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Exploring the effect of the long-run and short-run components of volatilities and correlations between TAIEX and TAIFEX markets

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Abstract:

The volatility linkages across market are based on the relation between volatility and information flow. We apply to the component GARCH model which was developed by Engle and Lee (1999) for the TAIEX and TAIFEX markets. The empirical results represent the trend and the transitory components are significance, and the estimations in both markets are similar. The leverage term is significance in the short-run component for both of markets. We also combine the component GARCH model and the Bi-variate GARCH model, trying to discuss complete information flow linkages. The last unexpected information flows affect the cross-market conditional covariance, and the long-run component play the important role between markets. It shows that the volatility linkages between markets are much more potent. Moreover, the correlation coefficient of the conditional covariance is quite high. Given this, it can be inferred that highly linkages between TAIEX and TAIFEX markets are indeed strong.

Keywords: component GARCH model, Bi-GARCH model, linkages, leverage effect, long- and short-run components.
JEL classification: G10

1. Introduction

To find a suitable proxy of risk was necessary in that the variable of risk wasn’t directly measured by the trading data in the market. There were abundant financial literatures supposed the point that volatility could be regarded as the proxy of risk. As the financial econometrics developed, the volatility was estimated from static evaluation to dynamic. Moreover, in consequence of the rapid evolution of traded derivative instruments, the derivative instruments of the same underlying asset were most affluence. The volatility forecasting would become more complex when we considered that the derivatives had influences on asset volatilities. Fleming, Kirby, and Ostdiek (1998) illustrated that the information flows of stock, bond, and money market and the volatilities were really possessed with some linkages. Sun, Tong, and Yan (2006) exhibited the financial markets integrated effects could use the variation of the volatility to measure the linkages between markets. However, the information flow was also the variable which couldn’t be direct quantification. Ross (1989) proposed using the proxy of variations in volatility to substitute for the changes of the information flow. For reason of unquantification, the effects of volatilities between different markets were worthy and intriguing to discussion. When the investor held the portfolio which contained spot asset and derivative with the same underlying, the volatilities linkage became weighty in that it might affect the asset allocation. Engle and Lee (1999) decomposed the volatility into the long-run and short-run components. This result could contribute to comprehend the essence of the volatility process.

While we observed many time series data of finance and of economy, volatilities represented the unusual property of volatility clustering. Engle (1982) proposed the ARCH (Auto-Regressive Conditional Heteroskedasticity) model which could deal with the phenomenon of heteroskedasticity. Bollerslev (1986) developed the GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) model based the ARCH model. By virtue of the GARCH model embedded both the lag terms of the conditional variance and the lagged squared residual, the GARCH model was more compressing than the ARCH model. Leverage effect was significance existing in stock market and then Nelson (1991) proposed the EGARCH (exponential GARCH) model which could capture the asymmetric term.[1] Brandt and Jones (2006) constructed further volatility forecasting by range-based EGARCH model. They proved the accuracy of the forecasting could persist for one year. This result was

[1] Leverage effect is used to explain the asymmetric effect of volatility which result from the variation of stock price. As the bad news was exposed, the stock price might decline. This moment the D/E ratio was raised. The shareholders took more risk in that the debt ratio was increased. The more risk the shareholders stood the more variation the volatility took.

different from the inference of the return-based volatility forecasting which constructed by West and Cho (1995) and Christoffersen and Diebold (2000).

Engle and Lee (1999) presented the component GARCH model which could decompose the volatility into long-run (permanent) component and short-run (transitory) component. They assumed the unconditional variance term with dynamic structure, and the short-run component was excluded the unconditional variance from conditional variance. The division of long-run and short-run effect could assist us in observing the efficiency of market. When the long-run effect expressed significantly, it meant that market was inefficiency. In other words, when the exogenous interfered in the market, the influence of exogenous on volatility couldn't decline in a moment, thus the market was kept insistent shaking. On the contrary, the short-run term showed significantly but the long-run term showed insignificantly, then it meant that the market was efficiency. That was to say the impact of the exogenous interfered in the market could rapidly revert to steady state.

There were enormous theses applying the component GARCH model in empirical analysis. Christofferson, Jacobs, and Wang (2006) connected the options pricing model with GARCH which proposed by Heston and Nandi (2000) and the component GARCH model which represented by Engle and Lee (1999). Then Christofferson, Jacobs, and Wang (2006) expressed the options pricing model with component GARCH which not only diminished the error of volatility estimation but also promoted to the accuracy of options pricing.

The quality of investment policy often depended on the controllable degree of changed information flow. Ross (1989) and Andersen (1996) suggested using the proxy, variations of the daily return volatilities, to replace the variable of information flows. Fleming, Kirby, and Ostdiek (1998) demonstrated that information flow existed spillover effect which could affect the correlation of the volatilities between different markets. Financial literatures often measured the correlation between volatilities by multi-variate GARCH model. The most diversity of GARCH model and multi-variate GARCH model was the latter comprehending the conditional covariance. In another word, the multi-variate GARCH model could model both the variances of asset returns and the process of covariance.[2]

[2]Bollerslev, Engle, and Wooldridge (1988) built the VECH model which could model the variance and covariance process of two assets returns and upward in the form of multi-variate GARCH model. Although the VECH model could be measured the conditional variance and conditional covariance of assets returns and upward, the VECH model had some drawbacks which contained uncertain positive semi-definite of covariance matrix and complicated parameters estimation. Engle and Kroner (1995) construct the BEKK model which was modified the disadvantage of the VECH model and confirmed that the sufficient and necessary conditions of stationarity.

Sun, Tong, and Yan (2006) used the bi-variate GARCH model to analysis the linkages between markets which came through the financial integration. They argued that volatility spillover effect became significantly after financial integration. It also meant that information flow could affect the correlation of the cross-market volatilities. The materials of analysis which we mentioned previously were suitable to illustrate the representation of volatilities in both TAIEX and TAIFEX markets. Both TAIEX and TAIFEX markets are the most popular financial markets. By the trading volumes we get both the trading volumes of TAIEX and TAIFEX markets with tendency towards acceleration year after year. The yearly trading volume of TAIEX market increased from NT$18,410,428 million in 2001 to NT$24,197,399 million in 2006. In addition, the yearly trading volume of TAIFEX market also enlarged from 2,844,709 contracts in 2001 to 9,914,999 contracts in 2006. All the evidences displayed that both the TAIEX and TAIFEX markets were most important markets and still continued expansion. It was a valuable and intriguing discussion to look into the structure forms of volatilities between markets. This paper is organized as follows: Section 2 presents empirical model. Section 3 describes the data analysis and presents empirical results. Section 4 discusses the correlation analysis of the cross-market volatility. Conclusions are offered in section 5.

2. Empirical model

Engle and Lee (1999) considered the unconditional variance contained the characteristic of time varying because they generalized volatility with the properties of time varying and of mean-reverting from the empirical result which involved the stock, exchange and interest rate data fitting GARCH model. Therefore, the unconditional variance which represented the long-run volatility was assumed time varying variable as q_t. To make more flexible in fitting model, the variable, q_t, was established to follow AR(1) process which was familiar with series of volatilities. The fundamental structure of component GARCH model was arrangement as

$$(h_t - q_t) = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta\left(h_{t-1} - q_{t-1}\right) \tag{1}$$

$$q_t = \omega + \rho q_{t-1} + \varphi\left(\varepsilon_{t-1}^2 - h_{t-1}\right) \tag{2}$$

where h_t is the conditional variance series of the asset return. Then assumption σ^2 of the traditional GARCH(1,1) model is the unconditional variance, the model of volatility equation could rearrange $h_t = \sigma^2 + \alpha(\varepsilon_{t-1}^2 - \sigma^2) + \beta(h_{t-1} - \sigma^2)$, where $(\varepsilon_{t-1}^2 - \sigma^2)$ is the shock of the asset return volatility. According to the previous inference, the equations of component GARCH model can express equation (1) and (2). Now we can treat the unconditional variance, q_t, as the trend term in the equation of the conditional volatility. Therefore $(h_t - q_t)$ can regard as the transitory part of volatility component or as the short-run component of volatility.

We also rewrite the component GARCH model in symmetrical form which is expressed as

$$h_t = q_t + s_t \tag{3}$$

$$s_t = (\alpha + \beta)s_{t-1} + \alpha(\varepsilon_{t-1}^2 - h_{t-1}) \tag{4}$$

$$q_t = \omega + \rho q_{t-1} + \varphi(\varepsilon_{t-1}^2 - h_{t-1}) \tag{5}$$

where s_t is the transitory term of volatility, and $(\varepsilon_{t-1}^2 - h_{t-1})$ is the innovation term of volatility.

Furthermore, when we take the leverage effect into account, the asymmetric component GARCH model is established. It could represent in equation (6) and (7):

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \delta_2\left(D_{t-1}\varepsilon_{t-1}^2 - 0.5q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right) \tag{6}$$

$$q_t = \omega + \rho q_{t-1} + \varphi\left(\varepsilon_{t-1}^2 - h_{t-1}\right) + \delta_1\left(D_{t-1}\varepsilon_{t-1}^2 - 0.5h_{t-1}\right) \tag{7}$$

where D_t is the dummy variable. As $\varepsilon_t < 0$ then D_t=1, and $\varepsilon_t > 0$ then D_t=0. By building on the assumption of the symmetrical return distribution, the factor, 0.5, shows the average effect of dummy variable. The long-run component volatility of asymmetric component GARCH model which reacts to the bad news is showed ($\varphi + \delta_1$) and good news is (φ). The parameter, ($\alpha + \delta_2$), shows the impact of short-run component volatility that reacts to the bad news and (α) reacts to the good news. The parameters (δ_1) and (δ_2) represent the long- and short-run leverage effects of the asymmetric component GARCH model. For instance, it shows significantly in the leverage effect if the long- and short-run influences of information reaction are difference. When the long-run asymmetric component volatility is significantly, the impact of information to return is permanence. Thus the market participants should consider the influence of leverage effect in the long-run. On the contrary, if the short-run asymmetric component volatility shows significance, the market participants should take it into account.

3. Data analysis and empirical results

3.1 Data

Our sample consists of the daily returns data on TAIEX and TAIFEX markets. There are 1392 observations of the daily returns from January 2, 2001 to August 18, 2006.[3] The sampling futures price data are selected from the front-month contract or the nearest-to-maturity contact. Our paper takes the contract price of the daily greatest volume as the daily futures price. We obtain the daily data from TEJ.

Our investigation is took the daily returns as the descriptive statistics of the sample period. The daily returns are transformed from the daily data of closed price on TAIEX and TAIFEX. Now we denote the calculated form of returns as:

$$\text{Returns of TAIEX} = 100 \times [\ln(P_t^{close}) - \ln(P_{t-1}^{close})]$$

$$\text{Returns of TAIFEX} = 100 \times [\ln(F_t^{close}) - \ln(F_{t-1}^{close})]$$

where P_t^{close} represents the TAIEX closed price at time t, and F_t^{close} represents the TAIFEX closed price at time t.

[3]The trading record on TAIFEX which contained six trading days every week began on January 2, 1999. After January 2, 2001 the trading record on TAIFEX changed into five days every week. In virtue of the trading days were inconsistency on different periods, and in order to avoided the affection of market structure changed. The period of this investigation is sampling from January 2, 2001 to August 18, 2006.

Table 1. The descriptive statistics of the daily returns on TAIEX and TAIFEX

	daily returns	
	TAIEX	TAIFEX
Observations	1392	1392
Mean	0.0222	0.0226
Maximum	5.6126	6.7657
Minimum	-6.9123	-7.2555
Standard deviation	1.4861	1.6773
Skewness	-0.0010	-0.0645
Kurtosis	4.7165	5.8027
Jarque-Bera	170.891(0.000)	456.557(0.000)

Note: 1. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

2. The Jarque-Bera test statistic present as: JB=$T[(sk^2/6)+(k-3)^2/24]$, where T is the numbers of observation, sk and k present the skewness and kurtosis, respectively. The Jarque-Bera statistic follows an appropriately chi-square distribution with 2 degrees of freedom, 5.99.

3. The calculated form of the daily returns on TAIEX expresses as: $100\times[\ln(P_t^{close})-\ln(P_{t-1}^{close})]$. The calculation of the daily returns on TAIFEX presents by: $100\times[\ln(F_t^{close})-\ln(F_{t-1}^{close})]$, where P_t^{close} indicates the TAIEX closed price at time t, and F_t^{close} presents the TAIFEX closed price at time t.

4. In parentheses are p-values.

Table 1 presents the descriptive statistics of the daily returns on TAIEX and TAIFEX. The sample distribution of normality test is proceeded by means of the statistic of Jarque-Bera（JB）test. Table 1 contains that the average and standard error of the daily data on TAIEX and TAIFEX are slight difference. This outcome implies the distribution of both markets which contain the same underlying assets being similar to each other. Both JB-values from the daily returns on TAIEX and TAIFEX are considerably rejecting the null hypothesis of normality distribution. Furthermore, both of the kurtosis on TAIEX and TAIFEX are larger than 3 which demonstrated data with the phenomenon of leptokurtic. Table 2 contains the results of ARCH-LM test which can examine the ARCH effect on conditional variance. Shortly, we want to check out the property of heteroskedasticity. From table 2, the LM statistics of least square estimation (LSE) are much bigger than 5% critical value of a χ^2 distribution. The results are showed using LSE can't illustrate the property of heteroskedasticity and the residual term still contain the ARCH effect. If we take the GARCH model to fit data, the residual term is excluded the ARCH effect and the property of heteroskedasticity is explained. Summing up the inferences given above can sustain us analyzing by the GARCH family model.

Table 2. The ARCH-LM test of the daily returns on TAIEX and TAIFEX

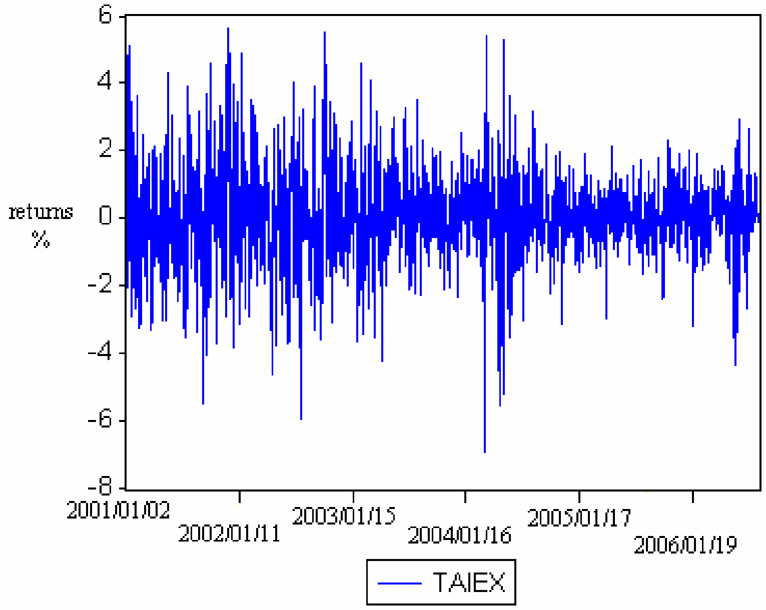
k	1	2	3	4	5
TAIEX	6.916**	31.602**	67.596**	85.176**	113.030**
TAIFEX	12.456**	30.333**	71.885**	91.002**	111.840**

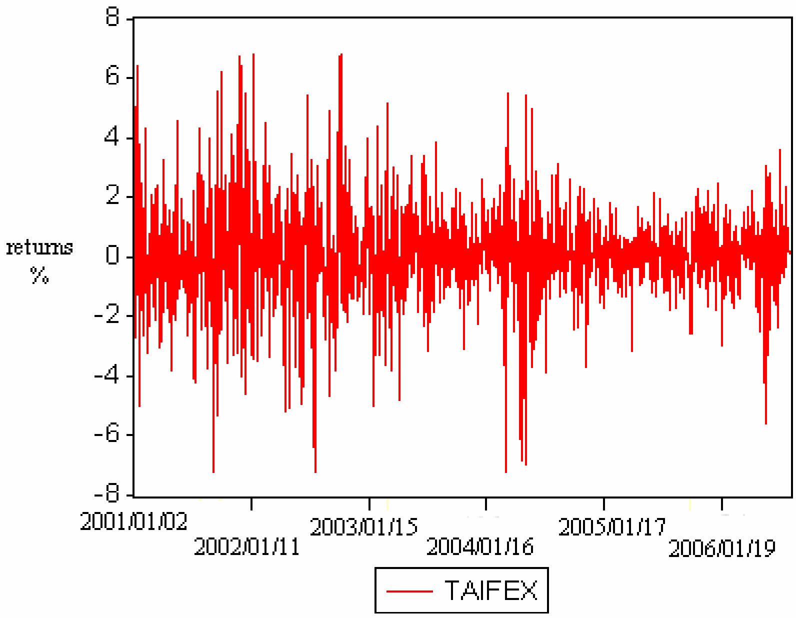
Note: 1. The symbol ** denotes significance at 5% significance level.

2. The values of the table shows LM test statistic, TR^2, which is followed a chi-square distribution withk degree of freedom, where T, R^2 and k are the numbers of sample, the coefficient of determination of auxiliary regression and the lagged term.

3. The hypothesis assumes that ARCH effect is inexsistence.

4. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.





Note: There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

Figure 1. The daily returns on TAIEX and TAIFEX

The daily returns on TAIEX and TAIFEX are depicted in figure 1. Figure 1 shows the time series data on TAIEX and TAIFEX actually had the characteristic of volatility clustering. This outcome supports us to use the GARCH family model evaluating the volatilities on both markets. Further, the variation of returns on TAIEX is softer than that on TAIFEX. The variations on TAIEX and TAIFEX vary with same signs in that the underlying assets are the same. The results of figure 1 agree with the inference of table 1.

3.2 Empirical results in component GARCH model

We demonstrate the property of heteroskedasticity actually existing in the chapter of data analysis. This outcome supports us to use the GARCH family model fitting the data. The developments of GARCH family model have had multitudinous extension. The conventional GARCH family model contains the E-GARCH model, GARCH-in-mean model, asymmetric GARCH model and the GJR-GARCH model etc. (see Brooks (2004) p.468). The models that we have noted are conferred on the topics of leverage effect and risk premium. Our investigation focuses on the performance of the long-run and short-run components on TAIEX and TAIFEX. For this reason, we hire the component GARCH model represented by Engle and Lee (1999) to investigate this topic. The effect of the long-run and short-run component which our investigation is mentioned had been widely applications containing the stock, futures and options market. Our investigation also debates the long-run and short-run leverage effect by the asymmetric component GARCH model. We discuss the empirical results in the component GARCH model, asymmetric component GARCH model on TAIEX and TAIFEX in this chapter. Finally, we also consult the impact of the long-run and short-run components causing by the noneconomic event.

The empirical results of the component GARCH model on TAIEX are expressed as table 3. Initially, we find that the short-run effect of immediate responding to the conditional variance, $\hat{\alpha}$, is even larger than the long-run effect of immediate responding to the conditional variance, $\hat{\varphi}$. The long-run and the short-run component are significantly. It also means that the data are displayed inefficiency in that the data can use the component GARCH model fitting and forecasting. The estimator of the effect of short-run component, ($\hat{\alpha}+\hat{\beta}$), is 0.978. In the other words, the conditional variance mean-reverts to the unconditional variance at a geometric rate of 0.978. The estimated result of the effect of the long-run component, $\hat{\rho}$, is 0.996. This consequence is accorded with the stationarity condition which is indicated the effect of the long-run component had lower mean-reverting rate than the effect of the short-run component. The half-lives of the effect of trend component reacting to the disturbance factor are 173 days for TAIEX, and that of the effect of transitory component reacting to the disturbance factor are 31 days for TAIEX. It also means that after 173 days the influence of disturbance factor acting on the trend component will decline to half, and the influence of disturbance factor effecting to the transitory component will decline to fifty percent. The outcome of our estimation is not only indicated that the continuance of the fluctuation of transitory term is more less than the fluctuation of permanent term, but also exhibited the shocks of the fluctuation of transitory term is more greater than the fluctuation of permanent term.

Table 3. The estimation results of the component GARCH model on TAIEX

$$
\begin{aligned}
& r_t = c + \varepsilon_t \\
& (h_t - q_t) = \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right) \\
& q_t = \omega + \rho q_{t-1} + \varphi\left(\varepsilon_{t-1}^2 - h_{t-1}\right) \\
& \varepsilon_t \left| I_{t-1} \sim N(0, h_t)\right.
\end{aligned}
$$

	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	Q(5)	Q(10)
TAIEX	0.081 (0.063)	0.897** (0.000)	0.734 (0.143)	0.996** (0.000)	-0.019 (0.596)	8.880 (0.114)	12.117 (0.277)

Note: 1. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

2. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

3. The component GARCH model is estimated by QMLE (Quasi-Maximum Likelihood Estimation).

4. The Q statistics, Q(5) and Q(10), are 5 lagged terms and 10 lagged terms. What the null hypotheses of the residuals are white noise.

5. r_t, h_t, q_t and ε_{t-1}^2 present the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t and the square residual of the daily returns at time t-1 on TAIEX, respectively.

The estimation results of component GARCH model on TAIFEX are showed as table 4. First, the short-run and the long-run effect of immediate responding to the conditional variance are represented by $\hat{\alpha}$ and $\hat{\varphi}$, then we can see that $\hat{\alpha}$ is larger than $\hat{\varphi}$ for TAIFEX. Both of the long-run and short-run components are represented significantly. The results imply that both TAIEX and TAIFEX markets are inefficiency, and both of them can be estimated and forecasted by the component GARCH model. The empirical results illustrate that the effect of the short-run, ($\hat{\alpha} + \hat{\beta}$), and long-run component, ($\hat{\rho}$), are 0.982 and 0.996, respectively. It shows the conditional variance mean-reverted to the unconditional variance at a geometric rate of 0.982, and the assuming condition of the component GARCH model is agreeable. This stationarity property accounts for the relationship between the effects of the long-run and the short-run component. The half-lives of the trend component are 173 days for TAIFEX. This outcome demonstrates that the affection of the disturbance term effecting to trend component sinks to half after 173 days. On the contrary, the half-lives of the transitory component are 38 days. It means the influence of the disturbance term caused transitory term to decay to bisection. Compared to the half-lives of the trend term for TAIEX, they are identical in representation. But the half-lives of the transitory term for TAIEX are shorter than that for TAIFEX. This result is expressed that TAIEX is more efficient than TAIFEX in the short-run component. Further compared table 3 and table 4, the effect of the long-run and short-run components for TAIEX and TAIFEX are similarity. This consequence may imply some linkages of volatility existing between TAIEX and TAIFEX markets.

Table 4. The estimation results of the component GARCH model on TAIFEX

$$\begin{aligned}
r_t^f &= c + \varepsilon_t^f \\
\left(h_t^f - q_t^f\right) &= \alpha\left((\varepsilon_{t-1}^f)^2 - q_{t-1}^f\right) + \beta\left(h_{t-1}^f - q_{t-1}^f\right) \\
q_t^f &= \omega + \rho q_{t-1}^f + \varphi\left((\varepsilon_{t-1}^f)^2 - h_{t-1}^f\right) \\
\varepsilon_t^f \left| I_{t-1} \right. &\sim N\left(0, h_t^f\right)
\end{aligned}$$

	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	Q(5)	Q(10)
TAIFEX	0.089 (0.052)	0.893** (0.000)	1.303** (0.005)	0.996** (0.000)	-0.026 (0.533)	3.579 (0.611)	8.245 (0.605)

Note: 1. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

2. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

3. The component GARCH model is estimated by QMLE (Quasi-Maximum Likelihood Estimation).

4. The Q statistics, Q(5) and Q(10), are 5 lagged terms and 10 lagged terms. What the null hypotheses of the residuals are white noise.

5. r_t^f, h_t^f, q_t^f and $(\varepsilon_{t-1}^f)^2$ present the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t and the square residual of the daily returns at time t-1 on TAIFEX, respectively.

3.3 Empirical results of the asymmetric component GARCH model

Table 5 is presented the estimation results of the asymmetric component GARCH model on TAIEX. By table 5 the long-run asymmetric effect, $\hat{\delta}_1$, is insignificantly, but the short-run asymmetric effect, $\hat{\delta}_2$, is significance and positive. This outcome indicates that the returns volatility on TAIEX merely has the short-run leverage effect. Briefly, in the short-run the effect of the stock price decline acting on the volatility is greater than that of the flowing stock price. This phenomenon is inexistence in the long-run, and accords with economy. The empirical results which consider the leverage effect decreasing progressively respond to the efficiency hypothesis.

Table 5. The estimation results of the asymmetric component GARCH model on TAIEX

$$
\begin{aligned}
r_t &= c + \varepsilon_t \\
h_t &= q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \delta_2\left(D_{t-1}\varepsilon_{i,t-1}^2 - 0.5q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right) \\
q_t &= \omega + \rho q_{t-1} + \varphi\left(\varepsilon_{t-1}^2 - h_{t-1}\right) + \delta_1\left(D_{t-1}\varepsilon_{t-1}^2 - 0.5h_{t-1}\right) \\
\varepsilon_t \left| I_{t-1} \right. &\sim N(0, h_t)
\end{aligned}
$$

	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	$\hat{\delta}_1$	$\hat{\alpha}$	$\hat{\delta}_2$	$\hat{\beta}$
TAIEX	1.841**	0.992**	0.075**	-0.033	-0.064**	0.109**	0.930**
	(0.000)	(0.000)	(0.000)	(0.194)	(0.023)	(0.000)	(0.000)

Note: 1. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

2. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

3. The asymmetric component GARCH model is estimated by QMLE (Quasi-Maximum Likelihood Estimation).

4. r_t, h_t, q_t and ε_{t-1}^2 present the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t and the square residual of the daily returns at time t-1 on TAIEX, respectively. D_{t-1} expresses the dummy variable, if $\varepsilon_{t-1} < 0$ then $D_{t-1} = 1$,and $\varepsilon_{t-1} > 0$ then $D_{t-1} = 0$ 。

The empirical results of asymmetric component GARCH model on TAIFEX are showed as table 6. It is illustrated that the parameter of short-run asymmetric effect, $\hat{\delta}_2$, is significant positive and that of the long-run asymmetric effect, $\hat{\delta}_1$, is insignificance. This result demonstrates that the returns volatility on TAIEX has considerable short-run leverage effect which means that in the short-run the influence of falling stock prices acting on returns volatility is greater than the influence of rising stock prices. On the contrary, in the long-run the impact of the exhibition of stock prices is consistency. The explanation of the asymmetric component GARCH model for the volatility of TAIFEX market is agreement on economy. Shortly, in the long-run the efficient market makes the influence of leverage effect declining. The inference replies to the description of the weak form market efficiency which is considered the stock price contained all the past information of the efficiency hypothesis.

Table 6. The estimation results of the asymmetric component GARCH model on TAIFEX

$$r_t^f = c + \varepsilon_t^f$$
$$h_t^f = q_t^f + \alpha\left((\varepsilon_{t-1}^f)^2 - q_{t-1}^f\right) + \delta_2\left(D_{t-1}^f(\varepsilon_{t-1}^f)^2 - 0.5q_{t-1}^f\right) + \beta\left(h_{t-1}^f - q_{t-1}^f\right)$$
$$q_t^f = \omega + \rho q_{t-1}^f + \varphi\left((\varepsilon_{t-1}^f)^2 - h_{t-1}^f\right) + \delta_1\left(D_{t-1}^f(\varepsilon_{t-1}^f)^2 - 0.5h_{t-1}^f\right)$$
$$\varepsilon_t^f \middle| I_{t-1} \sim N(0, h_t^f)$$

	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	$\hat{\delta}_1$	$\hat{\alpha}$	$\hat{\delta}_2$	$\hat{\beta}$
TAIFEX	1.797**	0.987**	0.067**	0.019	-0.929**	0.144**	0.727**
	(0.017)	(0.000)	(0.000)	(0.293)	(0.000)	(0.000)	(0.000)

Note: 1. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

2. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

3. The asymmetric component GARCH model is estimated by QMLE (Quasi-Maximum Likelihood Estimation).

4. r_t^f, h_t^f, q_t^f and $(\varepsilon_{t-1}^f)^2$ present the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t and the square residual of the daily returns at time t-1 on TAIFEX, respectively. D_{t-1}^f indicates the dummy variable as $\varepsilon_{t-1}^f < 0$ then $D_{t-1}^f = 1$, and $\varepsilon_{t-1}^f > 0$ then $D_{t-1}^f = 0$ 。

4.1 The impacts of noneconomic event respond to the long-run and short-run components

The period of research comprehends the presidential election on March 20, 2004. The political and economic policy may be changed as a result of election for president. Then we regard the presidential election as a grave noneconomic event. In this section, we discuss the representation of the noneconomic event effecting on the long-run and short-run component. Firstly, we define the pre-event period contained 790 observations of the daily returns from January 2, 2001 to March 19, 2004 and the post-event period involved 602 observations of the daily returns from March 22, 2004 to August 18, 2006. The estimation results of the component GARCH model on TAIEX with noneconomic event are reported in table 7. Comparing the estimation results of the different periods separated by noneconomic events, we find that the long-run component presents significance, but the short-run component presents insignificantly. Further comparing table 3 and table 7, we get the parameter of long-run component changed from 0.996 to 0.966. This outcome indicates that the impact of noneconomic event acting on the long-run component on TAIEX is slightly.

Table 7. The estimation results of the component GARCH model on TAIEX with noneconomic event

$$r_t = c + \varepsilon_t$$
$$(h_t - q_t) = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$
$$q_t = \omega + \rho q_{t-1} + \varphi(\varepsilon_{t-1}^2 - h_{t-1})$$
$$\varepsilon_t | I_{t-1} \sim N(0, h_t)$$

Before	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	Q(5)	Q(10)
TAIEX	-0.062 (0.183)	-0.007 (0.993)	2.505** (0.004)	0.989** (0.000)	0.052** (0.000)	3.783 (0.581)	7.341 (0.693)
After	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	Q(5)	Q(10)
TAIEX	0.249 (0.953)	0.710 (0.862)	0.827** (0.000)	0.966** (0.000)	-0.198 (0.962)	3.184 (0.672)	6.095 (0.807)

Note: 1. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

2. The pre-event period includes 790 observations of the daily returns from 01/02/2001 to 03/19/2004, and the post-event period contains 602 observations of the daily returns from 03/22/2004 to 08/18/2006.

3. The component GARCH model is estimated by QMLE (Quasi-Maximum Likelihood Estimation).

4. The Q statistics, Q(5) and Q(10), are 5 lagged terms and 10 lagged terms. What the null hypotheses of the residuals are white noise.

5. r_t, h_t, q_t and ε_{t-1}^2 indicate the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t and the square residual of the daily returns at time t-1 on TAIEX, respectively.

Table 8 shows the empirical results of the component GARCH model on TAIFEX with noneconomic event. Before the noneconomic event the long-run component on the TAIFEX presents significance but the short-run component presents insignificance. After the noneconomic event the long-run and short-run component on TAIFEX both presents considerably. The results are different to TAIEX market in that the different markets interpret inconsistency of this information. Hsieh (2002) considered that in contrast with the spot market TAIFEX market has stronger reaction on information interpreted. He also indicated information transmission had the effect of feedback. Furthermore, numerous empirical studies argue S&P 500 index futures getting ahead of S&P 500 index. In our study, the reaction on TAIFEX gets ahead of that on TAIEX. Consequently, the impact of noneconomic event may firstly affect the volatility process on TAIFEX then on TAIEX so that the short-run component is only significance on TAIFEX market. Comparing table 4 and table 8, we find the effect of the short-run component acutely declining from 0.982 to -0.930, but the effect of the long-run component changing from 0.996 to 0.974. In other wards, this noneconomic event deeply affects on the short-run component, but slightly affects on the long-run component.

Table 8. The estimation results of the component GARCH model on TAIFEX with noneconomic event

$$r_t^f = c + \varepsilon_t^f$$
$$\left(h_t^f - q_t^f\right) = \alpha\left((\varepsilon_{t-1}^f)^2 - q_{t-1}^f\right) + \beta\left(h_{t-1}^f - q_{t-1}^f\right)$$
$$q_t^f = \omega + \rho q_{t-1}^f + \varphi\left((\varepsilon_{t-1}^f)^2 - h_{t-1}^f\right)$$
$$\varepsilon_t^f \left| I_{t-1} \right. \sim N\left(0, h_t^f\right)$$

Before	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	Q(5)	Q(10)
TAIFEX	-0.101** (0.014)	0.055 (0.910)	4.366 (0.088)	0.986** (0.000)	0.100** (0.000)	8.150 (0.148)	14.791 (0.140)
After	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	Q(5)	Q(10)
TAIFEX	0.021 (0.362)	-0.930** (0.000)	1.076** (0.000)	0.974** (0.000)	0.042 (0.050)	3.468 (0.628)	4.972 (0.893)

Note: 1. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

2. The pre-event period includes 790 observations of the daily returns from 01/02/2001 to 03/19/2004, and the post-event period contains 602 observations of the daily returns from 03/22/2004 to 08/18/2006.

3. The component GARCH model is estimated by QMLE (Quasi-Maximum Likelihood Estimation).

4. The Q statistics, Q(5) and Q(10), are 5 lagged terms and 10 lagged terms. What the null hypotheses of the residuals are white noise.

5. r_t^f, h_t^f, q_t^f and $(\varepsilon_{t-1}^f)^2$ present the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t and the square residual of the daily returns at time t-1 on TAIFEX, respectively.

4. The correlation analysis of the cross-market volatilities

On above chapter, we illustrate that the component GARCH model is suitable to fit TAIEX and TAIFEX markets. The estimation parameters are resemblance between markets. This consequence implies some correlations of the cross-market volatilities are existed. Thus this investigation uses the Bi-GARCH model to discuss the correlation between TAIEX and TAIFEX markets. We use the market data to examine the correlation of two market volatilities. If the linkage between markets is existed, the market participators can base on that information to adjust the hedging or swap strategy rapidly. Then market participators get the purpose of hedging and arbitrage. In addition, we also consider the effect of the long-run and short-run components into the Bi-GARCH model further analyzing the linkages of the effect of the long-run and short-run components. This chapter contains two parts. Firstly, we briefly introduce the Bi-GARCH model and the Bi-GARCH model with component. Then we discuss the empirical results of the correlation of the cross-market volatilities.

4.1 Bi-GARCH model

Analysis of the cross-market which could assist us in comprehending the degree of correlation and definitely illustrated the movement and affection of the information flows. If market participators could get the sufficient information which contained the correlation of the cross-market volatilities, they could also formulate their trading strategy well-arranged. Fleming, Kirby, and Ostdiek (1998) pointed out that the information flows made the cross-market linkages. In consequence of unobservable the cross-market linkages as investigation on that, they suggested using the volatility of the daily returns to substitute for intraday information flow which was the proxy of information flow. Thus the estimation of simultaneous correlation of lagged information flows between markets was directly calculated. Our investigation of the cross-market linkages builds upon this notion and combines the Bi-GARCH model which applied by Sun, Tong, and Yan (2006).

Bi-GARCH model is expressed as equation (8) to equation (10):

$$h_{ii,t} = \omega_i + \beta_i h_{ii,t-1} + \alpha_i \varepsilon_{i,t-1}^2 + \tau_i \varepsilon_{f,t-1}^2 \tag{8}$$

$$h_{ff,t} = \omega_f + \beta_f h_{ff,t-1} + \alpha_f \varepsilon_{f,t-1}^2 + \tau_f \varepsilon_{i,t-1}^2 \tag{9}$$

$$h_{if,t} = \omega_{if} + \kappa \sqrt{h_{ii,t} h_{ff,t}} \tag{10}$$

where the variables $r_{i,t}$ and $r_{f,t}$ are the returns of the TAIEX and TAIFEX at time t, and $\varepsilon_{i,t}$ and $\varepsilon_{f,t}$ are the error terms of TAIEX and TAIFEX at time t. The conditional variances and covariance on TAIEX and TAIFEX are showed as $h_{ii,t}$, $h_{ff,t}$ and $h_{if,t}$. The parameters β_i and β_f are represented that the past cumulative information flows effect on the market conditional variances. The effects of the last unexpected information flows acting on the market conditional variances are expressed as α_i and α_f. The parameters τ_i and τ_f are the impacts of the information flows causing the cross-market conditional variances, and κ is the correlation of the conditional covariance. We consider the long- and short-run components into the Bi-GARCH model.

The Bi-GARCH model with component is presented as equation (11) to equation

(15):

$$h_{ii,t} - q_{i,t} = \alpha_i(\varepsilon_{i,t-1}^2 - q_{i,t-1}) + \beta_i(h_{ii,t-1} - q_{i,t-1}) + \upsilon_i q_{f,t-1} \tag{11}$$

$$q_{i,t} = \omega_i + \rho_i q_{i,t-1} + \varphi_i(\varepsilon_{i,t-1}^2 - h_{ii,t-1}) \tag{12}$$

$$h_{ff,t} - q_{f,t} = \alpha_f(\varepsilon_{f,t-1}^2 - q_{f,t-1}) + \beta_f(h_{ff,t-1} - q_{f,t-1}) + \upsilon_f q_{i,t-1} \tag{13}$$

$$q_{f,t} = \omega_f + \rho_f q_{f,t-1} + \varphi_f(\varepsilon_{f,t-1}^2 - h_{ff,t-1}) \tag{14}$$

$$h_{if,t} = \omega_{if} + \kappa\sqrt{h_{ii,t}h_{ff,t}} \tag{15}$$

where the variables $q_{i,t-1}$ and $q_{f,t-1}$ are the long-run components of TAIEX and TAIFEX at time t-1. The parameters ρ_i and ρ_f which can regard as the direct influence of the long-run component acting on the conditional variance equations are represented the long-run component effecting on the markets conditional variances. The estimated coefficients of the error terms of conditional variances are presented as φ_i and φ_f. The parameters, υ_i and υ_f, which can be considered the cross effect of the long-run component affecting the cross-market conditional equations are the estimated coefficients of the long-run component effecting on the cross-market conditional variances. The correlation coefficient of the conditional covariance equation is expressed as κ.

4.2 Empirical results of correlation in Bi-GARCH model with component

When speaking of the topic of the correlation, especially in the cross-market returns, the familiar analytic instruments contain the static are correlation analysis and the vector autoregression model. On the contrary, analyzing the correlation of the cross-market volatilities agree with the generalized method of moment (GMM) or multi-variate GARCH model. According to the characteristic of the second moment of returns which can be presented the volatility, returns directly correlate with volatilities. Before discussing the correlation of the cross-market volatilities, it is worthly to test the correlation of the cross-market returns. Table 9 shows the correlation of coefficient on the cross-market daily returns, where r, $|r|$ and r^2 indicate the daily returns, the absolute value of daily returns and the square daily returns, respectively. The absolute value of daily returns and the square daily returns can frequently regard as the proxy of return volatility. Both the daily returns and proxies of volatility with higher correlation on TAIEX and TAIFEX market are reported in table 9. This results support us to make a description of the cross-market linkages. If the behavior of hedging on markets is quit complicated, the assets returns must have linkages which can measure by correlation of coefficient. Accordingly, the correlation of coefficient of returns can be structure on the efficacious behavior of cross-market hedges. The behavior of hedge influences the degree of the information spillover. It says that the correlation of coefficient can view as one of the measurement of the information spillover. The cross-market volatilities equations briefly note the impact of information linkages acting on the correlation coefficient of volatility, but not on the correlation coefficient of returns. Although the absolute value of the daily returns and the square daily returns are conventional mensuration of volatility, both of them possess the property of white noise. It means that the correlations measure by the two proxies disagree with the degree of cross-market linkages. Thus we view the conditional variance estimated by the Bi-GARCH model as proxy of volatility, and discuss further correlation of markets by the conditional variance.

Table 9. The correlation of the cross-market daily returns

$$corr(r_i, r_f) = \rho(r)$$
$$corr(|r_i|, |r_f|) = \rho(|r|)$$
$$corr(r_i^2, r_f^2) = \rho(r^2)$$

	$\rho(r)$	$\rho(\|r\|)$	$\rho(r^2)$
Correlation	0.942	0.907	0.925

Note: 1. r_i, r_i^2 and $|r_i|$ present the daily returns, the square dialy returns and the absolute value of daily returns on TAIEX. r_f, r_f^2 and $|r_f|$ denote the dialy returns, the square daily returns and the absolute value of daily returns on TAIFEX.

2. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

The results of the Bi-GARCH model are reported in table 10. Firstly, we get that the influences of the past cumulative information flows responding to the conditional variances on TAIEX and TAIFEX market present 0.963 and 0.954 each. The affections of the last unexpected information reacting to the conditional variance on TAIEX and TAIFEX market are 0.191 and 0.263. The foregoing influences are much greater than the affections of the last unexpected information reacting to market conditional variances. It means that the main variable influencing the market conditional variance is the past cumulative information flows. This outcome accord with the economic intuition which signifies the market conditional variance composed of the past cumulative information flows and the last unexpected information. The impact of the last unexpected information on TAIEX market reacting to the conditional variance on TAIFEX market is 0.151, and the p-value is 0.000. On the contrary, the impact of the last unexpected information on TAIFEX market reacting to the conditional variance on TAIEX market is 0.130, and the p-value is 0.042. It shows the variable of the last unexpected information had alternant influences on markets. In other words, the variable of last unexpected information can view as an essential explanatory variable which can be explained the market conditional variance. The correlation coefficient of the cross-market conditional covariance is 0.972, and the p-value is 0.000. The consequence shows the information spillover indeed occurred. Further interpreting both the markets participators really take the strategies of hedging and arbitrage.

Table 10. The estimation results of the Bi-GARCH model

$$r_{i,t} = c_i + \varepsilon_{i,t} \qquad \varepsilon_{i,t} \big| I_{t-1} \sim N(0, h_{ii,t})$$
$$r_{f,t} = c_f + \varepsilon_{f,t} \qquad \varepsilon_{f,t} \big| I_{t-1} \sim N(0, h_{ff,t})$$
$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} + \tau_i \varepsilon_{f,t-1}^2$$
$$h_{ff,t} = \omega_f + \alpha_f \varepsilon_{f,t-1}^2 \beta_f h_{ff,t-1} + \tau_f \varepsilon_{i,t-1}^2$$
$$h_{if,t} = \omega_{if} + \kappa \sqrt{h_{ii,t} h_{ff,t}}$$

	$\hat{\omega}_i$	$\hat{\omega}_f$	$\hat{\alpha}_i$	$\hat{\alpha}_f$	$\hat{\beta}_i$	$\hat{\beta}_f$	$\hat{\tau}_i$	$\hat{\tau}_f$	$\hat{\omega}_{if}$	$\hat{\kappa}$
TAIEX	0.140**		0.191**		0.963**		0.130**			
	(0.000)		(0.000)		(0.000)		(0.042)		-0.004	0.972**
TAIFEX		0.151**		0.263**		0.954**		0.151**	(0.911)	(0.000)
		(0.000)		(0.000)		(0.000)		(0.000)		

Note: 1. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

2. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

3. $r_{i,t}$, $h_{ii,t}$ and $\varepsilon_{i,t-1}^2$ present the daily returns at time t, the conditional variance of the daily returns at time t and the square residual of the daily returns at time t-1 on TAIEX. $r_{f,t}$, $h_{ff,t}$ and $\varepsilon_{f,t-1}^2$ indicate the daily returns at time t, the conditional variance of the daily returns at time t and the square residual of the daily returns at time t-1 on TAIFEX.

The empirical results show the Bi-GARCH model with component in table 11. The effects of the past accumulated information flows responding to the conditional variances on TAIEX and TAIFEX market are both presented 0.950, and the p-values are both 0.000. The results are similar to table 10, and indicate the effects played the important role on market conditional variances. The impacts of the last unexpected information reacting to the conditional variance on TAIEX and TAIFEX market are showed 0.236 and 0.251 each. The effects of the long-run component on both markets are 0.999, and the p-value are 0.000. For this reason, the effect of the long-run component possesses considerable influence on market conditional variance. The reciprocal impacts of the effect of long-run component acting on the market conditional variance represent significantly. The results tally with the economic intuition which considers both markets with some linkages. The correlation coefficient of the cross-market conditional covariance which considers the effect of the long-run and shot-run components presents 0.970, and the p-value is 0.000. The parameter estimation in table 11 is similar to that in table 10. This outcome not only illustrates that the correlation between markets is indeed existed, but also demonstrates that the variation of taking Bi-GARCH model with component to fit the data is quite slighter than taking Bi-GARCH model.

Table 11. The estimation results of the Bi-GARCH model with component

$$r_{i,t} = c_i + \varepsilon_{i,t} \qquad \varepsilon_{i,t} \middle| I_{t-1} \sim N(0, h_{ii,t})$$
$$r_{f,t} = c_f + \varepsilon_{f,t} \qquad \varepsilon_{f,t} \middle| I_{t-1} \sim N(0, h_{ff,t})$$
$$h_{ii,t} = q_i + \alpha_i(\varepsilon_{i,t-1}^2 - q_{i,t-1}) + \beta_i(h_{ii,t-1} - q_{i,t-1}) + \upsilon_i q_{f,t-1}$$
$$q_{i,t} = \omega_i + \rho_i q_{i,t-1} + \varphi_i(\varepsilon_{i,t-1}^2 - h_{ii,t-1})$$
$$h_{ff,t} = q_f + \alpha_f(\varepsilon_{f,t-1}^2 - q_{f,t-1}) + \beta_f(h_{ff,t-1} - q_{f,t-1}) + \upsilon_f q_{i,t-1}$$
$$q_{f,t} = \omega_f + \rho_f q_{f,t-1} + \varphi_f(\varepsilon_{f,t-1}^2 - h_{ff,t-1})$$
$$h_{if,t} = \omega_{if} + \kappa\sqrt{h_{ii,t} h_{ff,t}}$$

	$\hat{\omega}_i$	$\hat{\omega}_f$	$\hat{\rho}_i$	$\hat{\rho}_f$	$\hat{\varphi}_i$	$\hat{\varphi}_f$	$\hat{\alpha}_i$
TAIEX	0.849**		0.999**		-0.000		0.236**
	(0.000)		(0.000)		(0.999)		(0.000)
TAIFEX		0.992**		0.999**		0.024	
		(0.000)		(0.000)		(0.320)	

	$\hat{\alpha}_f$	$\hat{\beta}_i$	$\hat{\beta}_f$	$\hat{\upsilon}_i$	$\hat{\upsilon}_f$	$\hat{\omega}_{if}$	$\hat{\kappa}$
TAIEX		0.950**		0.294**			
		(0.000)		(0.000)		0.006	0.970**
TAIFEX	0.251**		0.950**		0.358**	(0.350)	(0.000)
	(0.000)		(0.000)		(0.000)		

Note: 1. There are 1392 observations of the daily returns from 1/2/2001 to 8/18/2006.

2. In parentheses are p-values based on Bollerslev and Wooldridge (1991). The symbol ** denotes significance at 5% significance level.

3. $r_{i,t}$, $h_{ii,t}$, $q_{i,t-1}$ and $\varepsilon_{i,t-1}^2$ present the daily returns at time t, the conditional variance of dialy returns at time t, the long-run component at time t-1 and the square residual of the daily returns at time t-1 on TAIEX. $r_{f,t}$, $h_{ff,t}$, $q_{f,t-1}$ and $\varepsilon_{f,t-1}^2$ indicate the daily returns at time t, the conditional variance of the daily returns at time t, the long-run component at time t-1 and the square residual of the daily returns at time t-1 on TAIFEX.

5. Conclusion

Engle and Lee (1999) relaxed the restriction of the proxy of long-run component which assumed constant. They presumed the proxy of the long-run component as a random variable, further presenting the component GARCH model which could decompose the volatility process into long-run and short-run component. This approach makes the analysis of volatility more flexible, and supplies another analysis method of efficient market. Fleming, Kirby, and Ostdiek (1998) considered that the information flows may affect the linkages of markets. They demonstrate the linkages of volatilities among stock, bond and money market. Sun, Tong, and Yan (2006) took the Bi-GARCH model to discuss the linkages between financial markets which were integrated. They also illustrated the information flows affecting on the correlation of cross-market volatilities. The division of long-run and short-run component can be auxiliary illustration the market efficiency in that the information flows between markets may react to the correlation of markets volatilities. If we take more flexible volatility estimation to discuss the correlation of volatilities, we may clearly understand the influence of information flow between markets reacting to the long-run and short-run component. This investigation takes the component GARCH model to estimate the conditional volatility, further combines the component GARCH model and the structure of Bi-GARCH model. We try to discuss the effects of long-run and short-run component on TAIEX and TAIFEX market and the correlation of markets. In the chapter of data analysis, we prove that the returns volatilities on TAIEX and TAIFEX abound in the property of heteroskedasticity. Accordingly, this study can take the component GARCH model as the main fitting model. Then we will treat the deeper economic meaning. The empirical results are summed up below:

This investigation takes the component GARCH model to fit the market data. We find the short-run effect of immediate responding to the conditional variance is greater than the long-run effect of immediate responding to the conditional variance. This outcome corresponds with the stationarity assumption. The representations of the effect of the long-run and short-run components volatilities are resemblance. By calculated the half-lives of the trend component and of the transitory component, we illustrate that the impact of the disturbance term responding to trend component on both TAIEX and TAIFEX market declines to half after 173 days. The half-lives of the transitory component on TAIEX market are less than that on TAIFEX market. Briefly, the transitory term on TAIEX is even efficient than that on TAIFEX.

The results of the asymmetric component GARCH model illustrate that the short-run asymmetric effect on both TAIEX and TAIFEX market presents significantly, but the long-run asymmetric effect is insignificance. It means that the short-run leverage effect on both markets is existence. On the contrary, the long-run leverage effect on both markets is negation. Briefly, in the short-run the variety of the returns volatility of slumped stock price is greater than that of the returns volatility of rising stock price. But in the long-run the influence of the expression of stock price reacting to the returns volatility presents accordance. This consequence conforms to the economic intuition which involves efficient market making the influence of the leverage effect decaying in the long-run. It also responds to the weak form efficiency of efficient market hypothesis. That is to say that stock price had adequately reacting to the past related information. For this reason, leverage effect is inexistence in the long-run.

Our paper also discusses the impacts of long-run and short-run component with noneconomic event. The empirical results show inconsistency on the short-run component in different markets when faced the event. This outcome can due to the different effects of the information transmission. The impact of TAIFEX market responding to the information has acute representation so that the effect of the short-run component presents significantly. The impact of TAIEX market reacting to the information is not penetration, and therefore the effect of the short-run component is insignificance. Finally, the impacts of this event reacting to the long-run component on both markets are slight.

According to the discussion of information flow acting on the cross-market volatilities, this study takes the Bi-GARCH model to fitting market data. The empirical results indicate that the variables of affected volatility involve the past cumulative information flows and the last unexpected information. By the parameters estimation we detect the influence of the past accumulated information flows reacting to the conditional variance is larger than that of the last unexpected information. In addition, the unexpected information acts on the other market conditional variance. For this reason, the effect of the information transmission between TAIEX and TAIFEX market is existence. Finally, the correlation coefficient of cross-market conditional covariance is 0.972. It means that the information spillover effect really exists between markets, and the markets participators authentically take the strategies of hedge and arbitrage. This investigation also considers the Bi-GARCH model with component to fitting market data. We argue that the main variable reacting to the market conditional variance is the past cumulative information flows, and the effect of the long-run component acts on the single market conditional variance as well as on the other market conditional variance. The correlation coefficient of cross-market conditional covariance with the component is still highly and presents 0.970. It says that some linkages indeed exist on both markets.

References

1. Hsieh, Wen-liang G. (2002), "Market Integration, Price Discovery, and Information Transmission in Taiwan Index Futures Market," *Journal of Financial Studies*, 10, 1-31.
2. Andersen, T. G. (1996), "Return volatility and trading volume: an information flow interpretation of stochastic volatility," *Journal of Finance*, 51, 169-204.
3. Bollerslev, T. (1986), "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics* 31, 307-327.
4. Bollerslev, T. and J. Wooldridge (1992), "Quasi Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances," *Econometric Reviews* 11, 143-172.
5. Brandt, M. and C. Jones (2006), "Volatility forecasting with range-based EGARCH models," *Journal of Business and Economic Statistics* 24, 470-486.
6. Brooks, C, (2004), Introductory Econometrics for Finance (Cambridge), 468
7. Christoffersen, P., K. Jacobs and Y. Wang (2006), "Option Valuation with Long-run and Short-run Volatility Components," Working Paper, McGill University.
8. Christoffersen P. and F. X. Diedold (2000), "How Relevant is Volatility Forecasting for Financial Risk Management? ," *Review of Economics and Statistics*, 82, 1-11.
9. Engle, R. (1982), "Autoregressive conditional heteroscedasticity with estimates of the variance of U.K inflation," *Econometrica* 50, 987-1008.
10. Engle, R. and G. Lee (1999), "A Long-Run and Short-Run Component Model of Stock Return Volatility," in Cointegration, Causality and Forecasting, edited by R. Engle and H. White, Oxford University Press.
11. Fleming, J., C. Kirby and B. Ostdiek (1998), "Information and Volatility Linkages in the Stock, Bond, and Money Markets," *Journal of Financial Economics* 49, 111-137.
12. Heston, S. and S. Nandi (2000), "A closed-form GARCH option pricing model," *Review of Financial Studies* 13, 585-626.
13. Nelson, D. (1991), "Conditional heteroskedasticity in asset returns: a new approach," *Econometrica* 59, 347-370.

14. Ross S. A. (1989), “Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy,” *Journal of Finance*, 44, 1-17.
15. Sun Q., H. S. Tong and Y. Yan (2006), “Market Liberalization within a Country,” working paper, Xiamen University.
16. West K. D. and D. Cho (1995), “The Predictive Ability of Several Models of Exchange Rate Volatility,” *Journal of Econometrics*, 69, 367-391.

出席國際學術會議心得報告

計畫編號	NSC 95-2416-H-263-004
計畫名稱	波動性與資訊傳遞在權益與期貨市場之聯結
出國人員姓名 服務機關及職稱	巫春洲，致理技術學院財務金融系
會議時間地點	2007, June 27 - June 30
會議名稱	歐洲財務管理學會年會，EFMA2007
發表論文題目	“Estimating Value at Risk with a Dynamical Conditional Range Model”＆ “Forecasting Time-varying Covariance with a Range-Based Dynamic Conditional Correlation Model”

一、參加會議經過

這是歐洲財務管理學會年度的大會，在奧地利的維也納大學舉行，大會的專題演講者為 David Hirshelifer. 此人服務於美國柏克萊大學，在行為財務學領域方面，研究頗為豐富，但是此次之專題演講，念稿比重頗高，代表演講者相當重視此次的演講，然而，也因為如此，精彩度就稍微遜色了些。會中除發表我們研究團隊的論文之外，也接受他人提問並且雙向交流。過程有點緊張，但有實質收穫，吸收了不少新的觀點，也觀摩他人的研究心得，在腦力激盪的過程當中，大概也對自己下一步的研究重點有了具體的方向，相信這就是研討會帶給研究者最重要的反饋。會中也與其他國家各學校的研究人員交換研究心得並互留聯絡方式，目前亦處於良性互動聯繫狀態，對後續後學之跨國研究合作，有一定的幫助與鼓勵。

二、與會心得

台灣與歐洲國家的空中交通相對不方便，也許也是因為距離較遠的關係，轉機有點辛苦，而且搭機過程有些疲憊。會議期間，歐元價格亦持續升值，但我們補助的基礎是美元，因此會覺得歐洲地區物價特別昂貴。也會想到台灣是否有對等的研究實力與環境，吸引歐洲研究人員來台灣參加學術活動？我們有意願遠赴歐洲參加學術會議，是否外國人士也願意親臨台灣交流，或許這是身為學界一份子的同儕也可以思考的問題。當然，

如果還有機會的話，在不耽誤自身的研究時間限制之下，多參加國際性的學術研討會還是非常有幫助的。