The Relationship of Price Volatility between TSE Stock Index and TAIFEX Stock Index Futures with Different Maturities

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Abstract

Using the data set from January 2, 2004 to April 28, 2006, this study examines all aspects of the relation between volatility in the cash index and volatility in the nearby-month and nearby-quarter index futures. The GARCH model is first estimated to examine the impact of the futures volume growth on the conditional variance of the cash price and vice versa. Next, the conditional variances at the 10-day interval to derive the variance series and then perform the Granger causality test for the co-integrated variance series in the context of the error correction model.

Evidence from the GARCH (1,1) estimation indicates that the cash volume growth loses the power in explaining its own price volatility when the futures volume growth is included in the conditional variance equation of the cash index return, the cash volume growth has no influences on volatility in the futures markets, and the trading volume growth of nearby-month index futures is most influential in explaining volatility for the three markets.

Evidence form the Granger causality test in the context of the error correction model indicates that the volatility series are co-integrated I(1) series and display co-movement in the same direction in the long run, there are one-way volatility spillovers from the index futures to the cash index, and there are two-way volatility spillovers between the nearby-month and nearby-quarter index futures markets.

Keywords: TSE stock index, TAIFEX stock index futures, GARCH, ECM, Granger causality, volatility

I. INTRODUCTION

The Taiwan stock index futures contract is the first futures commodity introduced into the Taiwan futures market by the Taiwan Futures Exchange (TAIFEX) on July 21, 1998. Since then the Taiwan futures market has been steadily growing. Seven futures commodities are currently traded on the market. The daily average of the futures contracts traded rose dramatically from 4,512 in 1999 to 40,923 in 2005. The futures contracts traded on TAIFEX include TX, electronics futures (TE), financial futures (TF), small-size Taiwan index futures (MTX), Taiwan 50 futures

(T5F), 10-year government bond futures (GBF), 30-day commercial paper futures (CPF), MSCI (Morgan Stanley Capital International) Taiwan index futures (MSF), and gold futures (GD). The increasing importance of the futures market in the Taiwan financial markets has received considerable attention from academics and financial analysts.

The futures contract is extensively used as arbitrage, hedge, and price discovery. The value of the stock index futures is the future value of the cash index. The relation between the futures price and the cash price can be expressed as the cost of carry theory: $F_{t,T} = S_t \exp\{r(T-t)\}$, which states that the futures price ($F_{t,T}$) expected at time t is the compound interest growth of the cash price (S_t) from time t to time T at the cost of capital (r). If instantaneous arbitrage were possible, the index futures would neither lead nor lag the cash index. Price discovery implies that information could be transmitted from the futures market to the spot market because those participating in the futures market are generally informed traders. Arbitrage and information transmission are factors to link the two markets closely.

In the real world, neither instantaneous arbitrage nor efficient information transmission are present, the lead-lag relation between the index futures and the cash index is observed. Some studies suggested that the index futures price is uni-directionally causal with the cash price [Pizzi, Economopoulos, and O'Neill (1998), Nicto, Fermandez, and Jesus (1998), Frino and West (1999), Min and Najand (1999), Hsu and Chien (2003)]. Some studies found that the index futures price is bi-directionally causal with the cash price [Turkington and Walsh (1999), Hsu and Ho (2000), Huang and Hsu (1997)]. Others reported that the cash index is uni-directionally causal with the index futures [Chang and Goo (2003), Abhyankar (1998), Green and Joujon (2000)].

According to Darrat and Rahman (1995), two characteristics make investors easy access to stock index futures, i.e., close linkage of the index futures with the spot index and inexpensiveness to trade in the futures market. Both characteristics are considered as the factor for some observers to attribute stock market volatility to futures trading. Bookstabler and Pomerantz (1989) and Ross (1989) showed that the volatility of prices is directly related to the rate of information flow and thus any event that increases the rate of information flow simultaneously increases price volatility. The theory may lead to a conjecture that the futures trading activity causes volatility in the stock market.

Some studies found that stock prices have become more volatile since the introduction of stock futures [Lockwood and Linn (1990), Lee and Ohk (1992)], while other studies found no more volatility associated with the introduction of stock futures

[Yu and Wu (2000), Schwert (1990), Ely (1988)]. As for volatility spillovers between the two markets, some studies suggested for mutual volatility spillovers [Chang and Goo (2003), Chuang (2001), Min and Najand (1999)]. Some studies reported evidence for uni-directional volatility spillovers from the index futures to the cash index [Koutmos and Tucker (1996), Iihara, Kato, and Tokunaga (1996)], while few studies found evidence for uni-directional volatility spillovers from the cash index to the index futures [Chuang (2001)].

The purpose of this study is to examine all aspects of the relation between volatility in the cash index and volatility in the nearby-month and nearby-quarter index futures. We first use the generalized autoregressive conditional heteroscedastic (GARCH) model to examine the impact of futures trading volume growth on the conditional variance of the cash price and vice versa. Next, we calculate the variance series for the cash index, the nearby-month index futures, and the nearby-quarter index futures at the 10-day interval and then perform the Granger causality test for these co-integrated variance series in the context of the error correction model (ECM).[1] The results from the Granger causality test depict the cross-market volatility spillover effect. The daily data for Taiwan Securities Exchange (TSE) stock index and TAIFEX nearby-month and nearby-quarter stock index futures covers the period from January 2, 2004 to April 28, 2006. The data are collected from the Taiwan Economic Journal (TEJ) database.

This study is organized as follows. A brief introduction is provided in Section I. Section II presents a review of several relevant articles, a comment on them, and a brief introduction of methodology. Section III details the empirical results from the GARCH model and the Granger causality test. The summary and conclusions are presented in Section IV.

II. LITERATURE REVIEW

Chang and Goo (2003), utilizing EC-EGARCH(1,1) and EGARCH(1,1)-X, examined the dynamic relationship between the Taiwan stock index futures and cash prices. The results indicated that co-integration exists between both markets in spite of reducing the transaction tax and the error correction factor exerts significant influences on the conditional mean and variances in both markets. Moreover, it was found from EC-EGARCH (1,1) that, if the error correction factor is assumed to influence the conditional mean only, the cash market would display significant volatility asymmetry, volatility would be transmitted from the cash market to the futures market, and the volatility in the futures market would persist longer than that

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[1] The 10-day interval is arbitrarily chosen in order to retain a large sample (sample size > 50) and obtain the valid variance series.

in the cash market. However, the findings from EGARCH (1,1)-X suggested that both markets display significant volatility asymmetry and volatility spillovers are bi-directional.

Chuang (2001) investigated the volatility asymmetry and cross-market volatility spillovers among the spot, nearby-month, and nearby-quarter stock index futures markets traded on TAIFEX. The findings indicated that the nearby-month and nearby-quarter futures markets do not play the price discovery role in the spot market, Moreover, mutually cross-market volatility spillovers exist between the spot and nearby-month futures markets and the unexpected standardized innovation of the spot price shows uni-directional cross-market volatility spillovers to the nearby-quarter futures market.

Yu and Wu (2000), utilizing the modified Levene statistics and GARCH model, examined the impact of the index futures on the spot market volatility for the U.S., U.K., France, Japan, Australia, and Hong Kong. The results derived from the modified Levene statistics were quite different from those from the GARCH model. The former reported that cash market volatility for the period after introduction of the index futures significantly differs from that for the period before introduction of the index futures. The latter indicated that no evidence that the futures market increases the cash market volatility and no extensively structural changes after the introduction of the index futures are found.

Darrat and Rahman (1995) presented an empirical examination of the view that futures trading activity has contributed to jump volatility of the stock market. The futures trading activity is represented by the trading volume and the open interest in the S&P 500 index futures. They estimated the underlying cash market volatility by control for the possible impact from other market factors independent of futures trading. It was found that the coefficients on the measures of futures trading (albeit appearing with the correct positive signs) are statistically insignificant at conventional levels and non-rejection of the null hypothesis that futures trading volume does not Granger cause jump volatility in stock prices. It seems, therefore, that futures trading (however measured) should not be blamed for any increased volatility of stock prices in recent years.

The mixed empirical evidence regarding the cross-market volatility spillover effect for the Taiwanese case, one-way volatility spillovers from the cash index to the index futures or mutual volatility spillovers are found from Chang and Goo (2003) and Chuang (2001), depending on what empirical models are constructed or what maturities of futures contracts are in discussion. Darrat and Rahman (1995) found no evidence that the futures trading activity causes stock price volatility.

This study purports to examine the impact of the index futures with different maturities on volatility in the cash index. The methods used in this study include the ADF (augmented Dickey-Fuller) unit-root test, the PP (Phillips-Perron) unit-root test, the Johansen co-integration test, the ECM estimation, the Granger causality test, and the GARCH (1,1) model estimation. All the methods can be found in the standard econometrics or time-series econometrics textbooks. This study will not intend to detail any of the methods.

III. EMPIRICAL RESULTS

3.1 Data and Variables

The data collected for this study are from the Taiwan Economic Journal (TEJ) database at the daily interval, covering the period from January 1, 2004 to April 28, 2006. The arbitrarily chosen period excludes the year 2003 when Severe Acute Respiratory Syndrome (SARS) occurred, which is believed to have exerted a substantial impact on the Taiwanese securities markets. It also excludes the years 2001 and 2002 when the Taiwan economy was in the phase of recession. It could be said that the Taiwanese securities experienced relatively steady growth during the period under investigation.

This data set comprises of three pairs of time series, namely, the TSE (Taiwan Securities Exchange) stock index cash price and trading volume in shares, the TAIFEX (Taiwan Futures Exchange) nearby-month stock index futures price and trading volume in contracts as well as the TAIFEX nearby-quarter stock index futures price and trading volume in contracts. Each of the six series contains 574 observations and is transformed to the logarithmic form. For convenience, the TSE stock index cash price and trading volume in shares are denoted by P_s and Q_s, the TAIFEX nearby-month stock index futures price and trading volume are denoted by P_{1f} and Q_{1f}, and the TAIFEX nearby-quarter stock index futures price and trading volume are denoted by P_{2f} and Q_{2f}. Their first differences are denoted by DP_i and DQ_i, i=s, 1f, and 2f, where DP_i measures the daily return on Security i and DQ_i measures the daily growth for Security i. These series are used to check the volatility clustering effects associated with each of the markets and to examine how trading volume from each of the markets affect these effects.

The six series from the original data set are grouped as Sample I. The descriptive statistics for levels and first differences of the six series are presented in Table A3.1.1 in the appendix. It is found from the table that the trading volume series follow the normal distribution since their Jarque-Bera statistics are all significant at the 1% level. The correlations between the six series are presented in Table A3.1.2. It is noted that the correlations between the prices are as high as 0.99 and the correlations between the cash trading volume and the nearby-month and nearby-quarter futures prices are

0.572 and 0.574, higher than those between own prices and trading volumes.

The data set is also used to examine cross-market volatility spillovers in the context of the error correction model. In doing so, the variance of each price series is computed applying the sample variance formula to the series at the 10-day interval. Each of the price variance series has 57 observations. They are denoted by VAR_i, i=s, 1f, and 2f for the cash index, the nearby-month index futures, and the nearby-quarter index futures. Their first differences are denoted by $DVAR_i$, i=s, 1f, and 2f. The three series of price volatility computed on the original data set are grouped as Sample II. The descriptive statistics for levels and first differences of the three series are presented in Table A3.1.3 in the appendix. It is found from the table that all volatility series in levels and in first differences follow the normal distribution. The correlations between price volatility series in levels and in first differences all exceed 0.96 (Table not shown).

The results from the ADF unit-unit test for the series from Sample I are reported in Table 3.1.1. The table indicates that the six variables regarding prices and volumes are all I(1) series because their levels are non-stationary and their first differences become stationary. The PP (Phillips-Perron) test is also found to have the same results (Table not shown). Table 3.1.2 reports the results from the ADF unit-root test for the series from Sample II. It is found that the three variables regarding price volatility are all I(1) series because their levels are non-stationary and their first differences become stationary.

Table 3.1.1 The ADF Unit-Root Test for the Series from Sample I

Variable	Intercept	Trend and Intercept	None
P_s	-1.626(4)	-0.503(4)	0.368(4)
Q_s	-2.658(10)[c]	-2.614(10)	-0.049(10)
P_{1f}	-2.116(1)	-0.521(4)	0.254(4)
Q_{1f}	-4.310(6)[a]	-4.307(6)[a]	0.454(15)
P_{2f}	-1.493(4)	-0.456(4)	0.255(4)
Q_{2f}	-4.709(18)[a]	-4.879(18)[a]	-0.338(18)
DP_s	-17.566(1)[a]	-17.594(1)[a]	-17.567(1)[a]
DQ_s	-9.443(9)[a]	-9.465(9)[a]	-9.451(9)[a]
DP_{1f}	-7.119(16)[a]	-7.227(16)[a]	-7.103(16)[a]
DQ_{1f}	-9.699(18)[a]	-9.725(18)[a]	-9.693(18)[a]
DP_{2f}	-18.029(1)[a]	-18.049(1)[a]	-18.035(1)[a]
DQ_{2f}	-13.154(18)[a]	-13.155(18)[a]	-13.166(18)[a]

Notes: 1. The lag length chosen based on the AIC criterion is in the parenthesis. 2. a, b, and c denotes rejection of the null hypothesis at the 1%, 5%, and 10% significance levels.

Table 3.1.2 The ADF Unit-Root Test for the Series from Sample II			
Variable	Intercept	Trend and Intercept	None
VAR_s	-3.969(10)[a]	-1.848(10)	-3.200(10)[a]
VAR_{1f}	-2.221(6)	-2.537(10)	-3.462(10)[a]
VAR_{2f}	-2.162(6)	-2.506(10)	-3.569(10)[a]
$DVAR_s$	-4.590(9)[a]	-6.850(9)[a]	-4.325(9)[a]
$DVAR_{1f}$	-2.832(5)[c]	-6.370(9)[a]	-2.853(5)[a]
$DVAR_{2f}$	-4.266(9)[a]	-6.515(9)[a]	-2.872(9)[a]
Notes: 1. The lag length chosen based on the AIC criterion is in the parenthesis. 2. a, b, and c denotes rejection of the null hypothesis at the 1%, 5%, and 10% significance levels.			

3.2 The GARCH (1,1) Model

It has been found in many researches that stock prices display volatility clustering effects and the effects would reduce when trading volume is introduced in the conditional variance equation of the GARCH model [Bohl and Henke (2003), Lamoureux and Lastrapes (1990), Gallo and Pacini (2000)]. The GARCH (1,1) model given by equation 3.2.1 is estimated for the time series from Sample I.

$$\begin{aligned} DP_{i,t} &= \beta_0 + \beta_1 DP_{i,t-1} + \varepsilon_{i,t} \\ \sigma^2_{i,t} &= \alpha_0 + \alpha_1 \varepsilon^2_{i,t-1} + \alpha_2 \sigma^2_{i,t-1} + v_{i,t} \end{aligned} \tag{3.2.1}$$

where i=s, 1f, and 2f and v is a white noise. The results from estimating the variance equation in the GARCH (1,1) model are presented in Table 3.2.1. The Taiwan stock index cash and futures prices unexceptionally exhibit volatility clustering effects in Panel A. The sum of α_1 and α_2 (α_1+α_2) evaluates the degree of persistence in volatility. It is found that the sums for the three cases are all higher than 0.97, which indicates a high degree of volatility persistence for the cash and futures prices. The high degree of volatility persistence implies that shocks to the conditional variance would lead to future forecasts of high variances for a protracted period.

Next, the GARCH (1,1) model with the first difference of trading volume (trading volume growth) included in the conditional variance equation is given by equation 3.2.2.

$$\begin{aligned} DP_{i,t} &= \beta_0 + \beta_1 DP_{i,t-1} + \varepsilon_{i,t} \\ \sigma^2_{i,t} &= \alpha_0 + \alpha_1 \varepsilon^2_{i,t-1} + \alpha_2 \sigma^2_{i,t-1} + \alpha_3 DQ_{i,t} + v_{i,t} \end{aligned} \tag{3.2.2}$$

Panel B presents the empirical results from estimating the conditional variance equation for the time series from Sample I. The sum of α_1 and α_2 shows no substantial reduction in volatility persistence when the trading volume growth is considered. On the contrary, DP_{2f} is observed to have an increase in the sum α_1+α_2 from 0.981 to

0.986. To solve the possible simultaneity bias resulting from weak exogeneity of the contemporaneous trading volume growth, $DO_{i,t}$ is substituted by $DO_{i,t-1}$ in the conditional variance equation. The results, however, are unsatisfactory in the sense that volatility persistence remains about the same and α_3's are all significant with wrong signs except in the case of Q_{2f}.[2]

Finally, the following GARCH (1,1) model is constructed to allow for the possible cross-market effect of the trading volume growth in a market on the price volatility in another market.

$$
\begin{aligned}
&DP_{i,t} = \beta_0 + \beta_1 DP_{i,t-1} + \varepsilon_{i,t} \\
&\sigma^2_{i,t} = \alpha_0 + \alpha_1 \varepsilon^2_{i,t-1} + \alpha_2 \sigma^2_{i,t-1} + \alpha_3 DQ_{i,t} + \alpha_4 DQ_{j,t} + \alpha_5 DQ_{k,t} + v_{i,t}
\end{aligned}
\tag{3.2.3}
$$

where $DQ_{j,t}$ and $DQ_{k,t}$, $j,k \neq i$, denote the trading volume growth in other markets. Panel C documents the results from estimating equation 3.2.3. It is found that volatility persistence measured by $\alpha_1+\alpha_2$ has somewhat reduced by 0.046 to 0.150 compared with the counterparts in Panel A. Interestingly enough, we observe that α_2 in the conditional variance equation of DP_s becomes insignificant after inclusion of the futures trading volume growth. In particular, the coefficient of DQ_{1f} is 4.45 (=43.5/ 9.78) times as much as that of DQ_{2f}, indicating that trading volume of the nearby-month index futures is a better measure for the rate of daily information arrivals to the cash market. It is noted that, in the conditional variance equation of DP_{2f}, α_5 is 6.26 times (=6.57/1.05) as much as α_3, implying that the trading volume growth of nearby-month index futures is far more crucial in influencing volatility in DP_{2f} than its own trading volume growth. Finally, the trading volume growth of cash index plays no role in determining volatility in DP_{1f} and DP_{2f} since the coefficients (8.85E-06 and -6.35E-06) are both statistically insignificant.[3]

In order to capture asymmetry in volatility, the TGARCH (1,1) model is constructed and estimated. The results from the TGARCH (1,1) are basically the same as those from the GARCH (1,1) model. The asymmetric effect is observed in the three return series. However, the asymmetric effect disappears when the trading volume growth is included in the TGARCH (1,1) model. The own trading volume growth becomes insignificant when the volume growth of nearby-month and nearby quarter is furthermore included in the conditional variance equation of DP_s. It is found that the coefficient of DQ_{1f} is 4.57 (=43.4/ 9.49) times as much as that of DQ_{2f}, which indicates that trading volume of the nearby-month index futures is a better measure

[2] The estimation of the GARCH (1,1) models with trading volume growth $DO_{i,t}$ substituted by trading volume $O_{i,t}$ and lagged trading volume $O_{i,t-1}$ yields poor results in the sense that α_3 is insignificant or significant with the wrong signs. This differs from other studies in trading volume substituted by trading volume growth.

[3] The value 8.85E-06 is 8.85/1000000 or 0.00000885.

for the rate of daily information arrivals to the cash market. It is also found that, in the conditional variance equation of DP_{2f}, the coefficient of DQ_{1f} is 4.58 (=6.18/1.35) times as much as that of DQ_{2f}. Finally, the trading volume growth of cash index plays no role in determining volatility in DP_{1f} and DP_{2f} since the coefficient (1.25E-05) of DQ_s in the DP_{1f} conditional variance equation iss statistically insignificant and the coefficient (-2.14E-05), though significant at the 5% level, takes the wrong sign (Table not shown).

Table 3.2.1 The Estimation of the Variance Equation of GARCH (1,1)

Panel A: Estimation of Equation 3.2.1

Variable	α_0	α_1	α_2	$\alpha_1+\alpha_2$
DP_s	3.16E-06	0.075	0.901	0.976
	(2.637)[a]	(5.712)[a]	(45.019)[a]	
DP_{1f}	3.24E-06	0.074	0.905	0.979
	(3.287)[a]	(6.582)[a]	(65.792)[a]	
DP_{2f}	3.09E-06	0.072	0.909	0.981
	(3.208)[a]	(6.567)[a]	(65.184)[a]	

Panel B: Estimation of Equation 3.2.2

Variable	α_0	α_1	α_2	α_3	$\alpha_1+\alpha_2$
DP_s	5.24E-06	0.151	0.816	7.93E-05	0.967
	(2.396)[b]	(4.911)[a]	(19.536)[a]	(4.753)[a]	
DP_{1f}	1.68E-05	0.203	0.676	9.87E-05	0.879
	(5.610)[a]	(8.969)[a]	(16.067)[a]	(32.733)[a]	
DP_{2f}	2.49E-05	0.085	0.901	1.47E-05	0.986
	(2.479)[b]	(7.216)[a]	(60.656)[a]	(5.531)[a]	

Panel C: Estimation of Equation 3.2.3

Variable	α_0	α_1	α_2	α_3	$\alpha_1+\alpha_2$	α_4 and α_5		
						DQ_s	DQ_{1f}	DQ_{2f}
DP_s	9.97E-06	0.225	0.695	1.08E-06	0.920		4.35E-05	9.78E-06
	(3.107)[a]	(5.941)[a]	(13.510)[a]	(0.054)			(4.330)[a]	(3886.726)[a]
DP_{1f}	1.41E-05	0.214	0.656	8.68E-05	0.870	8.85E-06		1.00E-05
	(4.257)[a]	(8.250)[a]	(13.595)[a]	(8.172)[a]		(0.462)		(4.458)[a]
DP_{2f}	1.85E-05	0.197	0.634	1.05E-05	0.831	-6.35E-06	6.57E-05	
	(4.302)[a]	(5.280)[a]	(10.797)[a]	(17.002)[a]		(-0.295)	(6.085)[a]	

Note: a and b denote significance at the 1% and 5% levels.

3.3 The Volatility Spillover Effect

3.3.1 Co-integration and ECM

The three volatility series from Sample II are used to examine cross-market volatility spillovers. They are VAR_S, VAR_{1f}, and VAR_{2f} representing volatility in the stock index returns for the three markets, respectively. Since all the series are I(1), the Johansen method is used to detect whether they are co-integrated. The trace test is performed until the likelihood ratio is less than the critical value and thus the null hypothesis of i co-integrating vectors is accepted. The results from the co-integration test are reported in Table 3.3.1. The likelihood ratio (6.464) is larger than the 5% critical value (3.76), which leads to rejection of the null hypothesis of at most two co-integration vectors. The trace test is supposed to perform the null hypothesis of at most three co-integration vectors. We have only three variables and thus the maximum number of co-integrating vectors is two. They are written as:

$$\begin{aligned} VAR_{s,t} &= 0.00252 + \underset{(37.087)}{0.774} VAR_{2f,t} + \hat{e}_{1,t} \\ VAR_{1f,t} &= -0.000547 + \underset{(118.729)}{1.011} VAR_{2f,t} + \hat{e}_{2,t} \end{aligned} \tag{3.3.1}$$

where t-statistics are in parentheses.

Equation 3.3.1 indicates that the volatility series exhibit a long-run equilibrium relationship. The significant positive signs imply that they co-move in the same direction. The cash index volatility will increase by 0.774 units and the nearby-month index futures volatility will increase by 1.011 units with one-unit increase in the nearby-quarter index futures volatility.

Table 3.3.1 The Johansen Co-integration Test

Eigenvalue	Likelihood Ratio	5% Percent Critical Value	1% Percent Critical Value	Hypothesized No. of CE(s)
0.371	43.150[a]	29.68	35.65	r = 0
0.226	19.531[b]	15.41	20.04	r≦1
0.119	6.464[b]	3.76	6.65	r≦2

Note: a and b denote significance at the 1% and 5% levels.

Next, the error correction terms ($\hat{e}_1, \hat{e}_2$) are incorporated with the vector autoregressive (VAR) model to construct the error correction model which exhibits the long-run equilibrium relationship and the short-run dynamic process. The ECM with 5 lagged terms is estimated as follows:

$$DVAR_{k,t} = \alpha_{k,0} + \gamma_{k,1}\hat{e}_{1,t-1} + \gamma_{k,2}\hat{e}_{2,t-1} + \sum_{j=1}^{5} \sum_{i=s,1f,2f} \alpha_{i,t-j} DVAR_{i,t-j} + w_t \tag{3.3.2}$$

where $DVAR_k$ is the first difference of VAR_k,[4] k=s,1f,2f, $\hat{e}_{i,t-1}$ is the lagged error correction term, w is a white noise. The maximum likelihood method is employed to estimate the ECM and the results are reported in Table A3.3.1 in the appendix.[5]

3.3.2 Granger causality Tests

The Granger causality test is performed in the context of the error correction model. A variable causes another variable through two channels, i.e., correction for a deviation from the long-run equilibrium and the short-run dynamic adjustment. The null hypothesis for the Granger causality test is as follows:

$$H_0 : \gamma_{k,1} = \gamma_{k,2} = \alpha_{i,1} = ... = \alpha_{i,5} = 0 \tag{3.3.3}$$

which proposes that the i^{th} variable does not Granger cause the k^{th} variable, $i \neq k$=s, 1f, and 2f. The LR test is employed to conduct the Granger causality test and the results are presented in Table 3.3.2.[6] It is observed that volatility in the nearby-month and nearby-quarter futures returns uni-directionally Granger-causes volatility in the cash return since the LR statistics are even significant at the 1% level. There is a volatility spillover effect from the futures market to the cash market, but not vice versa. Volatility in the nearby-month index futures return is bi-directionally Granger causal with volatility in the nearby-quarter index futures return. A two-way volatility spillover effect is observed for the two futures markets.

Table 3.3.2 Chi-squared Statistics for the Granger Causality Test

Cause \ Effect	$DVAR_s$	$DVAR_{1f}$	$DVAR_{2f}$
$DVAR_s$		11.846 (0.106)	10.837 (0.146)
$DVAR_{1f}$	23.541 (0.001)[a]		22.193 (0.002)[a]
$DVAR_{2f}$	22.958 (0.002)[a]	21.598 (0.003)[a]	

Note: 1. Probabilities are in parentheses. 2. a denotes significance at the 1% level.

4 The variables in the ECM should be stationary. Since the VAR's are I(1) series, they enter the ECM in first differences.

5 The optimum lag length is chosen using the Akaike information criterion (AIC).

6 The LR test-statistic is computed using $-2(LLF_U-LLF_R)$, which follows the chi-squared distribution with the number of restrictions as its degree of freedom. In this case the number of restrictions is seven which equals the number of parameters set to zero in equation 3.3.3. LLF_U is the log likelihood function for the unrestricted model referred to equation 3.3.2. LLF_R is the log likelihood function for the restricted model. For instance, the restricted equation for the cash return volatility is obtained by substituting equation 3.3.3 into the cash return volatility equation 4.3.2 to remove the effects of the i^{th} variable (i=1f or 2f).

IV. CONCLUSION

The Taiwan Futures Exchange (TAIFEX) was instituted on September 9, 1997 based on the Futures Trade Act enacted on March 26, 1997. The Taiwan stock price index futures was the first contract listed on the exchange on July 21, 1998. Since then the Taiwan futures market has been steadily growing. Seven futures contracts are currently traded on the market. The daily average of the futures contracts traded rose dramatically from 4,512 in 1999 to 40,923 in 2005. The increasing importance of the futures market in the Taiwan financial markets has received considerable attention from academics and financial analysts.

The literature regarding cross-market volatility between the cash index and the index futures for Taiwan is unusual. Chuang (2001) found bi-directional spillovers between the cash index and the near-by month index futures and uni-directional spillovers from the cash index to the near-quarter index futures. Chang and Goo (2003) found bi-directional spillovers and uni-directional spillovers from the cash index to the index futures depending on what models (EC-GARCH (1,1) or EGARCH (1,1)-X) are used. However, more studies reported evidence for uni-directional volatility spillovers from the index futures to the cash index [Koutmos and Tucker (1996), Iihara, Kato, and Tokunaga (1996)]. It is thus necessary for us to reevaluate the Taiwanese case using different methods and different data sets.

Using the data set spanning from January 2, 2004 to April 28, 2006, this study examines all aspects of the relation between volatility in the cash index and volatility in the nearby-month and nearby-quarter index futures. We first use the GARCH model to investigate the impact of the futures volume growth on the conditional variance of the cash price and vice versa. Next, we calculate the variances at the 10-day interval to derive the variance series and then perform the Granger causality test for these co-integrated variance series in the context of the error correction model. The results from the Granger causality test documents the cross-market volatility spillovers effect.

The empirical results from the GARCH (1,1) model suggest that (1) the three markets display a high degree of volatility persistence, (2) the volatility persistence in the three markets does not reduce substantially when the trading volume growth is included in the conditional variance equation, (3) the cash volume growth loses power in explaining its own price volatility when the futures volume growth is included in the conditional variance equation of the cash index return, (4) there is no statistically significant association between the cash volume growth and volatility in the futures markets, and (5) the trading volume growth of nearby-month index futures is the most influential factor for volatility in the three markets.

The empirical results form the Granger causality test in the context of the error correction model document that (1) the volatility series are all I(1) and have two co-integrating vectors, which suggests for co-movement in the same direction in the long run, (2) there are uni-directional volatility spillovers from the index futures to the cash index, and (3) there are bi-directional volatility spillovers between the nearby-month and nearby-quarter futures markets.

APPENDIX

Table A3.1.1 Descriptive Statistics for the Variables from Sample I

Statistics	P_{1f}	Q_{1f}	P_{2f}	Q_{2f}	P_s	Q_s
Mean	8.720	10,211	8.718	6.626	8.721	21.983
Median	8.715	10.231	8.713	6.186	8.714	21.908
Maximum	8.883	11.385	8.881	10.847	8.878	23.177
Minimum	8.567	8.439	8.560	2.773	8.579	21.057
Std. Dev.	0.063	0.381	0.065	1.743	0.061	0.353
Skewness	0.146	-0.305	0.104	0.600	0.167	0.783
Kurtosis	2.842	3.510	2.856	2.521	2.746	3.454
Jarque-Bera	2.638	15.106	1.522	39.928	4.209	63.524
Probability	0.267	0.001	0.467	0.000	0.122	0.000
Observations	574	574	574	574	574	574
Statistics	DP_{1f}	DQ_{1f}	DP_{2f}	DQ_{2f}	DP_s	DQ_s
Mean	0.000297	0.000234	0.000271	0.000463	0.000299	-0.000192
Median	0.000498	-0.048562	0.000316	0.246860	0.000319	-0.005424
Maximum	0.064505	2.945679	0.067573	2.267776	0.054189	1.504854
Minimum	-0.072555	-2.138246	-0.072525	-7.195512	-0.069123	-1.106651
Std. Dev.	0.013	0.473	0.013	1.333	0.012	0.211
Skewness	-0.797	0.641	-0.727	-3.076	-0.581	0.480
Kurtosis	9.566	6.149	9.261	13.796	8.318	8.505
Jarque-Bera	1089.962	275.988	986.4082	3686.325	707.394	745.580
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	573	573	573	573	573	573

Table A3.1.2 Correlation Matrix for the Variables from Sample I						
Variable	P_{1f}	Q_{1f}	P_{2f}	Q_{2f}	P_s	Q_s
P_{1f}	1	0.144	0.998	0.118	0.996	0.572
Q_{1f}	0.144	1	0.140	-0.122	0.168	0.373
P_{1f}	0.998	0.140	1	0.110	0.992	0.574
Q_{1f}	0.118	-0.122	0.110	1	0.110	0.111
P_{1f}	0.996	0.168	0.992	0.110	1	0.567
P_{1f}	0.572	0.373	0.574	0.111	0.567	1

Table A3.1.3 Descriptive Statistics for the Variables from Sample II						
Statistics	VAR_{1f}	$DVAR_{1f}$	VAR_{2f}	$DVAR_{2f}$	VAR_s	$DVAR_s$
Mean	0.000275	2.63E-06	0.000277	2.58E-06	0.000236	3.35E-06
Median	0.000161	-1.47E-05	0.000163	-9.16E-06	0.000134	8.72E-06
Maximum	0.001523	0.001338	0.001503	0.001201	0.001310	0.000974
Minimum	2.20E-05	-0.001040	1.79E-05	-0.000911	3.01E-05	-0.000883
Std. Dev.	0.000313	0.000374	0.000305	0.000366	0.000252	0.000317
Skewness	2.448	0.513	2.297	0.458	2.400	0.251
Kurtosis	9.570	6.321	8.839	5.331	9.664	5.278
Jarque-Bera	159.444	28.192	131.080	14.638	160.191	12.700
Probability	0.000	0.000	0.000	0.001	0.000	0.002
Observations	57	56	57	56	57	56

Table A3.3.1 Estimation of the Error Correction Model (Sample II)			
Variable	$DVAR_{s,t}$	$DVAR_{1f,t}$	$DVAR_{2f,t}$
$\hat{e}_{1t-1}$	-3.379 (-1.878)	-3.189 (-1.450)	-2.943 (-2.147)
$\hat{e}_{2t-1}$	1.370 (0.372)	0.319 (0.071)	1.722 (0.392)
$DVAR_{s,t-1}$	1.482 (1.019)	1.847 (1.039)	1.758 (1.013)
$DVAR_{s,t-2}$	2.670 (2.062)	3.410 (2.155)	3.141 (2.032)
$DVAR_{s,t-3}$	1.920 (1.636)	2.065 (1.440)	1.989 (1.420)
$DVAR_{s,t-4}$	1.859 (1.954)	2.202 (1.894)	2.151 (1.895)
$DVAR_{s,t-5}$	0.734	1.059	0.974

	(0.957)	(1.130)	(1.065)
$DVAR_{1f,t-1}$	0.282 (0.086)	0.970 (0.242)	0.630 (0.161)
$DVAR_{1f,t-2}$	3.563 (1.289)	4.950 (1.466)	4.403 (1.335)
$DVAR_{1f,t-3}$	3.440 (1.342)	5.233 (1.671)	4.755 (1.555)
$DVAR_{1f,t-4}$	-0.084 (-0.038)	0.570 (0.213)	0.573 (0.219)
$DVAR_{1f,t-5}$	-0.642 (-0.445)	-0.165 (-0.093)	-0.173 (-0.101)
$DVAR_{2f,t-1}$	-2.087 (-0.582)	-3.268 (-0.746)	-2.857 (-0.668)
$DVAR_{2f,t-2}$	-6.020 (-2.029)	-8.230 (-2.269)	-7.449 (-2.104)
$DVAR_{2f,t-3}$	-5.189 (-1.880)	-7.211 (-2.138)	-6.690 (-2.031)
$DVAR_{2f,t-4}$	-1.502 (-0.599)	-2.412 (-0.787)	-2.422 (-0.809)
$DVAR_{2f,t-5}$	-0.028 (-0.016)	-0.733 (-0.351)	-0.700 (-0.343)
C	-2.77E-05 (-0.989)	-3.60E-05 (-1.054)	-3.44E-05 (-1.030)
Sum squared residuals	1.19E-06	1.78E-06	1.70E-06
Log likelihood	375.680	365.454	366.670
R-squared	0.772	0.758	0.758
Adj. R-squared	0.654	0.633	-0.633
AIC	-49.580		
SC	-47.307		
Note: t-statistics are in parentheses			

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