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碩 士 論 文

台灣指數期貨與現貨於台灣證券交易所升降單位縮小前後的非線性動態關係研究：門檻誤差修正模型

The Nonlinear Dynamic Relationship between the TAIEX Index Futures and Spot before and after the Reduction of Tick Size on the Taiwan Stock Exchange: Threshold VECM Approach

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摘要

本文採用門檻誤差修正模型(TVECM)來探討台灣證券交易所股市升降單位縮小前後，台指期貨與現貨間的非線性動態關係。資料從民國九十三年五月一日至民國九十四年十二月三十日，並將樣本期間以股市升降單位縮小前後區分成兩組樣本期間。實證結果顯示：台指期貨與現貨間存在著顯著的門檻共整合及非線性短期動態關係，意味著門檻誤差修正模型比線性誤差修正模型更能有效配適期貨對現貨的價格動態。而由於股市升降單位縮小可減少價差成本，因此套利門檻值降低，股市升降單位縮小確實有效提升期貨與現貨的長期連動關係。整體而言，台指期貨相對於台指現貨具有較強的領先性。最後，股市升降單位縮小可有效減少定價誤差，改善期貨與現貨的定價效率。

關鍵字： 定價效率; 套利; 非線性動態關係; 股價升降單位; 門檻共整合;
門檻誤差修正模型; 股價升降單位

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ABSTRACT

This study employs the threshold vector error correction model (TVECM) to model the price dynamics between futures and spot markets across the pre- and post-reduction of tick size periods. The sample period extends over two-year trading days from May 1, 2004 to December 31, 2005. The sample period is divided into two sub-periods before and after the reduction of tick size on March 1, 2005. First of all, the results confirm the presence of threshold cointegration, and nonlinear dynamic coefficients in both sub-sample periods, i.e., implying the threshold VECM model fits the price dynamics between futures and spot markets superior to the linear VECM model. Next, the threshold value decreases after the reduction of tick size, because the decrease of tick size reduces the spread cost which comprises the main transaction cost and lower the arbitrage threshold for arbitrageurs. Then, the long-run co-movement extent between these two financial markets turns stronger. This result is caused by the lower transaction costs after the reduction of tick size, which reduces the obstacles for the two prices to return to long-run equilibrium. Last, the dynamic coefficients show the futures clearly leads the spot in both sub-sample periods. Last but not least, the reduction of tick size can effectively lower the mispricing error and improve the pricing efficiency.

Keywords: pricing efficiency; arbitrage; nonlinear dynamic relationship; tick size;

threshold cointegration; TVECM; tick size

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柏鈞　于交通大學

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TABLES

1. Introduction

Tick size signifies the minimum stock price increment unit. Reduction of tick size is crucial for the government officials since it might affect market liquidity, and consequently the entire functioning of financial markets. If the price movement determined by investors turns out to be smaller than the minimum stock price increment unit settled by the stock exchange, the price movement will turn larger to the tick size restriction. As a result, the spread which constitutes a major part of investors' trading cost between best bid and ask prices will ascend. Because the larger transaction cost impedes the investors to trade and trigger arbitrage, mispricing error (MPE) between futures and spot would become larger, meaning worse pricing efficiency. Advocates of the adoption of reduction argue that the better formation of stock prices will benefit investors. Because the restriction of pricing increment dominates the possible minimum bid-ask spread for every stock. This spread means the difference between the lowest price an investor can get for selling the stock and the highest price an investor can pay for purchasing the same stock.

On the other hand, reduction of tick size may affect not only bid-ask spread. Harris (1994, 1997) and Furfine (2003) argue that a smaller tick size can inhibit incentives to provide liquidity, and potentially ruin market quality. For large traders, quoted depth at the best-quoted prices may be insufficient to fill the desired order. In consequence, the effective transaction price lies somewhere outside the best bid and ask prices. These costs originate from the lack of supply and demand shares that can be purchased and sold at the same price. In general, these studies find that the smaller tick size decreases quoted and effective bid-ask spread, but also reduces liquidity provision.

For the purpose of studying the evidently contradictory findings reported in previous papers, many studies use different estimators to examine whether and/or to what extent market liquidity was affected by decimalization. Most of them eventually find that decimalization do improve the decrease of overall transaction cost (Harris, 1997; Bollen and Whaley, 1998; Chakravarty, Van Ness, and Van Ness, 2005; Furfine, 2003; Bessembinder, 2003; Chakravarty, Panchapagesan, and Wood, 2003).

Taiwanese financial authorities enforce a succession of revolution in an endeavor to abate the trading restriction, liberalize financial market, attract more investors to enter into the market as well as connect to the international financial market further. On March 1, 2005, the Taiwan Stock Exchange (TSE) reduced the minimum change for stock prices and quotes to lower the trading costs of investors and to promote stock price continuity. Investors can memorize the new tick size and price interval combination much easier and have more tick to quote and trade according to their trading strategies.

This paper examines the effect of the decrease in transaction cost resulted from the shrink of tick size on Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) futures pricing efficiency. Lower transaction cost is supposed to bring about a decline in the index futures mispricing error (MPE) that triggers arbitrage. However, this supposition may be erroneous because of the following reasons. First, Goldstein and Kavajecz (2000) and Jones and Lipson (2001) discover that transaction costs decrease only for small orders because cumulative market depth falls after the reduction of tick size. Second, Neal (1996) finds that arbitrageurs earn on average only around half the quoted spread for each round-trip arbitrage trade. Therefore, arbitrageurs must be able to trade at prices inside the quoted spread for arbitrage to be profitable. With above considerations in mind, we identify and investigate two important empirical questions. First, does the reduction of the minimum price increment affect the level of the arbitrage costs, and second, has pricing efficiency improved in the new milieu.

Nevertheless, the volatility of spot and futures affects the arbitrage behavior heavily. Higher volatility leads to an increase in timing risk and in tracking error risk incurred from trading only a subset of the stocks underlying the index. Increased volatility of the futures and the underlying market will enhance the execution risk for the position. In periods of high volatility, one would expect arbitrageurs to initiate trades only at relatively higher MPEs to make up for the increased price risk of nonsimultaneous order execution (Henker, Thomas and Martin Martens (2005)). The MPEs may be affected not only by the transaction cost but also by spot and futures volatility. With the above consideration, this study will carry out the following examinations. First, do the volatility of the spot and futures market significantly alter across the pre- and post-reduction period, and second, if the volatility of futures and spot significantly alter across two sample periods, has pricing efficiency improved in the new milieu after controlling for the volatility effect.

The existence of transaction costs and other market imperfection factors might cause the error correction effects on the price adjustment be significant only when the deviation of price between futures and spot is larger than a certain threshold. Martens, Kofman and Vorst (1998) find strong evidence of nonlinear adjustment in the presence of transactions. Dwyer, Locke, and Yu (1996) discover that a threshold error correction mechanism could characterize nonlinear dynamic relationship between the S&P500 futures and spot more properly. Reduction of tick size would affect transaction costs heavily; therefore, we will further investigate the impact of the reduction of tick size on nonlinear dynamic relationship between TAIEX index futures and spot.

Most of the previous studies focus the effect of tick size changes on the liquidity, volatility, market depth of the stock markets. However, fewer studies investigated the impact of the reduction of tick size on index futures pricing efficiency, arbitrage behavior and nonlinear dynamic relationship. The theoretical price of index futures is derived from the spot index; therefore, spot index behavior is highly related with futures pricing efficiency. Hence, this paper will examine the pricing efficiency, arbitrage opportunities and nonlinear dynamic relationship between index futures and spot in the intraday level before and after the reduction of tick size.

The remainder of this paper is structured as follows. Section 2 discusses the tick size change on the stock exchanges. Section 3 is the literature review. Data and methodology are presented in Section 4, followed, in Section 5, by a discussion of the empirical results. Section 6 summarizes and concludes this paper.

2. Tick Size Changes on the Stock Exchanges

Many existent articles examine the impact of tick size through the viewpoint of bid-ask spread which is the difference between the bid and ask quoted price. The bid-ask spread is one of the main transaction costs for investors. When the bid-ask spreads get smaller, the trade price which the stock demander pays and the stock supplier gets will become closer to the true price. The stock demander just pays the price a little bit higher than the true price and the stock supplier just obtain the price a little bit lower than the true price; therefore, the liquidity-demander's transaction cost falls. If the tick size which stands for the minimum stock price increment unit is larger than the equilibrium bid-ask spread determined by the economy, the bid-ask spread representing the main transaction cost will turn larger to the tick size restriction and the market efficiency will get worse.

In order to improve the market efficiency, there is a trend at major stock exchanges in the world to reduce tick size with an intention to lower the investor's transaction cost in these years. For instance, the New York Stock Exchange (NYSE) reduced the tick size from eighths to sixteenths on June 24, 1997. Both the New

York Stock Exchange and the American Stock Exchange (AMEX) switched to a decimal pricing system in quoting bid and ask prices at $0.01 increment.[1] NASDAQ moved from eighths to sixteenths on June 2, 1997, and began converting to decimal pricing on March 12, 2001, finally completed the process on April 9, 2001.

Singapore Exchange (SGX) shrank the tick size on the stock price over SGD $25 from SGD $0.5 to SGD $0.1 on July 18, 1994. Toronto Stock Exchange (TSE) diminished the tick size on stock price over CAD $5 from CAD $0.125 to CAD $0.05 and on stock price between CAD $3 and CAD $5 from CAD $0.05 to CAD $0.01.

Taiwan Stock Exchange trades stocks in fractions and narrows the tick size in every fraction to lower the trading costs of investors and to promote stock price continuity after March 1, 2005. Investors can memorize the new tick size and price interval combination much easier and have more ticks to quote and trade according to their trading strategies. Table 1 presents the minimum price increment comparison prior to and posterior to the reduction of tick size for every price interval.

3. Literature Review

3.1 Tick Size Effect

Decimalization of the U.S. stock exchanges has incurred a large number of contemporaneous researches during the past decades. Harris (1994) uses data from a time when the minimum tick size is eighths and estimates the frequency of spreads at the minimum by fitting a regression model. Using this relationship, Harris estimates that the impact of reducing the minimum tick size to sixteenths would be accompanied by both lower bid-ask spreads and lower quoted depth. His results are therefore also consistent with the notion that optimal tick size is related to the size of a

[1] Specifically, the NYSE lowered the minimum tick size to a penny for seven securities on August 28, 2000, 57 more securities on September 25, 2000, and an additional 94 securities on December 5, 2000. All remaining securities began trading in decimals on January 29, 2001.

trade. He indicates that small traders would almost certainly benefit from smaller tick sizes, but that large traders might be hurt if the depth of the market falls sufficiently.

Unlike Harris (1994), Chakravarty, Panchapagesan, and Wood (2003) examine the effect of decimalization on institutional investors by using proprietary data. They find no evidence that decimalization increases trading costs for institutions. In fact, institutional trading costs appear to decline by about 23 basis points (or, roughly 5 cents per share) after decimalization. In economic terms, this decrease roughly translates to an average monthly saving of $133 million in institutional trading costs. Estimations involving robust multivariate techniques that condition on order, manager and market characteristics yield roughly similar reductions as well. They find significant changes in order routing practices overall because of increase usage of alternate brokers (represented by ECNs and crossing networks such as Instinet) for easy-to-fill (i.e., smaller) orders and independent research brokers for orders that are difficult to fill (i.e., larger size orders).

Goldstein and Kavajecz (2000) analyze the NYSE's reduction in tick size from eighths to sixteenths and address the relationship between minimum tick size, bid-ask spread, and market liquidity. What is unique about this study is that these authors not only look at the depth reported at the best bid and ask prices, they also collect data on liquidity available at some distance away from the best bid and ask prices. This complete collection of prices and available depth is called the limit order book. They find that not only depth at the best bid and ask declines, but also cumulative depth similarly declines throughout the limit order book after the reduction in minimum tick size on the New York Stock Exchange (NYSE). Using implied average price of a trade derived from the limit order book, these authors find that large traders are not better off under the smaller tick sizes and are worse off for infrequently traded stock.

Chakravarty, Van Ness and Van Ness (2005) examine adverse selection costs around decimalization and relationship between adverse selection costs and trade size by using a sample of NYSE stocks around the implementation of decimalization. They find a significant reduction in adverse selection costs after decimalization on the NYSE. This decline in adverse selection costs occurs for all stocks except the very small stocks. They further try to understand the source of this decrease in adverse selection costs. They find that both the number of trades and trading volume in medium and large trade size fall significantly after decimalization on the NYSE while those in small trade size increases significantly. On estimating the adverse selection component by trade size classes, they find a decline in adverse selection costs in trades of all sizes, with the strongest evidence coming from medium size trades, followed by small and large size trades. One implication of their findings is that there appears to be less stealth trading following complete decimalization and less institutional trading overall.

Furfine (2003) examine the impact of decimalization on the liquidity of NYSE stocks. Analyzing transaction data for a sample of 1,339 stocks listed on the NYSE over a five-week period. He find that decimalization lead to a narrowing of average bid-ask spreads. The largest declines in spreads are found for the most actively traded stocks, where the average decline in spread was over 35 percent. The decline in depth is also most pronounced for the most actively traded stocks. Because previous findings suggest that decimalization has an ambiguous impact on market liquidity using spreads and depth as proxies for liquidity, Furfine estimates the price impact of a trade for each stock in his sample and then find that actively traded stocks generally experience an increase in liquidity after decimalization.

Bessembinder (2003) assesses trade execution costs and market quality for NYSE and NASDAQ stocks before and after the change to decimal pricing in 2001. Quoted bid-ask spreads declined substantially on each market, with the largest declines for heavily traded stocks. The percentage of shares receiving price improvement increases on the NYSE, but not on NASDAQ. However, those trades completed at prices within or outside the quotes are improved or disimproved by smaller amounts after decimalization, and trades completed outside the quotes reveal the largest reduction in trade execution costs. Effective bid-ask spread as a percentage of share price which is the measure of execution costs for smaller trades is averaged 0.33% on a volume-weighted basis after decimalization for both NYSE and NASDAQ stocks.

Bollen and Busse (2003) measure changes in trading costs of equity mutual fund for two changes in tick size on NASDAQ and NYSE: the switch from eighths to sixteenths and the switch from sixteenths to decimals. They estimate trading costs by comparing a mutual fund's daily returns with the daily returns of a synthetic benchmark portfolio that matches the fund's holdings but has zero trading costs by construction. They find that index fund performance is unaffected by the switch to pennies. In contrast, actively managed funds underperform their benchmark by an additional one percent of fund assets per year after decimalization.

Chakravarty, Wood, and Van Ness (2004) find that both quoted and effective bid-ask spreads and depths decline significantly after decimalization on the NYSE. Both trades and trading volume significantly decline in all trade size and stock size categories. Stock return volatility reveals an initial increase but a latter decline during the longer period, probably when traders become more comfortable under their new regime.

Henker and Martens (2005) find that market efficiency increases and the arbitrage link between index futures and the stock market strengthens after the reduction of minimum change for stock prices and quotes from an eighth to sixteenth on Jane 24, 1997. They find a substantial increase in the number of arbitrage trades reported to the Securities and Exchange Commission after the change. The average number of stocks traded and the average dollar amount underlying each arbitrage trade increases and decreases respectively. The average mispricing error that triggers arbitrage reduces and reverts to zero more quickly.

3.2 Non-linear Adjustment Mechanisms

In the recent time-series literature, the examination of non-linear adjustment mechanisms has attracted a growing numbers of research. The ideal of threshold cointegration is introduced by Balke and Fomby (1997). Deviations may exhibit unit root behavior within the transactions cost band because no adjustment takes place. The process for deviations is mean-reverting out side the band because adjustment takes place. This phenomenon is referred to as a threshold cointegration. Stoll and Whaley (1986) and MacKinlay and Ramaswamy (1988) discuss the impact of transaction costs on index-futures arbitrage strategy, starting with the forward-contract pricing relation. The impact of transaction costs is to permit the futures price to fluctuate within a band around the formula value. The width of the band derives from round-trip commissions in the stock and futures markets and the market impact costs of putting on the trade initially.

Many empirical studies find evidence on the presence of nonlinear equilibrium relations on cost-of-carry model. For example, Martens, Kofman and Vorst (1998) use a threshold autoregressive model and a threshold VECM to explore the existence of different arbitrage regimes. First, they investigate the location of possible thresholds indicating a change in the pattern of mispricing error and possibly also in the relations between the index and futures returns and the error-correction term. They show that indeed different regimes exist for the S&P500 and that in fact the US markets respond to arbitrage opportunities in just a few minutes. Second, they estimate an error-correction model in each regime. By estimating transaction costs they also indicate which thresholds could indicate the band around the theoretical futures price in which arbitrage is not profitable. Dwyer, Locke, and Yu (1996) indicate that the thresholds are signals for index arbitrage, which can affect the speed of convergence of the basis to its equilibrium value. Further, their results indicate that nonlinear dynamics are important and are related to S&P500 index-futures arbitrage, and suggest that arbitrage is associated with more rapid convergence of the basis to the cost of carry than would be indicated by a linear model.

Other studies concerning economic behaviors affected by asymmetric transaction costs and institutional rigidities reveal that many economic variables and relations display asymmetry and nonlinear adjustment. Michael, Nobay, and Peel (1997) find a nonlinear adjustment process toward purchasing power parity (PPP). Hansen and Seo (2002) and Enders and Siklos (2001) applies nonlinear models to the term structure model of interest rates and finds strong evidence for the asymmetric mature of error correction among interest rates of different maturities. Chung, Ho, and Wei (2005) follow the Hansen and Seo's (2002) model to develop a multivariate threshold VECM. The model is employed to estimate the threshold parameters, to construct asymptotic confidence intervals for the threshold parameters, and to develop new tests for the threshold effects of ADRs and their underlying stocks prices. Their study provides strong evidence to show that threshold effect does exist in the prices of ADRs and their underlying stocks.

4. Data and Methodology

4.1 Data

The intraday data used for exploring the change of TAIEX futures-spot dynamic relationship before and after the reduction of tick size are extracted from the Taiwan Economic Journal Data Bank (TEJ) and are computed in five-minute intervals. In order to have better liquidity to trade and quote, this study takes the nearby contract into account at any given time until the first trading day prior to the maturity date of the nearby contract. We adopt the next maturing contract from the first day prior to the maturity date of the nearby contract, because the volume of the next maturing contract usually surpasses that of the nearby contract on that day. To form trading pairs, this investigation matches every reported index with the most recent futures trade prices prior to or at exact every five minute. Since there is a delay before the first trade of each stock on a new trading day and the bid-ask spread widens and quotes are older at the end of each trading day, futures and spot will have large and continuing deviations[2]. Therefore, we follow Henker and Martens (2005) to delete the first 30 and the last 10 minute of each day, leaving 47 observations from 9:30 to 13:20 per day (Henker, Thomas and Martin Martens (2005)). The sample period extends over two-year trading days from May 1, 2004 to December 31, 2005. The sample period is divided into two sub-periods according to the reduction of tick size on March 1, 2005. We eliminate the data on January 13, 2005, because of a large number of missing data after 10:00 am. Therefore, the first sample before the reduction of tick size from May 1, 2004 through February 28, 2005 comprises 203 trading days with 9,541 observations. The second sample after the reduction of tick

[2] See, for example, Aggarwal and Park (1994) for the effects of the staleness of the index at the start of the day.

size from March 1, 2005 through December 30, 2005 comprises 213 trading days with 10,011 observations.

4.2 Construction of the TAIEX Index Futures MPE

Futures and spot prices are connected by the following cost-of-carry model:

$$F_{t,i} = (S_{t,i} - Div_t)e^{r_t(T-t)} \tag{1}$$

$$Div_t = \sum_{\tau=t}^{T} d_\tau \times (1+\frac{r}{365})^{-(\tau-t)} \tag{2}$$

where $F_{t,i}$ stands for the theoretical futures price on day t in 5-minute interval i for a contract expiring at time T, Div_t is the present value of the cash dividends that will be paid during the remaining life of the futures contract from the 50 daily largest companies about 69% of overall market value on the stock market, and r is annualized one-month post office deposit rate as the risk-free rate of interest. r_t is the effective interest rate of r. The rate r_t is often refereed to as carrying charge, since it represents the opportunity cost of carrying the spot asset to maturity of the futures contract. The buyer of stock index securities incurs the opportunity cost of his funds but receives dividends. Therefore, the futures price should equal the cost of buying the spot index securities, including the opportunity cost adjusted for dividends paid during the remaining life of the futures contract. As the futures contract approaches maturity, the futures price converges to the value of the spot index. Equivalently, the basis meaning the difference between futures and spot prices converges to zero at expiration. The implicit assumptions underlying the cost-of-carry model include perfect markets and constant carrying charges. Any price deviations from Equation (1) will be corrected as arbitrageurs sell the overpriced instrument and buy the underpriced one. Furthermore, we take the logarithm on the Equation (1) and define the percentage mispricing error (MPE) as

$$MPE = \ln F_{t,i} - \ln(S_{t,i} - Div_t) - r_t(T - t) \quad (3)$$

4.3 Identifying Arbitrage Opportunities and Transaction Costs

Arbitrage opportunities can be identified as follows.

Buy program: purchase stocks and sell futures

$$MPE_{t,i} > U_{t,i} \quad (4)$$

Sell program: sell stocks and purchase futures

$$MPE_{t,i} < -L_{t,i} \quad (5)$$

An arbitrage buy program is triggered while the MPE penetrates the upper bound, $U_{t,i}$. An arbitrage sell program is triggered while MPE falls below the lower bound, $-L_{t,i}$. We introduce the Threshold Vector Error Correction Model (TVECM) to identify the upper and lower bound for arbitrage. The existence of transaction costs and other market imperfection factors might cause the error correction effects on the price adjustment be significant only when the deviation of prices between futures and spot is larger than a certain threshold.

4.4 Linear Vector Error Correction Model (VECM)

Let x_t be a p-dimensional $I(1)$ time series, with n observations, with d as the maximum lag length. A linear VECM of order d+1 can be written briefly as

$$\Delta x_t = A' X_{t-1}(\beta) + u_t \quad (6)$$

where

$$X_{t-1}(\beta) = [1 \;\; \mathrm{w}_{t-1}(\beta) \;\; \Delta \mathrm{x}_{t-1} \;\; \Delta \mathrm{x}_{t-2} \;\; \Delta \mathrm{x}_{t-3}, \ldots, \Delta \mathrm{x}_{t-d}]' \quad (7)$$

and Δ is the first-order difference operator; the repressor $X_{t-1}(\beta)$ is $k\times 1$; A is $k \times p$; and $k = pd+2$. The error term, $u_t = [u_{1t} \; u_{2t}]'$, is assumed to be a vector martingale difference sequence with finite covariance matrix $\Sigma = E(u_t u'_t)$. Note that $w_{t-1}(\beta) = \beta' x_{t-1}$ is an $I(0)$ error correction term. For the bivariate case of futures and index prices (p=2), Δx_t corresponding to $[\Delta F_{t,i} \quad \Delta S_{t,i}]$ denotes the first-order time difference $\Delta x_t = x_t - x_{t-1}$, β represents 2×1 cointegrating vector, $[1 \ \text{-}b]'$ and x_t stands for $[F_t \quad S_t]'$. The error term $u_t = [u_{1t} \ u_{2t}]'$ is *i.i.d.*(0, Σ).

The parameters (β,A,Σ) are estimated by maximum likelihood under the assumption that the errors u_t are *i.i.d.* Gaussian. Let these estimated parameters be denoted $(\tilde{\beta}, \tilde{A}, \tilde{\Sigma})$ and $\tilde{u}_t = \Delta x_t - \tilde{A}' X_{t-1}(\tilde{\beta})$ be the residual vectors.

4.5 Threshold VECM for Futures and Underlying Spot

Consider now an extension of Equation (1), provided by:

$$\Delta x_t = \begin{cases} A_1' X_{t-1}(\beta) + u_t, & \text{if } |\mathrm{w}_{t-1}(\beta)| \le \gamma \\ A_2' X_{t-1}(\beta) + u_t, & \text{if } |\mathrm{w}_{t-1}(\beta)| > \gamma \end{cases} \tag{8}$$

where γ is the threshold parameter. Note that this paper uses the absolute value of error correction term as a threshold variable. In addition to the merit of parsimony in the modeling of threshold effect, the assumption is reasonable since transaction costs tend to be symmetric for either long or short position in the futures for its arbitrage. Alternatively, this may be written as

$$\Delta x_t = A_1' X_{t-1}(\beta) d_{1t}(\beta,\gamma) + A_2' X_{t-1}(\beta) d_{2t}(\beta,\gamma) + u_t \tag{9}$$

where

$$\begin{aligned} d_{1t}(\beta,\gamma) &= 1(|\mathrm{w}_{t-1}(\beta)| \le \gamma) \\ d_{2t}(\beta,\gamma) &= 1(|\mathrm{w}_{t-1}(\beta)| > \gamma) \end{aligned} \tag{10}$$

and 1(.) denotes the indicator function. The existence of the threshold effect is confirmed if 0< $P(|\mathrm{w}_{\mathrm{t-1}}(\beta)| \le \gamma)$ <1, otherwise the model simplifies to linear cointegration.

The threshold VECM of futures and spot can be estimated using the maximum likelihood method proposed by Hansen and Seo (2002). Under the assumption that the errors u_t are *i.i.d.* Gaussian, the likelihood function is

$$L_n(A_1, A_2, \Sigma, \beta, \gamma) = -\frac{n}{2}\log|\Sigma| - \frac{1}{2}\sum_{t=1}^{n} u_t(A_1, A_2, \Sigma, \beta, \gamma)' \Sigma^{-1} u_t(A_1, A_2, \Sigma, \beta, \gamma) \quad (11)$$

where

$$u_t(A_1, A_2, \Sigma, \beta, \gamma) = \Delta x_t - A_1^{'} X_{t-1}(\beta) d_{1t}(\gamma) + A_2^{'} X_{t-1}(\beta) d_{2t}(\gamma) \quad (12)$$

$MLE(\hat{A}_1, \hat{A}_2, \hat{\Sigma}, \hat{\beta}, \hat{\gamma})$ are the values which maximize $L_n(A_1, A_2, \Sigma, \beta, \gamma)$ in order to maximize the log-likelihood, to hold (β, γ) fixed and to compute the constrained *MLE* for (A_1,A_2,Σ). This is just *OLS* regression:

$$\hat{A}_1(\beta, \gamma) = \left(\sum_{t=1}^{n} X_{t-1}(\beta) X_{t-1}(\beta)' d_{1t}(\beta, \gamma)\right)^{-1} \left(\sum_{t=1}^{n} X_{t-1}(\beta) \Delta x'_t \, d_{1t}(\beta, \gamma)\right) \quad (13)$$

$$\hat{A}_2(\beta, \gamma) = \left(\sum_{t=1}^{n} X_{t-1}(\beta) X_{t-1}(\beta)' d_{2t}(\beta, \gamma)\right)^{-1} \left(\sum_{t=1}^{n} X_{t-1}(\beta) \Delta x'_t \, d_{2t}(\beta, \gamma)\right) \quad (14)$$

$$\hat{u}_t(\beta, \gamma) = u_t(\hat{A}_1(\beta, \gamma), \hat{A}_2(\beta, \gamma), \beta, \gamma) \quad (15)$$

and

$$\hat{\sum}(\beta, \gamma) = \frac{1}{n}\sum_{t=1}^{n} \hat{u}_t(\beta, \gamma) \hat{u}_t(\beta, \gamma)' \quad (16)$$

Note that Equation (13) and (14) are the *OLS* regressions of Δx_t on $X_{t-1}(\beta)$ for the samples of which $|\mathrm{w}_{\mathrm{t-1}}(\beta)| \le \gamma$ and $|\mathrm{w}_{\mathrm{t-1}}(\beta)| > \gamma$, respectively.

$$L_n(\beta,\gamma) = L_n\left(\hat{A}_1(\beta,\gamma),\hat{A}_2(\beta,\gamma),\hat{\sum}(\beta,\gamma),\beta,\gamma\right)$$
$$= -\frac{1}{2}\log\left|\hat{\sum}(\beta,\gamma)\right| - \frac{np}{2} \tag{17}$$

To execute a grid search procedure, one needs to pick a region over which to search. Hansen and Seo (2002) suggest calibrating this region based on the consistent estimate $\tilde{\beta}$ obtained from the linear model. Set $\tilde{w}_{t-1} = w_{t-1}(\tilde{\beta})$, let $[\gamma_L,\gamma_U]$ denote the empirical support of $\tilde{w}_{t-1}$, and construct an evenly spaced grid on $[\gamma_L,\gamma_U]$. Let $[\beta_L,\beta_U]$ denote a (large) confidence interval for β constructed from the linear estimate $\tilde{\beta}$ (based, for example, on the asymptotic normal approximation) and construct an evenly spaced grid on $[\beta_L,\beta_U]$. The grid search over (β,γ) then examines all pairs (β,γ) on the 300×300 grids on $[\gamma_L,\gamma_U]$ and $[\beta_L,\beta_U]$, conditional on $0.05 < n^{-1}\sum_{t=1}^{n} 1(x_t'\beta \le \gamma) < 0.95$. For each value of (β,γ) on this grid, we calculate $\hat{A}_1 = \hat{A}_1(\beta,\gamma)$, $\hat{A}_2 = \hat{A}_2(\beta,\gamma)$, and $\hat{\sum} = \hat{\sum}(\beta,\gamma)$

From the grid search procedure, we find $(\hat{\beta},\hat{\gamma})$ as the value (β,γ) on this grid which yields the lowest value of $\log\left|\hat{\sum}(\beta,\gamma)\right|$ to provide the $MLE(\hat{\beta},\hat{\gamma})$, while the limitation of β is $\pi_0 \le P(|\mathrm{w}_{t-1}(\beta)| \le \gamma) \le 1-\pi_0$, where $0<\pi_0<1$ is a trimming parameter; this paper sets $\pi_0 = 0.05$. Finally, we set $\hat{A}_1 = \hat{A}_1(\hat{\beta},\hat{\gamma})$, $\hat{A}_2 = \hat{A}_2(\hat{\beta},\hat{\gamma})$, $\hat{\sum} = \hat{\sum}(\hat{\beta},\hat{\gamma})$, and $\hat{u}_t(\hat{\beta},\hat{\gamma})$ to obtain $MLE(\hat{\beta},\hat{\gamma})$.

4.6 Tests for Threshold Effects

Let H_0 represent the class of linear VECM in Equation (6), and H_1 represent the class of two regime threshold VECM in Equation (9). These models are nested, with the constraint H_0 being the models in H_1 which gratify $A_1' = A_2'$. Our test will compare H_0 (linear cointegration) with H_1 (threshold cointegration).

In order to assess the evidence, both linearity and the threshold VECM are tested by using the Lagrange Multiplier (*SupLM*) test developed by Hansen and Seo (2002). The LM statistic employed is:

$$LM(\beta,\gamma) = vec(\hat{A}_1(\beta,\gamma) - \hat{A}_2(\beta,\gamma))' \times (\hat{V}_1(\beta,\gamma) + \hat{V}_2(\beta,\gamma))^{-1} \times vec(\hat{A}_1(\beta,\gamma) - \hat{A}_2(\beta,\gamma)) \tag{18}$$

$$SupLM = \sup_{\gamma_L \le \gamma \le \gamma_U} LM(\tilde{\beta},\gamma) \tag{19}$$

where $\tilde{\beta}$ is the null estimate of β. The bootstrap method proposed by Hansen and Seo's (2002) is employed to calculate the asymptotic critical values and *p*-values.

4.7 Conditioning Mispricing Errors on Volatility

We hypothesize that the MPE is reduced after the reduction of tick size, but that any reduction might be caused by the lower market volatility or be offset by the higher market volatility in the second sample period. To test the robustness of these probable results, we implement the methodology of Jones and Lipson (2001). The goal is to test whether the reduction of tick size diminishes the average mispricing error that triggers arbitrage while controlling for changes in the volatility and other control variables. We estimate the regression in Equation (20) for all trades prior to the reduction of tick size and use the estimated coefficients to calculate MPE prediction errors under the second sample period in Equation (21).

$$MPE_{i,t}^{pre-reduction} = \alpha + \beta_1 VOLA_{i,t} + \beta_2 BUY_{i,t} + \beta_3 SHORT_{i,t} + e_{i,t}^{pre-reduction} \tag{20}$$

where $MPE_{i,t}$ is the absolute value of percentage mispricing error on day t and intraday period i, while the superscript indicates the minimum price increment at the period, $\text{VOLA}_{i,t}$ is the futures volatility in the 30 min prior to the every trade at time i, $\text{BUY}_{i,t}$ is an indicator variable with value one if the arbitrage trade is a buy program and zero otherwise, and $\text{SHORT}_{i,t}$ is an indicator variable with value one if the arbitrage trade involved short selling and zero otherwise. We do not control for the prevailing spread since the reduced spreads are the reasons why we expect the mispricing error to be smaller when arbitrage programs are initiated.

The coefficient estimates from Equation (20) are then used to predict the MPEs after the reduction tick size and, to compute the prediction errors,

$$\hat{e}_{i,t}^{post-reduction} = MPE_{i,t}^{post-reduction} - \hat{\alpha} - \hat{\beta}_1 VOLA_{i,t} - \hat{\beta}_2 BUY_{i,t} - \hat{\beta}_3 SHORT_{i,t} \quad (21)$$

where the hats for the coefficient estimates indicate the previously estimated coefficients are used. We can now, while controlling for volatility, test whether hypothesis of the test is $H_0 : \bar{\hat{e}}_{i,t}^{pre-reduction} = \bar{\hat{e}}_{i,t}^{post-reduction}$, while the alternative hypothesis is $H_1 : \bar{\hat{e}}_{i,t}^{pre-reduction} > \bar{\hat{e}}_{i,t}^{post-reduction}$. The bars indicate that we compute the average over all residuals.

5. Empirical Results

5.1 Sample Statistics for the Spot and Futures Returns and the MPE

Spot and futures 5-minute returns eliminating overnight returns are computed in log differences. The data are divided into two subsample periods. The pre-reduction of tick size sample period from May 3, 2004 through February 25, 2005 consists of 203 trading days with 47 observations each, but excluding January 13, due to TEJ data recording problems. The post-reduction of tick size period from March 1, 2005 through December 30, 2005 comprises 213 trading days with 47 observations each.

Table 2 displays the descriptive statistics of spot return, futures return, and absolute value of MPE including mean, standard deviation, and autocorrelation up to lag 4. As expected, the mean MPE shrinks significantly at the 1% level after the reduction of tick size; nevertheless, the volatility of spot and futures returns also decreases significantly at the 1% level in the meantime. This result implies two possible reasons. First, the reduction of tick size, causing smaller spread costs could make arbitrageurs implement the arbitrage trade more precisely at the price they want; therefore, the MPE contracts after the reduction of tick size. Second, the smaller volatility of index and futures returns could reduce the execution risk for the position. In consequence, arbitrageurs initiate trades only at relatively higher MPEs to compensate for the increased price risk of nonsimultaneous order execution. According to the above two reasons, we cannot figure out whether the reduction of tick size could cause the lower MPE only due to the lower spread costs. Hence, we will employ further empirical study in Section 5.7 to distinguish the two possible reasons.

The significantly smaller average MPE and significantly smaller volatility of MPE suggest that the extent of the two price series co-movement tends to turn stronger. The Pearson's correlation coefficient of the spot and futures returns reveals 0.5949 significantly at the 1% significance level before the reduction of tick size; whereas, 0.6203 significantly at the 1% significance level under the new tick size regime. The higher and closer to the unity correlation coefficient of spot and futures returns implies the stronger cointegration relationship between the two markets. The MPE autocorrelation up to lag 4 increases and the MPE volatility indicates less volatile significantly at the 1% significance level under the new tick size regime. Hence, the two prices series tend to evolve more consistently after the reduction of tick size, which the arbitrageurs can conduct the arbitrage trade more precisely.

5.2 Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Test

In order to examine the pure price dynamics between futures and spot markets precluding the cash dividend effect, we adjust the spot index price by subtracting the present value of the cash dividends that will be paid during the remaining life of the corresponding futures contract, because the futures prices drop about the present value of that dividends in advance as Equation (2). These futures and adjusted index prices will be employed to implement the following empirical research. The log-prices of the futures and the adjusted index are used to fulfill our sequentially empirical analysis. The returns of futures and adjusted index are calculated by taking the difference in the log-price.

Stationary time series react to the shock transitorily and return to the long-term equilibrium with the shock passing by. Conversely, nonstationary time series have permanent effects with the passage of shock. We employ the two unit root tests examined for stationarity.

1. Augmented Dickey-Fuller (ADF) Test

$$\Delta x_t = \alpha + \gamma\, \mathrm{t} + \delta \mathrm{x}_{\mathrm{t-1}} + \sum_{i=1}^{p} \theta_i \Delta x_{t-i} + \varepsilon_t$$

where the null hypothesis, H_0: δ=0, represents nonstationarity, and the alternative hypothesis, H_1: $\delta \neq 0$, interprets stationary. The model constructed here contains a drift term, α and a time trend, t. We employ Schwarz Bayesian Information Criterion (SBIC)[3] to choose the optimal lag length based on the parsimony principle.

2. Phillips-Perron (PP) Tests

[3] $SBIC(p)=N$ log(SSR)+p log(N), where SSR is the residual sum of squares, N is the sample size, and p is the total number of parameters.

$$x_t = \alpha^* + \delta^* x_{t-1} + \varepsilon_t^*$$
$$x_t = \tilde{\alpha} + \tilde{\gamma}(t - T/2) + \tilde{\delta} x_{t-1} + \tilde{\varepsilon}_t$$

where α^* and $\tilde{\alpha}$ illustrate drift terms, t represents time trend, and T indicates the numbers of observation. The null hypothesis, H_0: $\delta^* = \tilde{\delta}$ =0, stands for nonstationarity, and the alternative hypothesis, $H_1 \neq H_0$, is on behalf of stationarity.

Table 3 addresses the results of the two unit root tests examined for stationarity. The ADF results and PP results are similar, both of which fail to reject the null hypothesis of unit root tests for each price series in level data, but reject it in first difference data at 1% significance level. The results suggest all the data series are integrated of order one, $I(1)$. These results indicate that the futures price and spot price are integrated in the first difference, integrated of order one, $I(1)$, before and after the introduction of new tick size regulation, and thus verify the fulfillment of the cointegration test.

5.3 Johansen Cointegration Test

Given that the two price series are integrated of the same order one, $I(1)$, this study builds two Johansen multivariate cointegration tests to judge whether the price series are cointegrated. We set a 2×1 vector x_t=[F_t S_t]′ where F_t stands for futures price and S_t stands for spot in our study. If there exists a vector β (β≠0) that makes linear combination of two price series, $\beta' x_t$, reduce the integrated order to stationarity, we can say the two price series exist cointegration relationship andβis the so-called cointegration vector.

The reduced form error correction model formulates the test hypothesis as follows The test hypothesis is formulated as the restriction for the reduced rank of Π: $\Pi = \alpha\beta'$ for the reduced form error correction model:

$$\Delta x_t = \Pi x_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta x_{t-i} + u_t$$

where $\Pi = \alpha\beta'$ denotes the impact matrix, α and β are both 2×1 matrices representing the adjustment speed of the parameter and cointegrating vector, respectively. Δx_{t-i} denotes short-term relation of x_t. x_t is the error correction term. The rank of Π or the number of non-zero eigenvalue of Π determines the number of cointegration vector. Johansen proposed two likelihood ratio statistics to test the number of cointegration vector.

Two test statistics for cointegration under the Johansen approach are formulated as follows:

1. Trace Statistic

$$H_0 : rank(\Pi) \le r$$
$$H_1 : rank(\Pi) > r$$
$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{2} \ln\left(1 - \hat{\lambda}_i\right)$$

2. Maximum Eigenvalue Statistic

$$H_0 : rank(\Pi) = r$$
$$H_1 : rank(\Pi) = r + 1$$

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

where r is the number of cointegrating vectors under the null hypothesis, T is the sample size and $\hat{\lambda}_i$ is the estimated value for the *ith* ordered eigenvalue from the Π matrix. The null hypothesis for joint test statistics, λ_{trace}, is that the number of cointegrating vectors is less than or equal to r against the unspecified or general alternative one that the number of cointegrating vectors is more than r. Maximum Eigenvalue Statistic, $\lambda_{\max}$, conducts separate tests on each eigenvalue. The null hypothesis that the number of cointegrating vectors r is against an alternative that the number of cointegrating vectors r+1.

The result of the cointegration test reported in Table 4 demonstrates the rejection the null hypothesis of no cointegration at the 5% significance level in the both sample period and the rejection of the null hypothesis of only one cointegration relationship at the 5% significance level before the reduction of tick size. This evidence advocates that a stationary linear combination exists between the futures and spot prices in the both pre-reduction and post-reduction period. Thus, the futures and spot markets are cointegrated and have long-term equilibrium relationship.

5.4 Linear Vector Error Correction Model (VECM)

Since the futures and spot price are cointegrated, there must exists an error correction term in which so-called vector error correction model (VECM) constructing the dynamic system dominating the joint evolution of the futures and spot prices over time. From Equation (6), we can know that the error correction terms, $w_t(\beta)$, illustrate the long-term equilibrium dynamics between the price series, and the dynamic coefficients of the lagged price series which capture the short-run dynamics resulted from market imperfections. Similarly, we employ Schwarz Bayesian Information Criterion (SBIC) to determine the optimal lag length d applied not only to the linear VECM but also to the threshold VECM. Eventually, the optimal lag length is selected for four and three for the pre- and post-reduction of tick size, respectively. The results of the linear VECM estimation are proposed in Table 5.

For the pre-reduction of tick size period, we find the futures market have an obvious lead over the spot market. In Panel A of Table 5, all the coefficients of the lagged futures prices (ΔF) in the spot equation (ΔS) are statistically significant at the 1% level, but no for lagged spot prices (ΔS) in the futures equation (ΔF). These results indicate that the futures market leads the spot market. In addition, the coefficients of the error correction terms for futures prices (ΔF) and spot prices (ΔS) equations are not statistically significant, so we cannot confirm that long-run co-movement exists between these two financial markets in the pre-reduction of tick size period.

For the post-reduction of tick size period, we discover appearance of bi-direction relationship between two markets. In Panel B of Table 5, all the lagged futures prices (ΔF) in the spot equation (ΔS) are significant at 1% level; whereas, we detect only one significant impact of lag 1 spot price on futures at 1% level in the post-reduction period as opposed to that in the pre-reduction period, i.e., a feedback relation. Besides, the coefficient of the error correction terms is only significant in the futures equation, suggesting that futures prices are inclined to adjust significantly as the prices deviate from long-run equilibrium took place. The z statistics of the coefficient of the error correction term for both price series after the reduction of tick size are more significant than that before. Evidently, this result imply that the reduction of tick size, lowering the spread cost, makes the long-run co-movement extent between these two financial markets turns stronger. This can be confirmed by the higher and closer to the unity Pearson's correlation coefficient between the two market, which is described in Section 5.1. The cointegrating vector, 1.03697, in the post-reduction period is closer to unity than that, 1.03886, in the pre-reduction period. It implies the two price series approximate to each other stronger in the second sample period. This result is caused by the lower transaction costs after the reduction of tick size, which reduces the obstacles for the two prices to return to long-run equilibrium.

5.5 Threshold Vector Error Correction Model (TVECM)

In Table 6 and Table 7, we employ a threshold VECM to expound the price dynamics and further employ *SupLM* statistics and Wald statistics to test for the threshold cointegration and the non-linear model, respectively.

The empirical results in Table 6 and Table 7 indicate the existence of threshold cointegration in both sub-periods of the pre- and post-reduction of tick size. The Lagrange Multiplier threshold test statistic (*SupLM*) is significant at 1% level while adopting four and three lag length in the pre- and post-reduction of tick size periods, respectively. Moreover, the threshold value (γ) decreases from 0.347891 to 0.307617 after the reduction of tick size, because the decrease of tick size reduces the spread cost which comprises the main transaction cost and lower the arbitrage threshold for arbitrageurs, which is consistent with our expectation.

Next, the Wald test for the appearance of non-linearity in dynamic coefficients also advocates the nonlinear relationship between futures and spot markets in the both sub-periods.. On the other hand, the Wald test for the presence of non-linearity in the error correction terms does not support the nonlinear relationship in the both sub-periods. For the pre-reduction of tick size period, we further compare the estimated coefficients of error correction terms in Table 6 with those in Table 5. These results show that the coefficients of the error correction terms in the second regime of threshold VECM appear to be larger than those in the linear VECM, which indicate that two price series have a faster convergence or mean-reversion to the long-run equilibrium in the second regime of nonlinear VECM than that in linear VECM model. Our results in the pre-reduction of tick size period are consistent with Dwyer, Locke, and Yu's (1996), but not for those in the post-reduction period. To look at short-run dynamic coefficients across two regimes, the null hypothesis of no difference is rejected and the result shows the significant difference across two regimes for both two periods. By and large, the nonlinear relationship between futures and spot prices is remarkable thanks to transaction costs and the threshold VECM is more suitable than a linear model to interpret the dynamics between the two markets.

Then, we define the upper regime and lower regime depending on error correction terms and threshold value. In Table 6, the estimated cointegration relation is $w_t = F_t - 0.958673S_t$ and the estimated threshold value is $\hat{\gamma} = 0.347891$ for the first sample period. Thus, the first regime occurs while $|w_t| \leq 0.347891$. Given 15.94% observations of no arbitrage opportunity in this regime, we follow Hansen and Seo, 2002 to label this as the typical regime. By contrast, the second regime occurs while $|w_t| > 0.347891$ with 84.06% arbitrage observations. In this regime, arbitrageurs trigger buy or sell programs to buy (sell) the index securities and simultaneously sell (buy) index futures contracts. We follow Hansen and Seo, 2002 to label this regime as the extreme regime. In Table 6, we know that the error-correction phenomena in futures (ΔF) and spot (ΔS) equations are more significant in the second regime, since the triggers of arbitrage trades enhance the convergence speed of two price series to the long-run equilibrium. The sign of the error-correction coefficient is negative in both price series in the typical regime, but positive in the extreme regime. This indicates structural change across two regimes. For the short-term dynamics, all the coefficients of the lagged futures prices (ΔF) on the spot equation (ΔS) are statistically significant. These results confirm again that futures market leads the spot market before the introduction of new tick size, which is consistent with those in the linear VECM in Table 5.

Last but not least, for the second sample period shown in Table 7, the estimated cointegration relationship is $w_t = F_t - 0.9649373S_t$ and the estimated threshold is $\hat{\gamma} = 0.307617$. Consequently, the first regime, i.e., typical regime, occurs while

$|w_t| \leq 0.307617$ with 75.43 observations and the second regime i.e., extreme regime, occurs while $|w_t| > 0.307617$ with 24.57% observations. In the first regime, the error-correction phenomenon is only significant in the futures prices (ΔF) equation, which indicates that there exists mean reversion only in the futures price. However, as contrary to the first regime, the error-correction effect is not significant both in the futures (ΔF) and spot (ΔS) equations, which means that there does not have any long-run equilibrium relationship between futures market and spot market in the extreme regime. In other words, the two series behave like a random walk and free from the cointegration constraint (Tsay, 1998) probability due to the decrease of market depth at the best-quoted prices (Harris(1994, 1997) and Furfine (2003)) after the reduction of tick size. Equilibrium relationship between futures market and spot market in the extreme regime becomes insignificant. The decrease of arbitrage trade numbers might result from stronger co-movement between the two financial markets discovered in Section 5.4 after reduction of tick size. Similarly, for the short-term dynamic coefficients, the result seems consistent with earlier findings. The futures price tends to lead the spot price after the reduction of tick size.

5.6 The GARCH Model

We further examine the volatility alteration across the two sub-periods following Section 5.1 by constructing a GARCH mode in Equation (23), (24), (25), and (26). Before employing the GARCH model, we implement ARCH test in advance to investigate whether the futures and spot returns exist quadratic autocorrelation in the residuals. The ARCH test is conducted as following. First, we implement an OLS regression on the futures and spot returns with the constant as independent variable, and draw out the the residuals, $\hat{\varepsilon}_t$. Second, we square the residuals and run the autoregression on q own lags to test whether ARCH-effects exists in the residuals:

$$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{\varepsilon}_{t-1}^2 + \gamma_2 \hat{\varepsilon}_{t-2}^2 + \ldots + \gamma_q \hat{\varepsilon}_{t-q}^2 + \nu_t \quad (22)$$

where ν_t represents an error term. Third, we multiply the sample size by multiple correlation and get the test statistic, TR^2, which is the chi-square distribution with q degree of freedom, $\chi^2(q)$. Finally, the null and alternative hypotheses are

$\mathrm{H}_0 : \gamma_1 = 0$, $\gamma_2 = 0$, $\gamma_3 = 0$ … and $\gamma_q = 0$,

$\mathrm{H}_1 : \gamma_1 \neq 0$ or $\gamma_2 \neq 0$ or $\gamma_3 \neq 0$…or $\gamma_q \neq 0$.

Therefore, we test if any coefficient of the autoregression for q lags in Equation (22) significantly different from zero meaning the ARCH-effect exists in the residuals.

The chi-square test statistic is 315.4757 and 381.6646 for the futures and spot returns, respectively before the reduction of tick size, and 480.1283 and 502.4160 for the futures and spot returns, respectively after the reduction of tick size. The results above significantly reject the null hypothesis at 1% level expressing ARCH-effect in the residuals for the futures and spot returns in both sample periods. Thus, the conduction of following GARCH model is justified by the significant ARCH test results in both sample periods.

We construct the following GARCH Equation (23), (24), (25), and (26) to investigate the return and conditional volatility alteration before and after the reduction of tick size.

$$R_{F,t} = \alpha_{F,1} + \alpha_{F,2} R_{F,t-1} + \alpha_{F,3} R_{S,t-1} + \alpha_{F,4} D_1 + \varepsilon_{F,t} \quad (23)$$

$$R_{S,t} = \alpha_{S,1} + \alpha_{S,2} R_{S,t-1} + \alpha_{S,3} R_{F,t-1} + \alpha_{S,4} D_1 + \varepsilon_{S,t} \quad (24)$$

$$h_{F,t} = \beta_{F,0} + \beta_{F,1} \varepsilon_{F,t-1}^2 + \beta_{F,2} h_{F,t-1} + \beta_{F,3} D_1 \quad (25)$$

$$h_{S,t} = \beta_{S,0} + \beta_{S,1}\varepsilon^2_{S,t-1} + \beta_{S,2}h_{S,t-1} + \beta_{S,3}D_1 \qquad (26)$$

where $R_{F,t}$ and $R_{S,t}$ are the returns of the futures and spot prices. The conditional variance, h_t, is composed of the lagged squared errors ε^2_{t-1} in the return process and the lagged conditional variance, h_{t-1}. The variable $\varepsilon^2_{F,t-1}$ stands for the futures market lagged volatility and the variable $\varepsilon^2_{S,t-1}$ stands for the spot market lagged volatility. D_1 is the event dummy taking the value one for the period before the reduction of tick size and the value zero for the period after the reduction of tick size.

In the mean Equation (23) and (24), coefficient, $\alpha_{i,2}$, measures the lagged futures return (spot return) on present futures return (spot return) and the coefficient, $\alpha_{i,3}$, measures the effect of last period spot return (futures return). The coefficient, $\alpha_{i,4}$, measures whether the return exists structural change after introduction of new tick size. In the conditional variance Equation (25) and (26), coefficient, $\beta_{i,1}$, measures the lagged squared error effect on this period conditional variance. Coefficient, $\beta_{i,2}$, captures last period conditional variance impact on this period conditional variance. Coefficient, $\beta_{i,3}$, catches return volatility alteration across the two sample period.

From the result of Table 8, we can find last period futures and spot returns both have significant effect on the current period futures and spot returns at 1% level. By the dummy variables in the two mean equations, we find futures and spot returns do not significantly differ in the two periods at any common significance level. From the result of variance equation in the Table 8, we can find the lagged squared error and lagged conditional volatility both have significant effect on the current period conditional volatility for both futures and spot markets. By the dummy variables in the variance equations, we can find the second sample period volatility significantly decrease at 1% level for both futures and spot markets. This result is consistent with

Section 5.1. We will further use this conditional volatility in the variance equations to implement the empirical research in Section 5.7.

5.7 Conditioning Mispricing Errors on Volatility

In Section 5.1, we find MPE significantly decreases at 1% level in the second sample period; meanwhile, futures and spot volatility also significantly decreases at 1% level in the same sample period discovered in Section 5.1 and 5.6. Arbitrageurs can trigger arbitrage requiring smaller MPE, because the smaller volatility reduces the execution risk for them. Hence, we cannot figure out the smaller MPE in the second sample period originated from smaller volatility or reduced tick size. In order to identify the reason that results in the smaller MPE in the second sample period, we implement the methodology of Jones and Lipson (2001) that conditions the mispricing errors on volatility as introduced in Section 4.7.

The first regression of Table 9 shows the results of Equation (20) that conditions the data on the 30-minute volatility of the futures returns immediately preceding every trade following Henker and Martens (2005). Equation (20) also conditions on the GARCH conditional volatility of futures returns, whose result is shown in the second regression of Table 9. We choose the futures volatility over the volatility of the underlying stocks because the bid-ask bounce in futures prices is regarded to be a less serious problem than the serial correlation in index returns (Henker and Martens (2005)). The table demonstrates the empirical result in the first sample period. We can confirm the futures volatility has the significantly positive relation to the MPE at 1% level in both regressions of Table 9, because the higher volatility could result in higher timing risk and tracking error risk for arbitrageurs' position. The GARCH conditional futures volatility in the second regression has the similar result to the 30-minute futures volatility in the first regression. The indicator variables of buy program and sell program both reveal significantly negative relation to the MPE at 1% level, because the trigger of arbitrage trades would shrink the MPE. The high R-square in both regressions of Table 9, 0.7268 and 0.7389 respectively, means the independent variables have high explanatory power to the MPE in the first sample period.

We employ Equation (21) that uses the estimated coefficients in Equation (20) to calculate MPE prediction errors under new regime. While controlling for the change of volatility, buy program, and sell program effects, we further examine whether MPE shrinks after the reduction of tick size. The null hypothesis of the test is $H_0 : \bar{\hat{e}}_{i,t}^{pre-reduction} = \bar{\hat{e}}_{i,t}^{post-reduction}$, and the corresponding alternative hypothesis is $H_1 : \bar{\hat{e}}_{i,t}^{pre-reduction} > \bar{\hat{e}}_{i,t}^{post-reduction}$. The bar denotes the average residuals over the two sample periods, respectively.

In order to implement above mean residual difference test, we should fulfill residual volatility difference test above all[4]. The test statistic conditioning on 30-minute futures volatility is 2.8727, and that conditioning on GARCH conditional futures volatility is 0.2161. Clearly, the residual volatility is statistically significant different across two sample periods in both conditioning cases. Then, we further

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[4] s_1 denotes the residual volatility before the reduction of tick size, s_2 indicates the residual volatility after the reduction of tick size, and n_1 and n_2 are their respective number of observations. Test statistics $F = \frac{S_1^2}{S_2^2}$ is $F(n_1-1, n_2-1)$ distribution.

employ the mean residual difference test[5] to explore whether MPE decreases after the reduction of tick size, while conditioning on the change for volatility and buy and sell program effects. For conditioning on 30-minute futures volatility and GARCH futures volatility, the test statistics are 121.5890 and 115.6704, respectively. In both cases, the null hypothesis is rejected in favor of the alternative hypothesis at any conventional significance level. The results means the reduction of tick size can lower the mispricing error and improve the pricing efficiency.

However, we use the arbitrage data drawn from the second regime of threshold VECM model instead to run the OLS regression of Equation (20) and Equation(21) again. We find the mispricing error increases and pricing efficiency deteriorates for the arbitrage data after the reduction of tick size. Because the market depth might reduce after the reduction of tick size, the error-correction terms of the second regime of threshold VECM model are insignificant which means long-term equilibrium relationship of futures and spot does not exist after the reduction of tick size. Hence, mispricing error of arbitrage data does not reduce for the arbitrage data after the reduction of tick size.

6. Conclusion

This study investigates the impact of the introduction of new tick size on the pricing efficiency and the long-run and short-run price dynamics between futures and

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[5] $t = \dfrac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}}$ with degree of freedom, $\dfrac{\left(\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}\right)^2}{\dfrac{\left(\dfrac{s_1^2}{n_1}\right)^2}{n_1 - 1} + \dfrac{\left(\dfrac{s_2^2}{n_2}\right)^2}{n_2 - 1}}$, where $\bar{x}_1$ and $\bar{x}_2$ are mean residual, s_1 and s_2 are residual volatility, and n_1 and n_2 are number of sample in the two sample period, respectively.

spot markets. The non-linear VECM can evidently characterize the arbitrageurs' behavior. When the futures and spot prices deviate from no-arbitrage boundary settled by the transaction costs mainly composed of spread costs, arbitrageurs would trigger the buy or sell program to make arbitrage immediately. The smaller tick size settled by the Taiwan Stock Exchange Corporation (TSEC) after March 1, 2005 can effectively lower the spread costs between best bid and ask prices according to past researches. The lower transaction costs make the arbitrageurs trigger the arbitrage program more easily, which lead mispricing error to shrink and improve the pricing efficiency after the reduction of tick size.

For the Linear VECM, our results show that the long-run co-movement extent between these two financial markets turn stronger and the two price series tend to approximate to each other after the reduction of tick size. This result is caused by the lower transaction costs after the reduction of tick size, which reduces the obstacles for the two prices to return to long-run equilibrium. The dynamic coefficients show the futures clearly lead the spot in both sub-sample periods and the feedback relation which means the impacts of spot on futures in the second period.

For the threshold VECM model, the results show the presence of threshold cointegration, and nonlinear dynamic coefficients in both sub-sample periods. This implies the threshold VECM model fits the price dynamics between futures and spot markets superior to the linear VECM model. Furthermore, the threshold value (γ) decreases from 0.347891 to 0.307617 after the reduction of tick size, because the decrease of tick size reduces the spread cost which comprises the main transaction cost and lower the arbitrage threshold for arbitrageurs, which is consistent with our expectation.

In the first sample period, the error-correction phenomena in futures and spot equations are more significant in the extreme regime, since the triggers of arbitrage trades enhance the co-movement extent across two price series. The coefficients of error correction terms in the extreme regime of threshold VECM appear to be larger than those in the linear VECM, which indicates that two price series have a faster convergence or mean-reversion to the long-run equilibrium in the extreme regime of nonlinear VECM than that in linear VECM model. This result is consistent with Dwyer, Locke, and Yu's (1996).

In the second sample period, the error-correction phenomenon is only significant in the futures price equation in the typical regime, which indicates that there exists mean reversion only in the futures price. However, as contrary to typical regime, the error-correction effect is not significant both in the futures (ΔF) and spot (ΔS) equations, which means that there does not evidence any long-run equilibrium relationship between futures market and spot market in the extreme regime. In other words, the two series behave like a random walk and free from the cointegration constraint (Tsay, 1998) probability due to the decrease of market depth at the best-quoted prices (Harris(1994, 1997) and Furfine (2003)) after the reduction of tick size. Equilibrium relationship between futures market and spot market in the extreme regime becomes insignificant. The decrease of arbitrage trade numbers might result from stronger co-movement between the two financial markets discovered in linear VECM after reduction of tick size.

For the short-term dynamics, all the coefficients of the lagged futures prices on the spot equation are statistically significant in both periods. These results confirm again that futures market leads the spot market, which is consistent with those in the linear VECM. Nevertheless, we find some feedback relation which means the impact of spot on futures in the second period as the result in the linear VECM.

Finally, while conditioning the change for volatility and buy and sell programs effects, we find the reduction of tick size can lower the mispricing error and improve the pricing efficiency. However, we use the arbitrage data drawn from the second regime of threshold VECM model instead to run the OLS regression again. We find the mispricing error increases and pricing efficiency deteriorates for the arbitrage data after the reduction of tick size. Because the market depth might reduce after the reduction of tick size, the error-correction terms of the second regime of threshold VECM model are insignificant which means long-term equilibrium relationship of futures and spot does not exist after the reduction of tick size. Hence, mispricing error of arbitrage data does not reduce for the arbitrage data after the reduction of tick size.

In the future, we can improve the threshold VECM by considering ARCH-effect into its error term and estimating the optimal lag time for arbitrage threshold, because financial markets in Taiwan usually have ARCH-effect and arbitrage time might not be just at lag one period. We believe this improved model can fit the price dynamics more precisely. In the meantime, we can do more research in all different futures contracts and even longer empirical period to confirm the impact of the new policy more robustly.

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Table 1 Comparison of Old and New Tick Size Policy

The table presents the minimum price increment comparison prior to and posterior to the reduction for every price interval on March 1, 2005.

Old policy Before March 1, 2005		Tick Size	New policy After March 1, 2005	
Minimum stock price	Maximum stock price		Minimum stock price	Maximum stock price
$5 and below		$0.01	$10 and below	
$5	$15	$0.05	$10	$50
$15	$50	$0.1	$50	$100
$50	$150	$0.5	$100	$500
$150	$1000	$1	$500	$1000
$1000 and above		$5	$1000 and above	

Table 2 Properties of Index and Futures Returns and the MPE

Sample statistics includes sample mean, standard deviation (S.D.), and autocorrelation (ρ) of index returns, futures returns, and the absolute value of mispricing error (MPE). The data frequency is 5-minute intervals, with the first 30 and the last 10 min of each trading day excluded, leaving 47 observations per day (eliminating January 13, 2005due to TEJ data recording problems). Overnight price changes are excluded. The index and futures are the last index value and futures transaction price prior to or on the 5-minute mark. The MPE is based on the cost-of-carry model using the annualized one-month post office deposit rate as the risk-free rate of interest.

Series	Mean(%)	S.D.(%)	ρ_1	ρ_2	ρ_3	ρ_4
Panel A: Before the Reduction of Tick Size (May 3, 2004 - February 25, 2005)						
index return	-0.00002	0.00120	0.17254***	-0.12231***	-0.09679***	0.00576
			(<.0001)	(<.0001)	(<.0001)	(0.5739)
futures return	-0.00001	0.00135	0.03519***	-0.04222***	-0.00923	0.01485
			(0.0006)	(<.0001)	(0.3673)	(0.1470)
MPE	0.00484	0.00497	0.97477***	0.96450***	0.95971***	0.95530***
			(<.0001)	(<.0001)	(<.0001)	(<.0001)
Panel B: After the Reduction of Tick Size (March 1, 2005 - December 30, 2005)						
index return	-0.00002	0.00071 [a]	0.31747***	-0.09959***	-0.14862***	-0.04110***
			(<.0001)	(<.0001)	(<.0001)	(<.0001)
futures return	-0.00001	0.00081 [a]	0.00867	-0.05246***	-0.02859***	-0.00854
			(0.3855)	(<.0001)	(0.0042)	(0.3930)
MPE	0.00333 [a]	0.00318 [a]	0.98032***	0.97002***	0.96350***	0.95861***
			(<.0001)	(<.0001)	(<.0001)	(<.0001)

The p-value is showed in the parentheses below each coefficient estimate.

*: the coefficient estimate is statistically significant at 10% level.

**: the coefficient estimate is statistically significant at 5% level.

***: the coefficient estimate is statistically significant at 1% level.

[a] Indicates that mean or standard deviation in panel (B) is significantly smaller than the corresponding mean or standard deviation in panel (A) at the 1% significance level, respectively.

Table 3 Unit Root Test for Log-Prices of Futures and Underlying Spot

Panel A and Panel B present the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests of futures and spot during two sample periods. Spot represents Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), Futures stands for TAIEX Futures, and *** denotes significance at the 1% level.

Panel A: Before the Reduction of Tick Size (May 3, 2004 - February 25, 2005)				
	Augmented Dickey-Fuller test		Phillips-Perron test	
k=4	Level	First Difference	Level	First difference
Futures	-2.2407	-42.8296 ***	-2.2742	-94.6834 ***
Spot	-2.0284	-44.8171 ***	-2.0771	-82.4279 ***
Panel B: After the Reduction of Tick Size (March 1, 2005 - December 30, 2005)				
	Augmented Dickey-Fuller test		Phillips-Perron test	
k=3	Level	First Difference	Level	First difference
Futures	-0.9243	-52.2905 ***	-0.9587	-99.0363 ***
Spot	-1.0257	-51.8933 ***	-1.0345	-71.1728 ***

Note: k is the lag length and is chosen by minimum Schwarz Bayesian Information Criterion (SBIC). Critical values: 1%= -3.434 5%= -2.862 10%= -2.567.

Table 4 Johansen Cointegration Test for Log-Prices of Futures and Underlying Spot

Panel A and Panel B present the results of trace test (Trace) and maximum eigenvalue test (Max-Eign) used to evaluate whether the variables in each respective period are cointegrated during two sample periods. r is the number of cointegrating vectors, * denotes rejection of the hypothesis at the 5% level. Max-Eigen and Trace are two test statistics under Johansen's approach, that is, $\lambda_{\max}$ and λ_{trace} respectively.

Null Hypothesis	Trace Statistic	5 Percent Critical Value	Max-Eigen Statistic	5 Percent Critical Value
Panel A: Before the Reduction of Tick Size (May 3, 2004 - February 25, 2005)				
r=0	38.6766 *	15.4947	34.4722 *	14.2646
r=1	4.2044 *	3.8415	4.2044 *	3.8415
Panel B: After the Reduction of Tick Size (March 1, 2005 - December 30, 2005)				
r=0	39.0463 *	15.4947	37.8830 *	14.2646
r=1	1.1634	3.8415	1.1634	3.8415

Table 5 Linear VECM Estimations for Log-Prices of Futures and Underlying Spot

The linear VECM is applied to determine the long-run equilibrium and short-run dynamics between two markets for two periods. Std error indicates Eicker-White standard errors. Schwarz Bayesian Information Criterion (SBIC) determines the optimal lag length. S represents Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), F stands for TAIEX Futures, and EC is the error correction term. *, **, and *** denotes significant rejection of the hypothesis at the 10%, 5%, and 1% significance level, respectively.

Panel A: Before the Reduction of Tick Size (May 3, 2004 - February 25, 2005)				
Dep.	ΔF_t		ΔS_t	
Ind.	Estimate	Std error	Estimate	Std error
EC(w_{t-1})	-0.006095	0.005771	0.005433	0.004407
Constant	-0.002067	0.001948	0.001846	0.001489
ΔF_{t-1}	0.013459	0.024874	0.344751***	0.024350
ΔF_{t-2}	-0.024618	0.026965	-0.297760***	0.022986
ΔF_{t-3}	0.002089	0.024441	0.178521***	0.020433
ΔF_{t-4}	-0.043311	0.027151	-0.211223***	0.021827
ΔS_{t-1}	0.035073	0.023905	0.102990***	0.019846
ΔS_{t-2}	-0.040734	0.026881	-0.117381***	0.022092
ΔS_{t-3}	-0.000317	0.023815	0.039103**	0.017639
ΔS_{t-4}	0.009781	0.025218	-0.038580**	0.019510
AIC	--125,002		SBIC	-124,962
Cointegrating Vector 1.038860***				

Panel B: After the Reduction of Tick Size (March 1, 2005 - December 30, 2005)				
Dep.	ΔF_t		ΔS_t	
Ind.	Estimate	Std error	Estimate	Std error
EC(w_{t-1})	-0.007258***	0.002382	0.002652	0.002144
Constant	-0.002336***	0.000770	0.000860	0.000693
ΔF_{t-1}	-0.020466	0.017044	0.262395***	0.023332
ΔF_{t-2}	0.040090**	0.018470	-0.100863***	0.025669
ΔF_{t-3}	0.030867*	0.018577	0.163832***	0.022777
ΔS_{t-1}	-0.081018***	0.020520	-0.159828***	0.023789
ΔS_{t-2}	0.024244	0.015823	0.082322***	0.016841
ΔS_{t-3}	-0.023990	0.016719	-0.074518***	0.016144
AIC	--141,562		SBIC	-141,530
Cointegrating Vector 1.03697***				

Table 6 Threshold VECM Estimations for Log-Prices of Futures and Underlying Spot before the Reduction of Tick Size at TSE(May 3, 2004-February 25, 2005)

The threshold VECM is applied to determine threshold effect on the long-run equilibrium and short-run dynamics between two markets before the reduction of tick size. Std error indicates Eicker-White standard errors. Schwarz Bayesian Information Criterion (SBIC) determines the optimal lag length. S represents Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), F stands for TAIEX Futures, and EC is the error correction term. *, **, and *** denotes significant rejection of the hypothesis at the 10%, 5%, and 1% significance level, respectively.

First Regime: $\lvert w_{t-1}\rvert \leqq 0.347891$ Percentage of Obs = 0.159396				
Dep.	ΔF_t		ΔS_t	
Ind.	Estimate	Std error	Estimate	Std error
EC(w_{t-1})	-0.061548	0.048113	-0.030680	0.035392
Constant	0.021325	0.016565	0.010539	0.012185
ΔF_{t-1}	0.116192 **	0.056808	0.336968 ***	0.051529
ΔF_{t-2}	-0.155923 **	0.066102	-0.306816 ***	0.058421
ΔF_{t-3}	0.029596	0.051302	0.171139 ***	0.038922
ΔF_{t-4}	-0.118747 *	0.069930	-0.280836 ***	0.050378
ΔS_{t-1}	0.069487	0.049682	0.078356 **	0.037725
ΔS_{t-2}	-0.067445	0.066867	-0.121951 **	0.050034
ΔS_{t-3}	0.021720	0.053655	0.006932	0.036526
ΔS_{t-4}	0.015154	0.073989	0.028471	0.053958

Second Regime: $\lvert w_{t-1}\rvert > 0.347891$ Percentage of Obs = 0.840604				
Dep.	ΔF_t		ΔS_t	
Ind.	Estimate	Std error	Estimate	Std error
EC(w_{t-1})	0.008166 ***	0.005789	0.011112 **	0.004722
Constant	-0.002951 ***	0.002082	-0.003981 **	0.001697
ΔF_{t-1}	-0.022832	0.025150	0.366853 ***	0.022536
ΔF_{t-2}	0.018898 **	0.027715	-0.310540 ***	0.022479
ΔF_{t-3}	0.013230 *	0.028275	0.212948 ***	0.022476
ΔF_{t-4}	-0.030822	0.028101	-0.210293 ***	0.022738
ΔS_{t-1}	0.030769 ***	0.027363	0.135923 ***	0.022851
ΔS_{t-2}	-0.035558	0.028087	-0.135454 ***	0.024011
ΔS_{t-3}	-0.011124	0.023957	0.059589 ***	0.020041
ΔS_{t-4}	0.011075	0.023196	-0.067512 ***	0.019063

Threshold estimate = 0.347891 Cointegrating Vector = 0.958673;

AIC = -125,042 SBIC = -124,963

Lagrange Multiplier threshold test

Fixed regressor (asymptotic) bootstrap = 44.0753*** (p-value < 0.0001).

Residual bootstrap = 38.4376*** (p-value < 0.0001).

Wald test

Equality of dynamic coefficients = 68.0757*** (p-value < 0.0001).

Equality of EC coefficients = 2.35093 (p-value = 0.308675).

Table 7 Threshold VECM Estimations for Log-Prices of Futures and Underlying Spot after the Reduction of Tick Size at TSE(March 1, 2005-December 30, 2005)

The threshold VECM is applied to determine threshold effect on the long-run equilibrium and short-run dynamics between two markets after the reduction of tick size. Std error indicates Eicker-White standard errors. Schwarz Bayesian Information Criterion (SBIC) determines the optimal lag length. S represents Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), F stands for TAIEX Futures, and EC is the error correction term. *, **, and *** denotes significant rejection of the hypothesis at the 10%, 5%, and 1% significance level, respectively.

	First Regime: $\lvert w_{t-1}\rvert \leqq 0.307617$			
	Percentage of Obs = 0.754272			
Dep.	ΔF_t		ΔS_t	
Ind.	Estimate	Std error	Estimate	Std error
EC(w_{t-1})	-0.009054**	0.003709	-0.001640	0.003281
Constant	0.002767**	0.001125	0.000495	0.000994
ΔF_{t-1}	-0.014178	0.018843	0.260894***	0.027508
ΔF_{t-2}	0.021899	0.022373	-0.127880***	0.030391
ΔF_{t-3}	0.044826**	0.019836	0.183949***	0.026573
ΔS_{t-1}	-0.101275***	0.021890	-0.190072***	0.025869
ΔS_{t-2}	0.035083*	0.018046	0.096491***	0.020684
ΔS_{t-3}	-0.026505	0.019338	-0.074313***	0.020506
	Second Regime: $\lvert w_{t-1}\rvert > 0.307617$			
	Percentage of Obs = 0.245728			
Dep.	ΔF_t		ΔS_t	
Ind.	Estimate	Std error	Estimate	Std error
EC(w_{t-1})	0.000008	0.006032	-0.000662	0.005474
Constant	-0.000040	0.001881	0.000230	0.001706
ΔF_{t-1}	-0.026894	0.040385	0.288709***	0.040929
ΔF_{t-2}	0.085844***	0.032192	-0.032528	0.042143
ΔF_{t-3}	-0.005057	0.041419	0.110046***	0.039256
ΔS_{t-1}	-0.027249	0.043015	-0.082448**	0.043974
ΔS_{t-2}	-0.015277	0.035868	0.023320	0.030155
ΔS_{t-3}	-0.021268	0.034245	-0.084224***	0.024544

Threshold estimate = 0.307617 Cointegrating Vector = 0.964937

AIC = -141,557 SBIC = -141,493

Lagrange Multiplier threshold test

Fixed regressor (asymptotic) bootstrap = 42.4844* (p-value = 0.066667).

Residual bootstrap = 37.5842*** (p-value < 0.0001).

Wald test

Equality of dynamic coefficients = 21.9461** (p-value = 0.0381278).

Equality of EC coefficients = 3.13770 (p-value = 0.208284).

Table 8 GARCH Model

The table shows the result of the following GARCH model.

$$R_{F,t} = \alpha_{F,1} + \alpha_{F,2} R_{F,t-1} + \alpha_{F,3} R_{S,t-1} + \alpha_{F,4} D_1 + \varepsilon_{F,t}$$
$$R_{S,t} = \alpha_{S,1} + \alpha_{S,2} R_{S,t-1} + \alpha_{S,3} R_{F,t-1} + \alpha_{S,4} D_1 + \varepsilon_{S,t}$$
$$h_{F,t} = \beta_{F,0} + \beta_{F,1} \varepsilon^2_{F,t-1} + \beta_{F,2} h_{F,t-1} + \beta_{F,3} D_1$$
$$h_{S,t} = \beta_{S,0} + \beta_{S,1} \varepsilon^2_{S,t-1} + \beta_{S,2} h_{S,t-1} + \beta_{S,3} D_1$$

where $R_{F,t}$ and $R_{S,t}$ are the returns of the futures and spot prices. The variable $\varepsilon^2_{F,t-1}$ in the table stands for the futures market lagged volatility and the variable $\varepsilon^2_{S,t-1}$ stands for the spot market volatility. D_1 is the event dummy taking the value one for the period before the reduction of tick size and the value zero for the period after the reduction of tick size.

	Mean Equation			Variance Equation	
	$R_{F,t}$	$R_{S,t}$		$h_{F,t}$	$h_{S,t}$
Constant	0.000007	-0.000008	Constant	0.00000002 ***	0.00000004 ***
	(0.1749)	(0.1243)		(<.0001)	(<.0001)
$R_{F,t-1}$	-0.038800 ***	0.000002 ***	ε^2_{t-1}	0.106500 ***	0.157800 ***
	(<.0001)	(<.0001)		(<.0001)	(<.0001)
$R_{S,t-1}$	0.082900 ***	0.024700 ***	h_{t-1}	0.877700 ***	0.744500 ***
	(<.0001)	(<.0001)		(<.0001)	(<.0001)
D_1	0.000002	0.146400	D_1	0.00000001 ***	0.00000007 ***
	(0.7624)	(0.8107)		(<.0001)	(<.0001)

The p-value is showed in the parentheses below each coefficient estimate.

*: the coefficient estimate is statistically significant at 10% level.

**: the coefficient estimate is statistically significant at 5% level.

***: the coefficient estimate is statistically significant at 1% level.

Table 9 Ordinary Least Square (OLS) for Mispricing Errors in the Pre-Reduction of Tick Size Period

$$MPE_{i,t}^{pre-reduction} = \alpha + \beta_1 VOLA_{i,t} + \beta_2 BUY_{i,t} + \beta_3 SHORT_{i,t} + e_{i,t}^{pre-reduction}$$

where $MPE_{i,t}$ is the absolute value of percentage mispricing error on day *t* and intraday period *i*, while the superscript indicates the minimum price increment at the period, $VOLA_{i,t}$ is the futures volatility in the 30 min prior to every trade at time i in the first regression and GARCH conditional futures volatility at time i in the second regression, $BUY_{i,t}$ is an indicator variable with value one if the arbitrage trade is a buy program and zero otherwise, and $SHORT_{i,t}$ is an indicator variable with value one if the arbitrage trade involved short selling and zero otherwise.

	MPE	MPE
Intercept	0.01268 ***	0.01149 ***
	(<.0001)	(<.0001)
30-minute futures VOLA	0.72477 ***	
	(<.0001)	
Conditional VOLA		1.44625 ***
		(<.0001)
BUY	-0.01052 ***	-0.01011 ***
	(<.0001)	(<.0001)
SHORT	-0.00351 ***	-0.00365 ***
	(<.0001)	(<.0001)
R^2	0.72680	0.73890
adjR^2	0.72680	0.73880
Sample size	9541	9540

The p-value is showed in the parentheses below each coefficient estimate.

*: the coefficient estimate is statistically significant at 10% level.

**: the coefficient estimate is statistically significant at 5% level.

***: the coefficient estimate is statistically significant at 1% level.