average profit	23,282.65	25,740.49	30,802.42	30,609.73	45,750.17	60,975.71
Standard deviation	56,898.78	61,611.46	60,774.87	81,538.17	87,766.05	84,245.57
t-statistic	2.2412	2.0036	2.0897	1.7608	2.1493	2.8951
Probability	0.0328	0.0576	0.0530	0.0928	0.0473	0.0111
Overall positions						
Maximum profit	173,443.30	171,702.30	171,702.30	199,186.50	199,186.50	199,186.50
Minimum profit	-69,072.81	-69,072.81	-57,710.60	-147,237.00	-134,690.50	-103,001.40
Total profit	1,004,734.99	794,905.73	665,654.74	1,491,196.00	1,628,679.95	1,670,438.35
Average profit	19,321.83	19,872.64	22,953.61	36,370.63	52,538.06	69,601.60
Standard deviation	54,680.12	53,120.69	50,248.20	71,051.44	79,969.61	74,571.07
t-statistic	2.5481	2.3660	2.4600	3.2777	3.6579	4.5725
Probability	0.0139	0.0230	0.0203	0.0022	0.0010	0.0001

Notes: The t-statistic tests the null hypothesis that the average profits per trade are equal to zero, and the probability is computed from the t-distribution with n-1 degrees of freedom.

Table 3.8 reports the simulation results of index futures spread arbitrage after transaction costs. Although most of the average profits of long or short positions of Spread I are not significantly different from zero at the 5% level except short position with φ=0.75, the average profits of the overall positions are significantly greater than zero. On the other hand, most of the average profits Spread II are significantly except the short position with φ=0.75. The results indicate that index spread arbitrage is still a profitable strategy even after transaction costs.

Since the mean reverting property of the spreads ensures that any short-run deviations will return to the long-term equilibrium level, in theory, there should be no losses in spreading arbitrage, at least before transaction costs. Why is the percentage of winning trades not 100%? The reason is that we don't know how long the deviations will last. As revealed in Section 4.1, the half-lives of these index futures are from 7 to 18 days. Therefore, disequilibrium may last longer than the lifetime of a futures contract and then the spread position is still at a loss but forced to be liquidated as one or all futures contracts are expired. However, the loss can be offset by next new spread position traded in the new near-by contracts until the spread returns to its long-run equilibrium level.

Which filter threshold strategy is superior to others for the overall positions? In terms of the average profit, the trading strategy with bigger filter provides better average profit for both spreads, no matter before or after transaction costs. However, from the viewpoint of the total profit, it is hard to conclude which threshold is better. Although the strategy with $\varphi=0.75$ generates highest total profit before transaction costs for both spreads, the result is not the same after transaction costs. For Spread I, the smallest filter still produces the highest total profit but, for Spread II, the highest total profit is generated from the highest filter strategy. The inversion is caused by the differentials in transaction costs. Lower filter strategy not only provides higher trading frequency, but also involves larger total transaction costs. Moreover, since the transaction costs of contracts trading in the TAIFEX are higher than those in the SGX-DT, the degree of total transaction costs erodes away the total profit with lower filter strategy is deeper for Spread II than Spread I. Hence, the total profit of Spread II with lower filter becomes less than that with higher filter after transaction costs. Therefore, the maximal profit seeker should choose the strategy with $\varphi=0.75$ for Spread I and $\varphi=1.25$ for Spread II.

In additional to analyzing the profitability of trading strategies, concern has to be given to the risk-reward characteristics of the spread trades to provide a more comprehensive picture. In general, since risk has many aspects, one can assess the risk-reward characteristics of an investment in many ways. One way is to measure risk employing the standard deviation of returns or coefficient of variation. Assuming investors prefer more than less and are risk averse, a suitable tool to analyze the risk-reward characteristic is the reward-volatility (*RV*) ratio[39] which reveals the excess gain per unit of risk associated with the excess gain:

$$RV = \frac{x}{\sigma_x} \tag{3.8}$$

where x is the average profit and σ_x is the standard deviation of the average profit. The *RV* ratios calculated from (3.8) are showed in Table 3.9. It is clear that the *RV* ratios become bigger as the threshold is higher. Hence, the strategy with φ=1.25 is superior to others in terms of the risk-reward characteristic.

Table 3.9 Reward-volatility (*RV*) ratios

	Spread I (1 TX against 2 TW)			**Spread II** (3 TX against 2 TE & 2 TF)		
φ=	0.75	1	1.25	0.75	1	1.25
RV	0.3534	0.3741	0.4568	0.5119	0.6570	0.9334

4.4 Rates of return of spread arbitrage

All profits in Tables 3.7 and 3.8 are measured in terms of New Taiwan Dollars rather than rates of return. If a rate of return could be defined for futures spreading arbitrage, the concept and tests of market efficiency could also be extended to futures spread arbitrage. However, there are difficulties in defining rates of return on futures spread arbitrage. First, there is no agreement in the literature about what should be regarded as the initial investment. One possible definition of the initial investment is the initial value of the shares corresponding to one futures contract or the initial market value of the futures contract (Sutcliffe, 1997, p.187). Nonetheless, the spread arbitrage includes trading long and short positions at the same time. Should the initial investment be the summation of the market value of all futures contracts, or the difference between long and short positions? Another possible definition of the initial investment is the initial margin payment. However, the initial margin is not an investment, but a credit risk deposit. The initial margin payments do not flow from the buyer to the seller. Instead, both buyer and seller have to pay an initial margin and these payments are held by the clearing house. Another difficulty in measuring rates of return is that the spreading arbitrage strategy does not require maintaining an open position continuously. Trade is initiated only when there is a profitable trading opportunity, as indicated by the trading

[39] The *RV* ratio is a variety of the Sharpe ratio (see http://www.stanford.edu/~wfsharpe/art/sr/sr.htm)

rules mentioned before. Otherwise, no positions are held in the market.

Assuming an investor is interested in spread arbitrage, he or she needs capital to engage in such a trading behaviour. The capital includes the initial margin and extra money to cover subsequent margin payments to ensure the margin in the account is well above the maintenance. Therefore, the initial investment for spreading arbitrage can be defined as the initial margin requirement plus the liquidity reserve. The latter should not be less than the possible maximum loss (minimum profit) in the spread arbitrage. Based on this analysis the initial investment of NTD 344,089.06 for Spread I and of NTD 957,237 for Spread II is sufficient for the margin requirement and the liquidity reserve[40]. To simplify the calculation of rates of return, the margin requirements for each futures contract are assumed to be constant. If a spread is recognised by the exchange, the margin requirements and the commissions are usually less than the sum of individual margins and commissions. However, since the index futures spreads in this study are not recognised, the margin requirement and the commission are treated as if they were traded separately. Moreover, all contracts are traded in the same account. Therefore, the loss in one contract can be covered by the revenue from the other. Besides, the profits from trade are assumed not to be used for reinvestment. Only one spread position is opened at most for each type of spread even if the proceeds from trades are sufficient to open more spread positions. Finally, since the investor intends to trade spread for the whole period, he or she leaves all the money in the account even if there are no arbitrage opportunities. So, returns during the non-trading periods are zero.

Based on the assumptions mentioned above, the annual rate of return is determining by first computing the returns of each trade, converting them into the holding period return, and then transforming the holding period return into annual rate of return. The return of each trade is the profit divided by the investment for each trade:

$$r_i = \frac{p_i}{I_i} \tag{4.2}$$

where r_i is the return of the i^{th} trade, p_i is the profit from the i^{th} trade, I_i is the investment for i^{th} trade, $i=1,2,3...,m$, I_1 is the initial investment, and $I_{i+1} = I_1 + \sum_{i=1}^{n} p_i$.

[40] On 17 May 2002, the initial margin of TW, TX, TE and TF is $2,375, NTD120,000, NTD135,000 and NTD 90,000, respectively. The average exchange rate USD/NTD in the sample period was 32.635.

The product of 1 plus the returns of each trade is equal to one plus the holding period return (H):

$$\prod_{i=1}^{m}(1+r_i)=1+H$$

or

$$H=\prod_{i=1}^{m}(1+r_i)-1 \qquad (3.8)$$

After the holding period return is derived, the annual rate of return (R') is calculated as follows:

$$1+R'=(1+H)^{1/n}$$

or

$$R'=(1+H)^{1/n}-1 \qquad (3.9)$$

where n the number of years. Assuming there are 252 trading days in a year, n is equal to 713/252=2.8294 years in this study. The annual rate of return is used to measure the performance of spread arbitrage.

In fact, the calculation of H can be simplified as[41]:

$$H=\frac{TP}{I_1} \qquad (3.10)$$

where TP is the total profit, $TP=p_1+p_2+\ldots+p_m$

Table 3.10 presents the results of rates of return determining by (3.9) and (3.10) for Spread I and II after transaction costs. It is clear that the annual rates of return are very attractive. The range of annual rates is from 39.37% to 62.06%. However, Spread I may not be as attractive as it appears because the regulation in Taiwan restricts futures denominated in foreign currencies to be traded in the same account with domestic contracts. Therefore, the loss in either TX or TW cannot be covered by the other and then, the capital for maintaining margin requirement could be much higher that expected. Besides, TE and TF are relatively immature in this study because the sample period starts at 21 July 1999 which was the issue day of these two contracts. Some of the arbitrage opportunities in Spread II may arise from the inexperience of traders in the new markets. The evidence of immaturity is that the average volume of TE and TF is only 1/4 and 1/8 of the average volume of TX, respectively, during the sample period.

[41] The proof of the simplification is demonstrated in Appendix B.

The arbitrage opportunities in the matured markets may not be as frequent as those in the sample period.

Table 3.10 Rates of return

Rates of Return	Spread I			Spread II		
φ=	0.75	1	1.25	0.75	1	1.25
Initial Capital (I_I)		344,089.06			957,237	
Holding period return (H)	292.00%	231.02%	193.45%	155.78%	170.14%	174.51%
Annualised return (R')	62.06%	52.66%	46.30%	39.37%	42.08%	42.89%

Note: The number of holding years (n) is 2.8294

Why do arbitrage opportunities exist? If arbitrage is quick and effective enough because substitute securities are readily available and the arbitrageurs are competing with each other to earn profits, the price of a security can never get far away from its fundamental value, and indeed arbitrageurs themselves are unable to earn much of an abnormal return. However, the evidence from the study reveals that spreads are quite persistent at the daily interval and spread arbitrage is a profitable strategy. One possible reason is the inexperience of traders in the new markets which is explained above. Another reason is insufficient volume of arbitrage transactions to move prices toward their long-run equilibrium. Shleifer and Vishny (1997) present an agency model of limited arbitrage to explain why the supply of arbitrage capital is limited. A fundamental feature of arbitrage is that brains and resources are separated by an agency relationship. Most arbitrage is conducted by relatively few professionals, combining their knowledge with resources of outside investors to take large positions. When an arbitrageur manages other people's money and these people do not know or understand exactly what he is doing, they will only observe him losing money if prices deviate further. They may therefore infer from this loss that the arbitrageur is not as competent as they thought, refuse to provide him with more capital, and even withdraw some of the capital—even though the expected return from the trade has increased. Shleifer and Vishny (1997) show that performance-based arbitrage is particularly ineffective in extreme circumstances, where prices are significantly out of line and arbitrageurs are fully invested. In this circumstance, arbitrageurs might bail out of the market when their participation is most needed.

5. Conclusion and Summary

The paper has explained the rationale of intercommodity spread arbitrage between index futures. A necessary condition for spread arbitrage is the availability of a good substitute for a futures contract. If the underlying assets of two index futures virtually represent the same market, even though the underlying indices are not identical, they could be close substitutes for each other. Moreover, if the combination of two or more index futures' underlying assets is approximately equal to another futures' cash index, then these futures may be each other's close substitutes for arbitrage. Cointegration tests are employed to identify whether two or more index futures are good substitutes for spread arbitrage. The cointegration relationships are found among index futures in Taiwan, i.e., TX and TW, and TX, TE and TF. This indicates that there is a long-term equilibrium level between related index futures, and the spreads derived from cointegration relationships are stationary. Any short-term deviations will revert to the fundamental value. Trading rules and filters are set to take advantage of the disequilibrium and to test the profitability of index futures spread arbitrage. The following are summaries of simulation findings.

First of all, simulation results reveal that spread arbitrage is profitable given that average profits under different filters are all significantly greater than zero after transaction costs. Secondly, this research suggests that the trading strategy with greater filter threshold is superior to lower filters in terms of the risk-reward characteristics and the average profit. Thirdly, under certain assumptions, the rates of return of spread arbitrage are found to be highly attractive. The existence of arbitrage opportunities may result from market immaturity and lack of sufficient volume of arbitrage transactions to remove disequilibrium.

Due to the availability of samples, this study only has performed in-sample simulation. The research on index futures spread arbitrage will be more complete and meaningful if in-sample coefficients could have been used to test the profitability of out-of-sample data. This study may be extended when out-of-sample observations are available.

Intercommodity spread arbitrage between index futures is not limited to Taiwanese markets. The approach outlined in this study can be applied to other countries as long as the good substitutes for futures contracts can be identified by cointegration tests.

Appendix A

In Section 4 the four futures contacts in Taiwan are arranged into two subsets, TX and TW (Group I), and TX, TE and TF (Group II), to test the cointegration relationship between index futures prices in each group. Another way to identify the cointegration relationships is: 1) test the cointegration relationship among these four futures contacts; and 2) impose restrictions on the cointegrating coefficients to see whether the restrictions identify all cointegrating vectors.

Table A.1 Cointegration tests in a system of four futures prices

Variables: TX, TW, TE and TF							
		Critical Values				Critical Values	
H_0	Trace	5 %	1 %	H_0	Max-Eigenvalue	5 %	1 %
$r = 0$	105.30**	53.12	60.16	$r = 0$	48.49**	28.14	33.24
$r \leq 1$	56.82**	34.91	41.07	$r = 1$	44.36**	22.00	26.81
$r \leq 2$	12.46	19.96	24.60	$r = 2$	10.00	15.67	20.20
$r \leq 3$	2.46	9.24	12.97	$r = 3$	2.46	9.24	12.97

Note: ** Significant level at 0.01

The results of the Johansen tests for multivariate cointegration in the system of the four index futures in Taiwan are reported in Table A.1. The trace tests reject the null hypotheses of no cointegration ($r = 0$) and at most one cointegrating vector ($r \leq 1$) at 1% significance level but fails to reject the other null hypotheses that there is at most two and three cointegrating vectors. The maximum eigenvalue tests produce similar results. The null hypotheses of $r = 0$ and r=1 are rejected at 1% level but the other null hypotheses of $r = 2$ and $r = 3$ cannot be rejected. Therefore, there are two cointegrating vectors in the system of the four futures contracts. Since the purpose of the study is to identify whether TX and TW, and TX, TE and TF are cointegrated, the restrictions impose on the first cointegrating vector are: TX = 1, TE = 0 and TF = 0, which identify the cointegration relationship between TX and TW, and the restrictions impose on the second vector are: TX = 1 and TW = 0, which identify the cointegration relationship among TX, TE and TF. The LR test reveals that the null hypothesis of the restrictions are binding is not rejected[42].

[42] The unrestricted and the restricted log-likelihood functions are -14122.66 and -14122.672, respectively, therefore, $\lambda = 0.02501$, which has a χ^2 distribution with one degree of freedom, and p=0.8743.

Appendix B

Given:

$$\prod_{i=1}^{m}(1+r_i)=1+H \qquad \text{(B.1)}$$

or

$$H=\prod_{i=1}^{m}(1+r_i)-1 \qquad \text{(B.2)}$$

where $r_i=\frac{p_i}{I_i}$ (B.3), r_i is the return, p_i is the profit, I_i is the investment of each trade, $i=1,2,3...,m$, I_1 is the initial investment, and $I_{i+1}=I_1+\sum_{i=1}^{n}p_i$ (B.4)

Prove:

$$H=\frac{TP}{I_1} \qquad \text{(B.5)}$$

where TP is the total profit, $TP=p_1+p_2+...+p_m$

PROOF:

Replace Equation (B.3) into Equation (B.2):

$$1+H=\prod_{i=1}^{m}(1+\frac{p_i}{I_i})$$

$$1+H=(1+\frac{p_1}{I_1})(1+\frac{p_2}{I_2})(1+\frac{p_3}{I_3})...(1+\frac{p_m}{I_m}) \quad 1+H=(\frac{I_1+p_1}{I_1})(\frac{I_2+p_2}{I_2})(\frac{I_3+p_3}{I_3})...(\frac{I_m+p_m}{I_m})$$

(B.6)

Since $I_2=I_1+p_1$, $I_3=I_1+p_1+p_2$...,and $I_m=I_1+p_1+p_2+...+p_{m-1}$

Then Equation (B.6) becomes

$$1+H=(\frac{I_1+p_1}{I_1})(\frac{I_1+p_1+p_2}{I_1+p_1})(\frac{I_1+p_1+p_2+p_3}{I_1+p_1+p_2})...(\frac{I_1+p_1+p_2+p_3+...+p_{m-1}+p_m}{I_1+p_1+p_2+p_3+...+p_{m-1}})$$

$$1+H=(\frac{I_1+p_1+p_2+p_3+...+p_{m-1}+p_m}{I_1}) \qquad \text{(B.7)}$$

Since $TP=p_1+p_2+...+p_m$

Then Equation (B.7) becomes

$$1+H=(\frac{I_1+TP}{I_1})=1+\frac{TP}{I_1}$$

Therefore, $H = \frac{TP}{I_i}$ (B.8)

Chapter Four: Long memory and fractional dynamics in the spreads of index futures

Abstract

The chapter is the first study on the properties of long-range dependence in the spreads of index futures. Although the spreads have the same property of mean-reverting with stationary process, their autocorrelations decay at a much slower rate than the latter. However, they do not go on as persistently as the integrated process. The empirical evidence reveals that both spreads are mean-reverting but non-stationary long memory processes. Moreover, there is strong evidence that Spread II is a double long memory process but Spread I has no the property of long memory in the conditional variance. The results may be useful to improve the index futures spread arbitrage trading.

1. Introduction

This chapter examines the properties of long-range dependence in the spreads in Chapter three. In particular, the fractionally integrated ARMA model and long memory ARCH model are applied to investigate the persistence in the spread levels and volatility.

The spreads between index futures share the same property of mean-reverting with stationary series because any deviations in the spreads will revert to the long-term equilibrium eventually. However, it has been revealed that the autocorrelation functions of the spreads between index futures in Taiwan are much more persistent than those of usual stock returns. The first-order autocorrelation is higher than 0.9 for both series and the autocorrelation coefficients of first five lags range from 0.69 to 0.95, indicating that both spread series tend to persist above or below zero, rather than fluctuate randomly around zero. Figures 4.1 and 4.2 plot the sample autocorrelation of Spread I and Spread II, respectively, and show the persistence of the autocorrelation functions of the spreads. In spite of this, they are not as persistent as the autocorrelations of an integrated series which remain persistently high at long lags. Such series having a slowly declining correlogram are argued to process long memory. One way to represent this phenomenon is using a fractionally integrated model. That is, a series is integrated of a given order d if it becomes stationary on differencing a minimum of d times.

Figure 4.1 The autocorrelation correlogram function (ACF) of Spread I

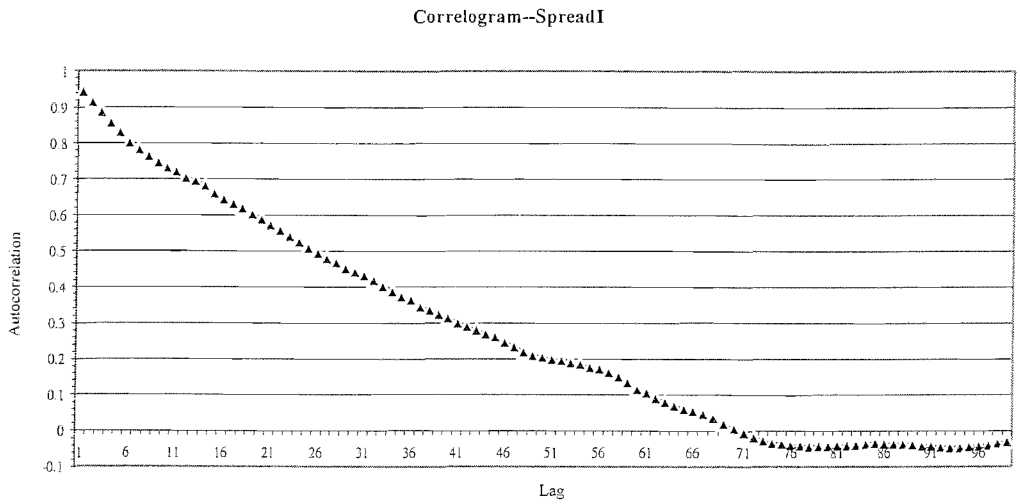


Figure 4.2 The ACF of Spread II

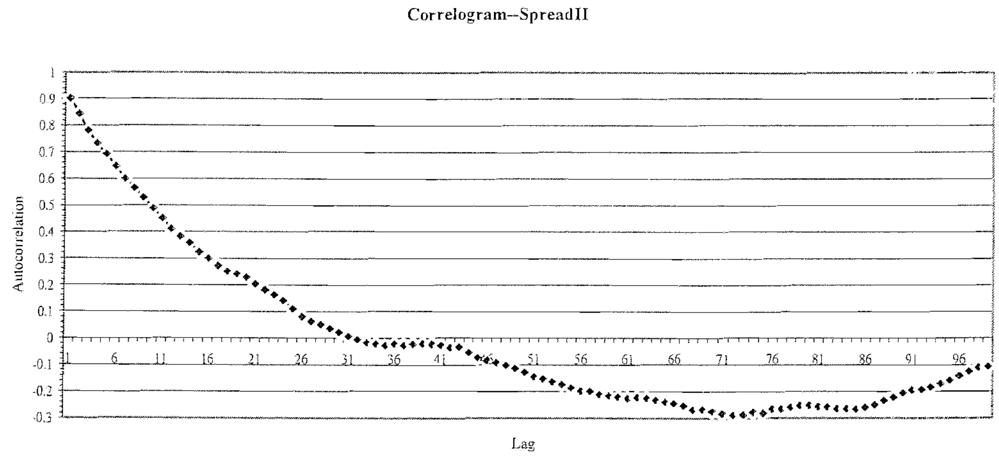


Figure 4.3 The ACF of the absolute value of Spread I

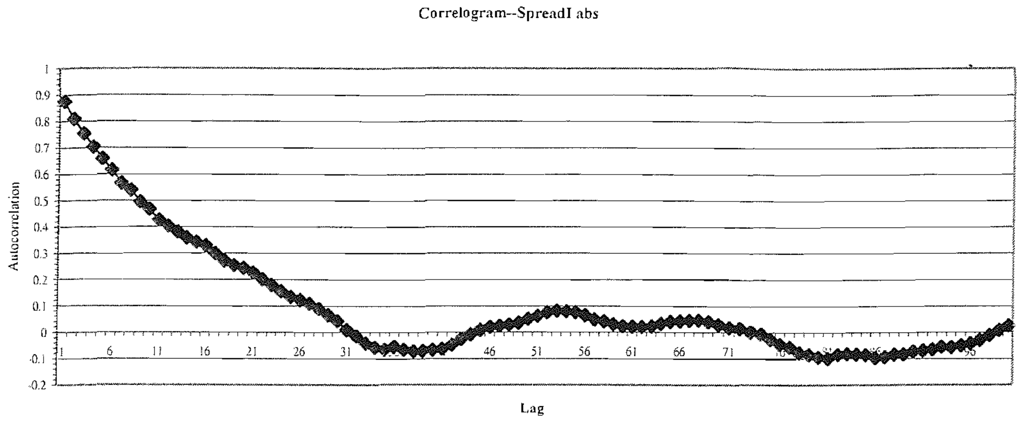
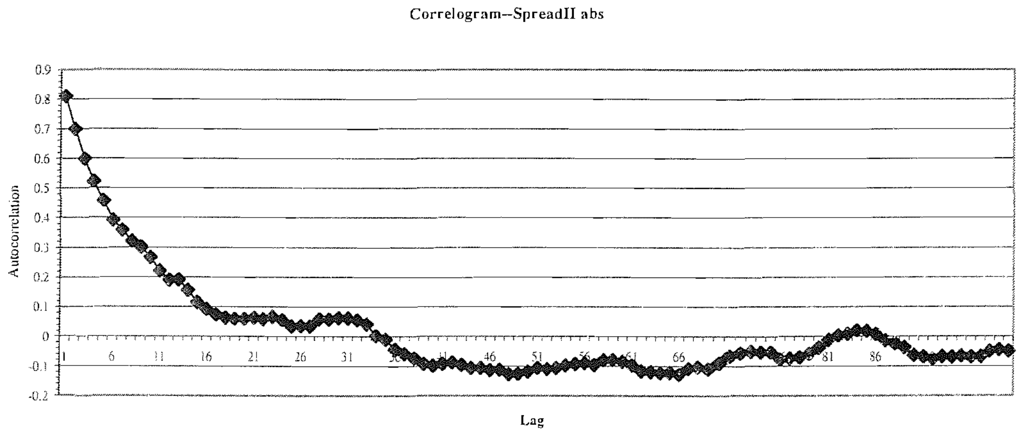


Figure 4.4 The ACF of the absolute value of Spread II



The fractionally integrated models have been used to explore the nonlinear dynamics in financial markets, e.g. stock market returns (Barkoulas and Baum, 1996; Henry, 2002), exchange rates (Baillie and Bollerslev, 1994a; Masih and Masih, 1995), forward premia (Baillie and Bollerslev, 1994b) and interest rates (Tsay, 2000). However, as far as the author is aware, there has been no study applied long memory models on the index futures spreads derived from cointegration relationship. In addition to the long memory in levels, several studies (see Baillie, 1996; Bollerslev and Mikkelsen, 1996; Ding and Granger, 1996) also point out that the absolute returns and their power transformations are highly correlated. For that reason, the spread volatility might be best described by a fractionally integrated ARCH model. Figures 4.3 and 4.4 illustrate the sample autocorrelation of the absolute value of Spread I and Spread II, respectively. Although the autocorrelation functions of the absolute value of spreads are not as persistent as those of spreads, they are obviously different from an exponentially decreasing function.

Therefore, the study on the long-range dependence properties of the index futures spreads concentrate on two parts: the first one is to investigate the long memory in spread levels, and the second part is to examine the volatility persistence of spreads. The results from the study may be used to improve the forecasting of the changes in the index futures spreads.

A flexible and parsimonious way to model both the short-term and the long-term behaviour of a time series is by means of an autoregressive fractionally integrated moving-average (ARFIMA) model. A time series $y = \{y_1 \cdots y_t\}$ with mean δ follows an ARFIMA process of order (p, d, q), denoted by ARFIMA (p, d, q), if

$$\phi(L)(1-L)^d(y_t - \delta) = \Theta(L)\varepsilon_t \quad \varepsilon_t \sim \text{IID } (0,\ \sigma_y^2)$$

where L is the backward-shift operator, $\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p$,

$\Theta(L) = 1 + \vartheta_1 L + \cdots + \vartheta_q L^q$ and $(1\text{-}L)^d$ is the fractional differencing operator defined by

$$\begin{aligned}(1-L)^d &= 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \cdots \\ &= \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}\end{aligned}$$

with $\Gamma(\bullet)$ denoting the gamma is defined as $\Gamma(g) = \int_0^{\infty} x^{g-1}e^{-x}dx$

The methodology to estimate the fractional-integration parameters in levels and volatility is as follows. The first step is to find out the order of integration of the spreads by applying the PP unit root test and the KPSS (1992) statioanrity test on the spreads. Rejection by both tests indicates evidence that the spreads are well described by neither an I(*1*) or an I(*0*) process. The next step is to employ the GPH (Geweke and Porter-Hudak, 1983) methodology on the spreads estimate the fractional-integration parameter (d). However, there is still no agreement on the choice of the number of Fourier frequencies. Usually, several estimated d are reported based on the different number of Fourier frequencies. Therefore, the results from the GPH spectral regression are served to find out the possible value of d. Since one of the prerequisites of the ARFIMA models is $-0.5 < d < 0.5$, if $0.5 < d < 1$, then the first differences of spreads are generated to be used in the ARFIMA models which are estimated by the Sowell's (1992) exact maximum likelihood method.

The fractionally integrated GARCH (FIGARCH) models are employed to estimate the long-range dependence in the volatility of spreads. However, if *d* in the ARFIMA is significant, ignoring the long memory in the conditional mean can lead to serious biases in the estimation of the conditional volatility process(Teyssiere, 1997). Accordingly, the spreads are treated as double long memory processes (i.e. long-range dependence in both the mean and the variance) and estimated by the ARFIMA-FIGARCH models. This chapter is organised as follows. In Section 2, the concept of long memory is presented and literature on long memory in returns and in volatility is reviewed. Data and methodology are described in Section 3. All tests are based on the index futures spreads used in the previous chapter. Tests for unit roots and stationarity are applied to both spreads to determine their order of integration. Models for long memory in the conditional mean and in the conditional variance are estimated to find out the long-range dependence properties of these two spreads. The empirical results are reported in Section 4. The chapter concludes in Section 5 with a summary.

2. Theory and literature review

2.1 The concept of long memory

It is widely believed that asset prices contain a unit root, so the autocorrelations of the integrated series remain persistently extremely high at long lags. These processes are said to be integrated of order one, denoted I(1). On the other hand, asset returns, which are the first differences of prices, do not possess a further unit root and therefore their autocorrelations typically decay at an exponential rate which means large values typically disappear after only a few lags. These processes are denoted I(0) because they are stationary. Much of the analysis of financial time series treats processes as either I(0) or I(1). However, the knife-edge distinction between I(0) and I(1) processes can be far too restrictive. Some processes appear to behave between these two benchmarks; their autocorrelations decay at a much slower rate than the stationary process but do not remain as persistently as the integrated process. When observations from a given series take some distance apart, show signs of dependence, such series are argued to possess long memory which is defined as a series having a slowly declining correlogram or, equivalently, an infinite spectrum at zero frequency (Granger and Ding, 1996). One way to represent this phenomenon is using a fractional integrated model. In simple terms, a series is integrated of a given order d if it becomes stationary on differencing a minimum of d times. In the fractionally integrated framework, d is allowed to take on non-integer values. For example, let y_t satisfy the following difference equation:

$$(1-L)^d y_t = \varepsilon_t, \quad \varepsilon \sim WN(0,\sigma_\varepsilon^2) \qquad (4.1)$$

where L is the lag operator and ε_t is white noise. Granger and Joyeux (1980) and Hosking (1981) show that when the quantity $(1\text{-}L)^d$ is extended to noninteger powers of d in the mathematically natural way, the result is a well-defined time series that is said to be fractionally-differenced of order d.

The y_t process is stationary and mean-reverting when $|d| < 0.5$. For $0 < d < 0.5$, it is said to exhibit long memory, or long-range positive dependence. For $-0.5 < d < 0$, the process is said to exhibit intermediate memory, or anti-persistence, or long-range negative dependence. When $0.5 \leq d < 1$,the y_t process is covariance nonstationary because its variance is not finite (Hosking, 1981). However, it is mean-reverting since an innovation has no permanent effect on the value of y_t. This is contrary to an I(1) process, which is both convariance nonstationary and not mean-reverting because the effect of an innovation can persist forever.

The notion of long memory has also been applied to GARCH models, where volatility has been found to exhibit long-range dependence. A new class of models known as fractionally integrated GARCH (FIGARCH) have been proposed by Baillie, Bollerslev, and Mikkelsen (1996) to allow for this phenomenon. The primary purpose of this new approach is to develop a more flexible class of processes for the conditional variance that are more capable of explaining and representing the observed temporal dependencies in financial market volatility. The FIGARCH model implies a slow hyperbolic rate of decay for the lagged squared innovations in the conditional variance function and persistent impulse response weights. Shocks to the error process die away at a slower, hypergoemetric rate rather than the short-term exponential decay typical of a short memory process.

2.2 Literature review

2.2.1 Long memory in return series

The behaviour of stock returns over long horizons as opposed to short terms has been a hotly contested issue. Shiller (1984) and Summers (1986) demonstrate that in simple models of fashions, large and slowly decaying swings away from fundamental values can occur in stock markets, without significant autocorrelation in short-term returns. As stated by Summers (1986), market inefficiency can exist but the standard statistical tests on short-term returns have very low power to detect it. The long-run swings away from fundamental values imply the presence of negative autocorrelation in long-horizon returns because the swings are not permanent (Stambaugh, 1986).

Fama and French (1988) examine autoregressions of multiperiod returns on industry portfolios of NYSE shares and their findings are seemly consistent with Shiller and Summers' model. While the autocorrelation is weak for the daily and weekly holding periods, it is strongly negative for long-horizon returns. However, Fama and French (1988) note that although the predictability of long-horizon returns is consistent with common models of an irrational market in which stock prices take long temporary swings away from fundamental values, it can also result from time-varying equilibrium expected returns generated by rational pricing in an efficient market.

An alternative approach to study the behaviour of stock returns over short versus long horizons is explored by Lo(1991) based on modified rescaled range (R/S) test to detect long memory. He examines US stock return data based on the value-and-equally-weighted CRSP (Center for Research in Security Prices) indexes, and no significant evidence of long memory can be found in stock returns. Cheung and Lai (1995) employ Lo's (1991) modified R/S procedure and GPH test devised by Geweke and Porter-Hundak (1983) to investigate stock market indexes in 17 countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore/Malaysia, Spain, Sweden, Switzerland, and the United Kingdom. Several other studies also examine the long memory in stock returns and stock index returns, e.g. Barkoulas and Baum (1996) on the US markets, Berg and Lyhagen (1998) on Swedish stock returns, Grau-Carles (2000) on the US, UK, Japan, and Spain, Henry (2002) on the US, Japan, Germany, UK, Hong Kong, Taiwan, South Korea, Singapore and Australia, and Vougas (2004) on the Greek market. Although some evidence of long memory in some countries in some periods of study, the empirical results in general provide little evidence in favour of long memory in international stock index returns.

2.2.2 Long memory in volatility

The studies on the long memory in volatility were motivated by the persistence of the autocorrelations of absolute returns. Taylor (1986) finds that the absolute returns of speculative assets have significant positive autocorrelation over long lags. Ding, Granger, and Engle (1993) discover that not only there is substantially more correlation between absolute returns than returns themselves, but the power transformation of the absolute return $|r_t|^d$ also has quite high autocorrelation for long lags. They characterise $|r_t|^d$ to be long memory and this property is strongest when d is around 1. To allow for long memory in volatility, Baillie, Bollerslev, and Mikkelsen (1996) propose the fractionally integrated generalised autoregressive conditional heteroscedasticity

(FIGARCH) model by combining the fractionally integrated process for the mean with the regular GARCH process for the conditional variance. The FIGARCH model implies a slow hyperbolic rate of decay for the lagged squared innovations in the conditional variance function and persistent impulse response weights.

Bollerslev and Mikkelsen (1996) investigate the long-run dependence in U.S. stock market. The FIGARCH model is applied to the daily prices of the Standard and Poor's 500 composite index (S&P 500) from 1953 to 1990. The evidence suggests that the conditional variance for S&P 500 is best modelled as a mean-reverting fractionally integrated process. Baillie, Bollerslev, and Mikkelsen (1996) employ the FIGARCH model to estimate the persistence of volatility in Deutschmark-U.S. dollar spot exchange rate from 1979 to 1992. The results reveal that although the standard GARCH model does a very good job of tracking the short-run volatility dependencies, the long-run dynamics are better modelled by the fractional differencing parameter. The results from Beine, Benassy-Quere, and Lecourt's (2002) study show that the traditional GARCH estimations tend to underestimate the effects in terms of volatility. The FIGARCH model outperforms the GARCH one on measure of volatility.

A variety of the FIGARCH model is the ARFIMA-FIGARCH model which estimates the parameters of the long memory in the conditional mean and in the conditional variance simultaneously. Granger and Terasvirta (1993) suggest that misspecification in the conditional mean may affect the estimation of the conditional variance parameters. Through Monte Carlo simulations, (Teyssiere, 1997) demonstrates that neglecting the long memory in the conditional mean of a double long memory process, i.e. long run dependence in both the mean and the variance, can lead to serious biases in the estimation of the conditional volatility process. Beine, Laurent, and Lecourt (2002) analysis the behaviour of the conditional variance of the four major exchange rates, i.e. GBP, DEM, FRF and YEN, against US dollar between 1980 and 1996 using the ARFIMA-FIGARCH model. The empirical results show that both long memory parameters are significant, and the persistence of volatility shocks is much less important than reported by Baillie, Bollerslev, and Mikkelsen (1996).

3. Data and Methodology

3.1 Data

The variables used in this Chapter are the index futures spreads derived from the cointegrated relationships in Chapter three. Spread I was generated from TX against TW and Spread II was made from TX against TE and TF. TX, TW, TE and TF are index futures contracts based on Taiwan stock market. The details of these index futures and have been shown in Chapter 3. Because the spreads were generated from those futures contracts, the sample period was the same as the data in Chapter three which was collected from the daily closing price and the sample period was from 21 July 1999 to 30 April 2002. So, there are 713 observations for each variable in this study. However, the data used in this chapter are divided by 10000 to reduce the size of estimated coefficients. This will not change the quality of the results.

3.2 Methodology

The expected relationship between the value of a process at time t and its value at time t-k is a measure of the correlation present in the series. A stationary time series has correlation that depends only on the time lag k between the two observations and decays to zero as k increases, indicating the fact that the influence of the past values decreases with the lags under consideration. The speed of this decay is a measure of the memory of the stochastic process. A process in which all observations are uncorrelated is called white noise, and the stochastic process is said to have no memory. When a process has autocorrelations decaying to zero at a geometric rate, it is described as a process with short memory. On the other hand, a long memory process has autocorrelations that decay much more slowly, asymptotically following a hyperbolic decay. More precisely, a stationary process Y_t is said to have long memory if its autocovariance function, $r(k) = E[(Y_t - \mu)(Y_{t+k} - \mu)]$, has asymptotic behaviour

$$|r(k)| \sim C|k|^{2d-1} \text{ as } k \to \infty$$

where $C > 0$, $d < 0.5$ and $d \neq 0$. If $d > 0$, so that $\sum |r(k)| = \infty$, the process is said to be persistent.

Given a discrete time series process y_t with autocorrelation function ρ_j at lag j, the according to McLeod and Hippel (1978), the process possesses long memory if

$$\lim_{n\to\infty}\sum_{j=-n}^{n}|\rho_j|=\infty$$

The basic building block of the long memory models is the fractionally differenced time series model of Granger and Joyeux (1980), and Hosking (1981):

$$(1-L)^d y_t=\varepsilon_t,\ \varepsilon_t\sim IID(0,\sigma_\varepsilon^2) \quad (4.2)$$

where L is the backward-shift operator, $Ly_t = y_{t-1}$. Granger and Joyeux (1980) show that

$$(1-L)^d y_t=\sum_{k=0}^{\infty}A_k y_{t-k}=\varepsilon_t \quad (4.3)$$

where the autoregressive coefficients A_k are in terms of the gamma function

$$A_k=(-1)^k\binom{d}{k}=\frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)}$$

where $\Gamma(\cdot)$ denoting the gamma, or generalized fractional function.

A flexible and parsimonious way to model both the short-term and the long-term behaviour of a time series is by means of an autoregressive fractionally integrated moving-average (ARFIMA) model. A time series $y=\{y_1\cdots y_t\}$ with mean δ follows an ARFIMA process of order (p, d, q), denoted by ARFIMA (p, d, q), if

$$\phi(L)(1-L)^d(y_t-\delta)=\Theta(L)\varepsilon_t\ \ \varepsilon_t\sim \text{IID }(0,\ \sigma_y^2) \quad (4.4)$$

where L is the backward-shift operator, $\phi(L)=1-\phi_1 L-\cdots-\phi_p L^p$, $\Theta(L)=1+\vartheta_1 L+\cdots+\vartheta_q L^q$ and $(1\text{-}L)^d$ is the fractional differencing operator defined by

$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}$$

The parameter d is allowed to assume any real value. The arbitrary restriction of d to integer values gives rise to the standard autoregressive integrated moving average (ARIMA) model. For $|d| < 0.5$, the autocorrelations of y_t show a hyperbolic decay at a rate proportional to k^{2d-1} as $k\to\infty$, in contrast to a faster, geometric decay of a stationary ARMA process (Granger and Joyeux, 1980, and Hosking, 1981). Therefore, the y_t process is both stationary and invertible if all roots and lie outside the unit circle and $|d| < 0.5$. For $0 < d < 0.5$, The ARFIMA process is said to exhibit long memory, or long-range positive dependence. For $-0.5 < d < 0$, the process is said to exhibit intermediate memory, or anti-persistence, or long-range negative dependence. The process exhibits short memory for $d = 0$, corresponding to stationary and invertible ARMA modelling. When $0.5 \leq d < 1$,the y_t process is covariance nonstationary because its variance is not finite (Hosking, 1981). However, it is mean-reverting since an innovation has no permanent effect on the value of y_t. This is in opposition to an I(1) process, which is both convariance nonstationary and not mean-reverting. For an I(1) process, the effect of an innovation can persist forever.

Since a long memory process is neither an I(1) or an I(0) process, it is necessary to test the stationarity of the time series before proceeding to long memory test. Most of the standard tests, e.g. Augmented Dickey Fuller test and Phillips Perron test, for stationarity involve a null hypothesis containing a unit root[43]. Classical statistical hypothesis testing is carried out ensures that a null hypothesis is accepted unless there is strong evidence against it. If an investigator wishes to test stationarity as a null and has strong priors in its favour, then it is not clear that the conventional tests are very useful. Schwert (1987) has discussed the performance of the Dickey and Fuller (1979; 1981) and Phillips Perron (PP) tests of Phillips (1987), Phillips and Perron (1988) and Perron (1988), when the true data-generating process is I(1) with a large negative moving-average coefficient. Schwert notes that size distortions can give rise to rejecting a unit root too often in favour of an I(0) stationary process. Kwiatkowski, Phillips, Schmidt, and Shin (1992) (henceforth KPSS) have developed an alternative approach of testing for unit roots and they impose stationarity as the null hypothesis. On assuming that a process can be decomposed into the sum of a deterministic trend, rand walk, and stationary I(0) disturbance, KPSS show that a score test of the null of stationarity can be based on the statistic

$$\eta = T^{-2} \sum_{t=1}^{T} S_t^2 \Big/ s^2(k)$$

where $S_t = \sum_{i=1}^{t} e_t$

[43] Dolado, Gonzalo and Mayroal (2002) propose a fractional Dickey-Fuller test that allows to test the null hypothesis of the fractional parameter $d = 1$ against alternative hypothesis $d < 1$.

is the partial sum of the residuals e_i, when the series has been regressed on an intercept and possibly also a time trend, and T is the sample size. $s^2(k)$ is a consistent non-parametric estimate of the disturbance variance; it is computed in an identical manner to its equivalent in the PP test by using a Bartlett window adjustment based on the first k sample autocovariances as suggested by Newey and West (1987).

According to Baillie, Chung, and Tieslau (1996), there are four possible outcomes from the combined use of the ADF and KPSS test statistics:

(1) Rejection by the ADF statistics and failure to reject by the KPSS appears to be strongly indicative of covariance stationarity, i.e. an I(0) process.

(2) Failure to reject by the ADF but rejection by the KPSS statistic is viewed as strong evidence of a unit root, i.e. an I(1) process.

(3) Failure to reject by both the ADF and KPSS statistics gives no indication on the order of integration of the process. This result is probably due to the data being insufficiently informative on the long-run characteristics of the process.

(4) Rejection by both the ADF and KPSS statistics presumably indicates evidence of the process that is well described by neither an I(1) nor an I(0) process.

The existence of a fractional order of integration can be determined by testing for the statistical significance of the sample differencing parameter d, which is also interpreted as the long memory parameter. To estimate d and perform hypothesis testing, the semi-parametric procedure proposed by Geweke and Porter-Hudak (1983) (henceforth GPH) is employed. They obtain an estimate of d based on the slope of the spectral density function around the angular frequency $\xi = 0$. More specifically, let $I(\xi)$ be the periodogram of y at frequency ξ defined by

$$I(\xi) = \frac{1}{2\pi T} \mid \sum_{t=1}^{T} e^{it\xi} (y_t - \bar{y}) \mid^2$$

Then the spectral regression is defined by

$$\ln\{I(\xi_\lambda)\} = \beta_0 + \beta_1 \ln\{\sin^2(\frac{\xi_\lambda}{2})\} + \eta_\lambda, \ \lambda = 1,2,\ldots,v \qquad (4.5)$$

where $\xi_\lambda = \frac{2\pi\lambda}{T}$ denotes the Fourier frequencies of the sample, T is the number of observations, and $v = g(T)$ is the number of Fourier frequencies included in the spectral regression. Assuming that $\lim_{T\to\infty} g(T) = \infty$, $\lim_{T\to\infty}\{\frac{g(T)}{T}\} = 0$, and $\lim_{T\to\infty}\frac{\ln(T)^2}{g(T)} = 0$, the negative of the OLS estimate of the slope coefficient in (4.5) provides an estimate of d. Despite the fact that the GPH test is potentially robust to non-normality, Agiakloglou, Newbold, and Wohar (1992) argue that the GPH test may yield large finite sample biases when short-memory ARMA components are also present. Cheung (1993) shows that the GPH procedure may also yield positively biased estimates of d when the underlying process has infrequent shifts in mean, but is robust to ARCH effects.

The GPH test only estimates the differencing parameter. An alternative approach employed in this chapter is Sowell's (1992) exact maximum likelihood estimator (MLE) which derives the unconditional exact likelihood function for simultaneous estimation of all the parameters of the ARFIMA(p, d, q) process with normally distributed innovations. Under normality, the logarithm of the likelihood can be expressed in the time domain as

$$L(\mu, d, \phi, \Theta, \sigma^2) = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma| - \frac{1}{2}(y-\mu)'\Sigma(y-\mu)$$

where y is the T-dimensional vector of y_t and Σ is the corresponding $T \times T$ autocovariance matrix, where each element is a nonlinear function of hypogeometric functions.

It has long been recognised that share returns are approximately uncorrelated but not independent through time, as most return processes tend to exhibit clustering of extreme volatility. Engle (1982) introduces the autoregressive conditional heteroscedasticity (ARCH) model to capture the extreme degree of persistence of shocks to the conditional variance process. Following Engle's ARCH model, several ARCH family models have been proposed, e.g. GARCH (Bollerslev, 1986), EGARCH (Nelson, 1991) and IGARCH (Engle and Bollerslev, 1986). The ARCH models allow the conditional variance to change over time as a function of past errors leaving the unconditional variance constant enable the econometrician to estimate the variance of a series at a particular point in time, and capture parts or all of the stylised facts revealed by Engle and Patton (2001). They point out that there are three stylised facts about the volatility of financial asset prices should be captured by a good volatility model: clustering, mean reverting and asymmetric impact. First, volatility clustering indicates that many economic time series exhibit periods of unusually large volatility followed by periods of relative tranquillity. It implies that volatility shocks today will influence the expectation of volatility in the futures. Second, mean reversion in volatility means that there is a normal level of volatility to which volatility will eventually return. Very long run forecasts of volatility should all converge to this same normal level of volatility, no matter when they are made. Third, innovations may have an asymmetric impact on volatility, especially, of equity returns. As the price of a stock falls, its debt-to-equity ratio goes up, increasing the volatility of returns to equity holders. This leverage effect causes the asymmetry on volatility.

Motivated by the presence of long memory in the squared or absolute returns of various financial assets, Baillie, Bollerslev, and Mikkelsen (1996) propose the fractionally integrated generalised autoregressive conditional heteroscedasticity (FIGARCH) model by combining the fractionally integrated process for the mean with the regular GARCH process for the conditional variance. The FIGARCH model implies a slow hyperbolic rate of decay for the lagged squared innovations in the conditional variance function and persistent impulse response weights. A FIGARCH process exhibits the characteristic volatility effect captured by standard GARCH models, but with the difference that shocks to the error process die away at a slower, hypergeometric rate rather than the short-term exponential decay typical of a short memory process.

Analogously to the ARFIMA(p, d, q) process for mean, the FIGARCH(k, f, l) process for ε_t is defined by

$$\theta(L)(1-L)^f \varepsilon_t^2 = \omega + [1-\beta(L)]v_t \tag{4.6}$$

where $0 < d < 1$, $v_t \equiv \varepsilon_t^2 - \sigma_t^2$ is mean zero serially uncorrelated, $\theta(L) = \{1-\alpha(L)-\beta(L)\}(1-L)^{-1}$[44], and all the roots of $\theta(L)$ and $[1-\beta(L)]$ lie outside the unit circle. An alternative representation for the FIGARCH(k, f, l) model by rearranging the equation above is

$$[1-\beta(L)]\sigma_t^2 = \omega + [1-\beta(L)-\theta(L)(1-L)^f]\varepsilon_t^2 \tag{4.7}$$

Thus, the conditional variance of ε_t is simply given by

[44] $\alpha(L)$ and $\beta(L)$ are polynomials of order p and q in the GARCH(p, q) specification of Bollerslev (1986) which is defined as $\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2$

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\theta(L)(1-L)^f\}\varepsilon_t^2 \quad (4.8)$$

$$\equiv \omega[1-\beta(L)]^{-1} + \lambda(L)\varepsilon_t^2 \quad (4.9)$$

where $\lambda(L) = \lambda_1 L + \lambda_2 L + \cdots$. For the FIGARCH(*k*, *f*, *l*) process to be well-defined and the conditional variance to be positive almost surely for all t, all the coefficients in the infinite ARCH representation in (4.8) must be nonnegative; i.e. $\lambda_k \geq 0$ for $k = 1, 2, \ldots$ (Baillie, Bollerslev, and Mikkelsen, 1996).

Although many studies employ FIGARCH to detect the long memory in volatility, Granger and Terasvirta (1993) advocate that misspecification in the conditional mean may affect the estimation of the conditional variance parameters. Through Monte Carlo simulations, Teyssiere (1997) demonstrates that ignoring the long memory in the conditional mean of a double long memory process, i.e. long memory in both the mean and the variance, can lead to serious biases in the estimation of the conditional volatility process. Therefore, a fractional root in the mean is introduced into the FIGARCH model estimation. Consequently, this study estimate the spread series using ARFIMA-FIGARCH model to see the possible double long memory in these processes. The ARFIMA(*p*, *d*, *q*)-FIGARCH(*k*, *f*, *l*) process is defined as

$$\phi(L)(1-L)^d(y_t - \delta) = \Theta(L)\varepsilon_t \quad \varepsilon_t \sim \text{IID } (0, \sigma_y^2) \quad (4.10)$$

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\theta(L)(1-L)^f\}\varepsilon_t^2 \quad (4.11)$$

Since in most practical applications with financial data the standardised innovations $z_t = \varepsilon_t / \sigma_t$ are leptokurtic and not i.i.d. normally distributed through time, the estimation of the FIGARCH model relies on the quasi maximum likelihood (QML) procedure following Baillie, Bollerslev, and Mikkelsen's (1996) method. As shown by Bollerslev and Wooldridge (1992)and Baillie, Bollerslev, and Mikkelsen (1996), the QML estimates obtained with a Gaussian assumption behave relatively well. However, as explained by Pagan(1996), a Student-*t* distribution may be more appropriate to account for the leptokurticity characterizing the high frequency financial data. For that reason, Normal and Student-*t* distributions are both applied for the comparison of results.

4. Empirical Results

Table 4.1 shows the descriptive statistics of Spread I, the first difference of Spread I, Spread II and the first difference of Spread II. First of all, the assumption of normality is accepted for Spread I but rejected for the other series as indicated by Jarque-Bera statistics. Secondly, the Ljung-Box Q-statistics at lag 20 reveal that the null hypothesis of no autocorrelation up to order 20 is rejected for all the levels and the first differences of spreads. Finally, the ARCH $F(1)$ statistics in the last row are the results of the ARCH Lagrange multiplier tests which examine the null hypothesis that there is no ARCH effects up to order 1. Since the F-statistics are rejected for all series, indicating ARCH effects exist in all series.

Table 4.1 Descriptive statistics of Spread I, first difference of Spread I, Spread II and first difference of Spread II

	Spread I	Δ Spread I	Spread II	Δ Spread II
Observations	713	712	713	712
Mean	0.480576	-0.001577	0.084295	0.003892
Std deviation	5.844256	1.930385	2.347419	1.020735
Maximum	17.89261	19.69020	9.453652	4.699603
Minimum	-13.74971	-14.47917	-8.342018	-5.733199
Skewness	-0.176015	0.667210	-0.127962	-0.375229
Kurtosis	2.826554	26.65005	3.650446	7.884165
Jarque-Bera	4.575343	**16646.13****	**14.51482****	**724.4081****
Probability	0.101503	0.000000	0.000705	0.000000
$Q(20)$	**8112.8****	**71.306****	**4219.5****	**53.872****
ARCH F(1)	**1651.565****	**152.546****	**860.279****	**50.342****

** Significant at the 0.01 level

The results of applying the ADF tests and the KPSS tests to both spreads are reported in Table 4.2. The number of lags in the ADF tests is 1, which chosen by the AIC and the lag length for computing statistic in the KPSS tests is 3, selected by the recommendations in Kwiatkowski, Phillips, Schmidt, and Shin (1992) and also in Schwert (1989), who recommended basing the number of lags in residual autocorrelations for unit root tests as $\text{int}[12(\frac{T}{100})^{1/4}]$. For both of the spreads, the null hypothesis of a unit root is rejected by the ADF tests at 5% level and the null hypothesis of stationarity is rejected by the KPSS tests as well. Rejection by both the ADF and

KPSS statistics presumably indicates evidence of the process that is well described by neither an I(1) nor an I(0) process and is at least indicative of fractional integration.

Table 4.2 The ADF and KPSS statistics of Spread I and Spread II

	ADF			KPSS	
Lags	$l = 1$			$l = 3$	
	$\hat{\tau}$	$\hat{\tau}_u$	$\hat{\tau}_\tau$	$\hat{\eta}_u$	$\hat{\eta}_\tau$
Spread I	**-3.3788****	**-3.3904***	**-3.4337***	**1.9673****	**1.9655****
Spread II	**-5.1091****	**-5.1162****	**-5.1941****	**0.5057***	**0.3368****
Critical value					
1%	-2.5682	-3.4393	-3.9710	0.7390	0.2160
5%	-1.9413	-2.8654	-3.4162	0.4630	0.1460

** and * denote significant at the 0.01 and 0.05 level, respectively.

$\hat{\tau}$, $\hat{\tau}_u$ and $\hat{\tau}_\tau$ are the ADF test statistics of the lagged dependent variable in a regression without intercept and time trend, with intercept only and intercept and time trend included, respectively.

$\hat{\eta}_u$ and $\hat{\eta}_\tau$ are the KPSS test statistics based on residuals from regressions with an intercept and intercept and time trend, respectively.

Table 4.3 The GPH estimates of the fractional differencing parameter *d*

Panel A				
k=	0.5	0.55	0.6	0.65
Spread I				
d	**0.7612****	**0.7815****	**0.7516****	**0.7898****
t-statistic	4.9692	6.3345	7.3631	9.3429
Spread II				
d	**0.5290****	**0.5504****	**0.7416****	**0.7448****
t-statistic	3.4535	4.4619	7.2653	8.8109
Panel B				
k=	0.5	0.55	0.6	0.65
ΔSpread I				
$\tilde{d}$	-0.2302	-0.2289	**-0.2481****	**-0.1992****
t-statistic	-1.5028	-1.8551	-2.4306	-2.3566
Δ Spread II				
$\tilde{d}$	-0.2902	**-0.3259****	-0.164	**-0.1747***
t-statistic	-1.8947	-2.6417	-1.6069	-2.0668

** and * denote significant at the 0.01 and 0.05 level, respectively.

k denotes the power associated with the number of low-frequency ordinates (v) used in the GPH spectral regression is given by $v = T^k$.

The t-statistics are computed based the known theoretical error variance of $\pi^2/6$.

Table 4.3 exhibits the results of the GPH estimates of fractional differencing parameter d. Since the periodogram is used as an estimator of the spectral density, d may be approximated by regression. However, a choice of a truncation parameter needs to be made for the number of low Fourier frequencies, v, to be used in the spectral regression. While a too large value of v will cause contamination of the d estimate due to medium- or high-frequency components, a too small value of v will lead to imprecise estimates due to limited degrees of freedom in estimation. Although Geweke and Porter-Hudak (1983) recommend using $v = T^{0.5}$, where T is the number of observations, to balance these two consideration factors, a range of k values is used for the sample size function, $v = T^{k}$. The results reported below are for k = 0.5, 0.55, 0.6 and 0.65. Panel A of Table 4.3 reports the spectral regression estimates of d for the spreads for the sample size function of $v = T^{0.5}$, $v = T^{0.55}$, $v = T^{0.6}$, and $v = T^{0.65}$. According to the GPH estimates, the estimated d of Spread I and II are significantly different from 0 and 1 for all the sample size functions. Moreover, all the estimated d are greater than 0.5. That means both spreads are mean-reverting but covariance nonstationary. To ensure that stationarity and invertibility are achieved, the GPH tests are applied to the first differences of the spreads. The first differences of Spread I and Spread II are denoted by Δ Spread I and Δ Spread II, respectively, and the fractional differencing parameter of the differenced spreads are denoted by $\tilde{d}$, where $\tilde{d} = d - 1$. The GPH estimates of $\tilde{d}$ are presented in the Panel B of Table 4.3. The evidence of long memory in Δ Spread I can be found for k = 0.6 and 0.65, and the evidence of long memory in Δ Spread II can be found for k = 0.55 and 0.65. Although not all the estimated $\tilde{d}$ are significant, the overall evidence shows that Δ Spread I and Δ Spread II are anti-persistence long memory processes as $-0.5 < \tilde{d} < 0$. Given that $d = \tilde{d} + 1$, the results from Panel B confirm the results from Panel A that both spreads are non-stationary long memory processes with fractional differencing parameter greater than 0.5.

Table 4.4 ARFIMA(p, $\tilde{d}$, q) models

Δ Spread I	(0, $\tilde{d}$, 0)	(1, $\tilde{d}$, 0)#	(0, $\tilde{d}$, 1)	(1, $\tilde{d}$, 1)
Constant	-0.0078	-0.0070	-0.0071	-0.0072
std error	0.0172	0.0252	0.0247	0.0237
$\tilde{d}$	**-0.2389****	**-0.1473****	**-0.1504****	**-0.1629****
std error	0.0287	0.0487	0.0569	0.0509
ϕ_1	–	**0.1427***	–	-0.2752
std error	–	0.0581	–	0.2246
ϑ_1	–	–	**-0.1295***	0.1487
std error	–	–	0.06538	0.2502
Log-Likelihood	-1451.48	-1448.77	-1449.28	-1448.59
AIC	4.0856	4.0808	4.0822	4.0831
$Q(20)$	25.998	21.421	22.163	21.195
ARCH 1-1 test	**47.438****	**33.588****	**36.155****	**33.571****

Δ Spread II	(0, $\tilde{d}$, 0)	(1, $\tilde{d}$, 0)	(0, $\tilde{d}$, 1)	(1, $\tilde{d}$, 1)#
Constant	0.0014	0.0019	0.0018	0.0018
std error	0.0111	0.0145	0.0136	0.0136
$\tilde{d}$	**-0.2049****	**-0.1434****	**-0.1574****	**-0.1605****
std error	0.0304	0.0549	0.0559	0.0411
ϕ_1	–	-0.0882	–	**-0.6192****
std error	–	0.0647	–	0.2168
ϑ_1	–	–	-0.0662	**0.5432****
std error	–	–	0.0630	0.2396
Log-Likelihood	-1005.57	-1004.72	-1004.98	-1003.27
AIC	2.8331	2.8335	2.8342	2.8322
$Q(20)$	22.436	19.826	20.432	18.336
ARCH 1-1 test	**22.572****	**21.424****	**21.655****	**21.725****

Notes: ** and * denote significant at the 0.01 and 0.05 level, respectively.
ARFIMA Parameterisation selected using AIC denoted as #

$$\phi(L)(1-L)^d(y_t-\delta)=\Theta(L)\varepsilon_t$$

Table 4.4 summarises the results of Sowell's (1992) estimation procedure of ARFIMA(p, $\tilde{d}$, q) models, where p, q = 0, 1. That is, there are four combinations of the ARFIMA models fitted to each spread. Since the fractional differencing parameter of both spreads is greater than 0.5, the ARFIMA estimations are only applied to the first differenced spreads (Δ Spread I and Δ Spread II) because one of the assumptions of Sowell's estimation procedure is $d < 0.5$. The model selection criterion is based on the

AIC. For Δ Spread I, the estimated $\tilde{d}$ of all the four models are significant and less than 0. The results are consistent with the evidence from Panel B of Table 4.3 and reveal that Δ Spread I is an anti-persistent long memory process and Spread I is a mean-reverting but nonstationary long memory process. The estimated results for Δ Spread II are similar to the results for Δ Spread I. All the estimated $\tilde{d}$ are significant and negative, so Δ Spread II is long-range negative dependence as well. The AIC selects an ARFIMA(1, $\tilde{d}$, 0) for Δ Spread I and an ARFIMA(1, $\tilde{d}$, 1) for Δ Spread II as the best fitted model. The portmanteau test for remaining serial correlation in the residuals, $Q(20)$, shows that the ARFIMA model provides a good description of temporal dependencies for both spreads. The null hypothesis of no autocorrelations up to order 20 cannot be rejected for both of the first differenced spreads. However, the ARCH tests reveal that there exist ARCH effects in the residuals after taking the short- and long-run dependencies into account. The ARCH test examines the joint significance of lagged squared residuals in the regression of squared residuals on a constant and lagged squared residuals. In the ARCH 1-1 test, the null hypothesis that there is no ARCH up to order one in the residuals is rejected for both of the differenced series. Thus, ARFIMA-FIGARCH models are employed to estimate the parameters of long memory in the conditional mean and long memory in conditional variance simultaneously.

Table 4.5 reports the estimated results of ARFIMA(p, $\hat{d}$, q) —FIGARCH(k, $\hat{f}$, l) models for Δ Spread I, where $p = 1$ and $q = 0$ according to the AIC selection in Table 4.4, and k, $l = 0, 1$. In addition, two distributions are employed for the estimation: the Gaussian distribution and the Student-t distribution. Therefore, there are eight combinations of ARFIMA-FIGARCH fitted for Δ Spread I. However, because of no convergence, the estimated results cannot be generated for the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(1, $\hat{f}$, 1) with the Gaussian distribution, the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(1, $\hat{f}$, 0) and the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(1, $\hat{f}$, 1) with the Student-t distribution. Moreover, the negatively significant GARCH coefficient of the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(1, $\hat{f}$, 0) with Gaussian distribution violates one of the assumptions for GARCH models, that is, the GARCH coefficients should not be less than zero (Bollerslev, 1986). Consequently, these four models are not considered for Δ Spread I. The AIC and SC select the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(0, $\hat{f}$, 1) with the Student-t distribution as the best fitted model. The fractional integration coefficient in the conditional mean is significant but that in the conditional variance is not. The long memory in the conditional variance equation is mostly explained by the ARCH coefficient which is significantly greater than zero. The hypotheses of no serial correlation and no ARCH effect in the residuals are accepted by the Q(20), $Q(20)^2$ and ARCH 1-1 tests. Therefore, the ARIFMA—FIGARCH specification is a good description to take account of the long memory in conditional mean and conditional variance for Δ Spread I.

Table 4.5 ARFIMA(1, $\hat{d}$, 0)—FIGARCH(k, $\hat{f}$, l) models for Δ Spread I

Dist	Gaussian				Student-t			
	$(0, \hat{f}, 0)$	$(1, \hat{f}, 0)$	$(0, \hat{f}, 1)$	$(1, \hat{f}, 1)$ &	$(0, \hat{f}, 0)$	$(1, \hat{f}, 0)$ &	$(0, \hat{f}, 1)$#	$(1, \hat{f}, 1)$ &
Cst(M)	0.0119	-0.0002	0.0106		0.0025		0.0003	
Std error	0.0395	0.0339	0.0344		0.0188		0.0192	
$\hat{d}$	-0.0775	-0.1037	-0.1093		**-0.1803****		**-0.1779****	
Std error	0.0650	0.0724	0.0654		0.0588		0.0572	
AR	-0.0820	0.0201	-0.0159		0.0709		0.0851	
Std error	0.0760	0.0657	0.0798		0.0733		0.0733	
Cst(V)	**1.6732****	**3.6681****	**2.9094****		**0.9070***		**1.9438****	
Std error	0.2943	0.2717	0.2479		0.3824		0.4052	
$\hat{f}$	**0.0867****	**-0.0147****	-0.0157		**0.1241***		0.0081	
Std error	0.0261	0.0052	0.0085		0.0578		0.0221	
GARCH	—	**-0.2023****	—		—		—	
Std error	—	0.0181	—		—		—	
ARCH	—	—	**0.2337****		—		**0.2474****	
Std error	—	—	0.0591		—		0.0794	
DF	—	—	—		**4.4642****		**4.7986****	
Std error	—	—	—		0.7449		0.7839	
LL	-1421.112	-1403.524	-1410.747		-1318.137		-1311.366	
Q(20)	16.4451	1.92168	16.0869		15.5449		14.8555	
Q(20) ^2	1.79532	1.92168	1.75575		1.05032		0.9474	
ARCH 1-2 test:	0.3198	0.1055	0.0472		0.12314		0.0351	
Akaike	4.0059	3.9593	3.9796		3.7195		3.7033	
Schwarz	4.0380	3.9978	4.0181		3.7580		3.7482	

Notes: ** and * denote significant at the 0.01 and 0.05 level, respectively.
ARFIMA-FIGARCH Parameterisation selected using AIC and SIC denoted as #
& denotes that there is no convergence in this model.

The estimated results of ARFIMA(p, $\tilde{d}$, q) —FIGARCH(k, $\hat{f}$, l) models for Δ Spread II are given details in Table 4.6, where $p = 1$ and $q = 0$ according to the AIC selection in Table 4.4, and k, $l = 0$, 1. Also, the Gaussian distribution and the Student-t distribution are used for the estimation. Although all the eight results are reported, the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(1, $\hat{f}$, 1) with Gaussian distribution is excluded from consideration because the sum of the ARCH and GARCH coefficients are greater than one which does not comply with the assumption described in Bollerslev's (1986) work. All the fractional parameters in the conditional mean and the conditional variance are significant for all specifications, Δ Spread II is obviously a double long memory process, i.e. long-range dependence in both the mean and the volatility. The AIC and SC select the ARFIMA(1, $\hat{d}$, 0)—FIGARCH(0, $\hat{f}$, 0) with Student-*t* distribution as the best fitted model. Again, the hypotheses of no serial correlation and no ARCH effect in the residuals are accepted by the Q(20), $Q(20)^2$ and ARCH 1-1 tests. Thus, the ARIFMA—FIGARCH model is a good specification to take the long memory in conditional mean and conditional variance into account for Δ Spread II.

Table 4.6 ARFIMA(1, $\hat{d}$, 0)—FIGARCH(k, $\hat{f}$, l) models for Δ Spread II

Dist	Gaussian				Student-*t*			
	(0, $\hat{f}$, 0)	(1, $\hat{f}$, 0)	(0, $\hat{f}$, 1)	(1, $\hat{f}$, 1)	(0, $\hat{f}$, 0)#	(1, $\hat{f}$, 0)	(0, $\hat{f}$, 1)	(1, $\hat{f}$, 1)
Cst(M)	0.0171	0.0167	0.0166	0.0095	0.0085	0.0084	0.0083	0.0082
Std	0.0143	0.0143	0.0143	0.0129	0.0093	0.0093	0.0094	0.0094
$\hat{d}$	**-0.1139***	**-0.1137****	**-0.1136****	**-0.1285****	**-0.1681****	**-0.1681****	**-0.1681****	**-0.1677****
Std	0.0441	0.0439	0.0439	0.0417	0.0384	0.0384	0.0383	0.0383
AR	**-0.6523****	**-0.6556****	**-0.6561****	**-0.6508****	**-0.6482****	**-0.6497****	**-0.6504****	**-0.6521****
Std	0.2205	0.2169	0.2164	0.2180	0.2453	0.2437	0.2428	0.2395
MA	**0.5995***	**0.6027****	**0.6032****	**0.6021****	**0.6345***	**0.6361***	**0.6368***	**0.6387***
Std	0.2328	0.2293	0.2289	0.2309	0.2559	0.2542	0.2533	0.2498
Cst(V)	**0.1060****	**0.1134****	**0.1108****	0.0102	**0.1404***	**0.1460***	**0.1418***	0.1149
Std	0.0349	0.0406	0.0373	0.0065	0.0687	0.0734	0.0682	0.0807
$\hat{f}$	**0.3103****	**0.2991****	**0.2962****	**0.6293****	**0.3059****	**0.3017****	**0.2930****	**0.2705***
Std	0.0516	0.0602	0.0614	0.1449	0.0833	0.1055	0.1116	0.1076
GARCH	—	-0.0234	—	**0.8456****	—	-0.0109	—	0.2357
Std	—	0.0634	—	0.0471	—	0.0924	—	0.4136
ARCH	—		0.0267	**0.5386****	—	—	0.0179	0.2885
Std	—		0.0687	0.1044	—	—	0.1108	0.4359
DF	—		—	—	**4.4219****	**4.4054****	**4.4367****	**4.4495****
Std	—		—	—	0.7367	0.7387	0.7437	0.7430
LL	-942.239	-942.164	-942.164	-936.323	-902.243	-902.210	-902.230	-902.135
Q(20)	14.1445	14.1413	14.1392	13.7685	17.7759	17.7735	17.7609	17.7475
Q(20)^2	12.541	12.1457	12.1151	12.418	13.176	13.0054	12.9747	12.6987
ARCH 1-1 test:	0.1896	0.1145	0.1097	0.1013	0.1602	0.1271	0.11633	0.0813
Akaike	2.6636	2.6662	2.6662	2.6526	2.5541	2.5568	2.5568	2.5594
Schwarz	2.7021	2.7111	2.7111	2.7039	2.5990	2.6081	2.6082	2.6171

Notes: ** and * denote significant at the 0.01 and 0.05 level, respectively.
ARFIMA-FIGARCH Parameterisation selected using AIC and SIC denoted as #

5. Conclusion and Summary

This chapter investigates the properties of long-range dependence in the spreads of index futures. Although the spreads possess the same property of mean-reverting with stationary process, their autocorrelations decay at a much slower rate than the stationary process. On the other hand, they do not remain as persistently as the integrated process. Rejection by both the ADF and KPSS statistics presumably indicates evidence of both spreads are well described by neither an I(1) nor an I(0) process and is at least indicative of fractional integration. According to the GPH estimates, the fractional integration parameter of both spreads are greater than 0.5. The GPH estimates and ARFIMA models are applied to the first differenced spreads to estimate the fractional integration parameter. Both spreads are revealed to be mean-reverting but non-stationary long memory processes. However, the ARCH tests confirm that there exist ARCH effects in the residuals after taking the short- and long-run dependencies into account. Consequently, ARFIMA-FIGARCH models are employed to estimate the parameters of long memory in the conditional mean and in conditional variance simultaneously. The estimated results of ARFIMA-FIGARCH models show the Spread I have different long memory property from Spread II. There is strong evidence that Spread II is a double long memory process but Spread I lacks the property of long memory in the conditional variance. Most of the conditional variance is explained by the ARCH coefficient, instead of the long memory parameter in the conditional variance equation.

Chapter Five: Conclusion and Summary

The thesis investigates the predictability of stock index futures in Taiwan. The first part of thesis examines the lead-lag relations between the intraday cash index and index futures returns, as well as across futures returns. Empirical results confirm previous findings that there is an asymmetric lead-lag relation between cash and futures markets— the feedback from the futures markets into the cash market is much stronger than the reverse. Moreover, the weak evidence that the spot index leads the futures diminishes as interval enlarges and the leadership becomes a unidirectional relation that only the futures leads the cash index. There is no evidence that the spot index lags futures longer under the short-sales constraints. This may indicate that short selling is not a main approach for informed traders to reflect information. Although short-selling constraint is a reasonable hypothesis to conjecture the lead-lag relationship between the stock index and index futures, there is no evidence to support it from Taiwan markets or any others.

Furthermore, the results of lead-lag relationship are not the same under different intervals. Futures returns can lead the cash returns as long as 30 minutes in 30-minute returns data or as short as 5 minutes in 5-minutes returns. However, as the interval widens, the meaningfulness of lag or lead coefficients drops compared with contemporaneous coefficients. Therefore, the lead-lag relationship between the cash and futures markets should not be overemphasized when the contemporaneous relationship is much stronger than the lead-lag relationship.

The second part of thesis employs the cointegration approach to construct spread arbitrage between stock index futures. A necessary condition for spread arbitrage is the availability of a good substitute for a futures contract. Cointegration tests are employed to identify whether two or more index futures are good substitutes for spread arbitrage. The cointegration relationships are found among index futures in Taiwan, indicating that there is a long-term equilibrium level between related index futures, and the spreads derived from cointegration relationships are stationary. Any short-term deviations will revert to the fundamental value. Simulation results reveal that spread arbitrage is profitable given that average profits under different filters are all significantly greater than zero after transaction costs. Under certain assumptions, the rates of return of spread arbitrage are found to be highly attractive. The existence of arbitrage opportunities may result from market immaturity and lack of sufficient volume of arbitrage transactions to remove disequilibrium.

The third part of thesis investigates the properties of long-range dependence in the spreads derived from the cointegration relationships. Although the spreads share the same property of mean-reverting with stationary process, their autocorrelations decay at a much slower rate than the stationary process. On the other hand, they do not remain as persistently as the integrated process. Rejection by both the ADF and KPSS statistics presumably indicates evidence of both spreads are well described by neither an I(1) nor an I(0) process and is at least indicative of fractional integration. According to the GPH estimates, the fractional integration parameter of both spreads are greater than 0.5. The GPH estimates and ARFIMA models are applied to the first differenced spreads to estimate the fractional integration parameter. Both spreads are revealed to be mean-reverting but non-stationary long memory process. However, the ARCH tests confirm that there exist ARCH effects in the residuals after taking the short- and long-run dependencies into account. Consequently, ARFIMA-FIGARCH models are employed to estimate the parameters of long memory in the conditional mean and in conditional variance simultaneously. The estimated results of ARFIMA-FIGARCH models show the Spread I have different long memory property from Spread II. There is strong evidence that Spread II is a double long memory process but Spread I lacks the property of long memory in the conditional variance. Most of the conditional variance is explained by the ARCH coefficient, instead of the long memory parameter in the conditional variance equation.

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