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EXPLORING THE RETURNS AND VOLATILITY SPILLOVER EFFECT IN TAIWAN AND JAPAN STOCK MARKETS

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ABSTRACT

This study examined the returns on the Taiwan Capitalization Weighted Stock Index (TAIEX) and NIKKEI Stock Average Index (NIKKEI) and explored the volatility spillover effect between the Taiwanese and Japanese stock market. The results revealed cointegration between the two indices, suggesting a long-term, stable relationship between the two stock markets. An examination of inner-market effects showed that the returns on stock indices in both markets are greatly influenced by the returns of previous time periods. Additionally, a cross-market effect investigation showed that past returns on NIKKEI were found to affect the current returns on TAIEX significantly, while the past returns on TAIEX had no impact on the current returns on NIKKEI. A volatility analysis revealed the existence of an inner-market leverage effect, a negative cross-market volatility spillover effect, and a mutual price leading effect. According to the relative asymmetry analysis results, the two stock markets are more sensitive to falling than rising trends in the counterpart market. These results suggest that the two markets are more likely to crash due to a retreat in the counterpart market. The impact of previous volatility shocks on the current volatility of TAIEX and NIKKEI are 46.44 and 6.98 days, respectively.

Keywords: Bi-EGARCH, Co-integration test, Unit-root test, NIKKEI stock index, TAIEX stock index, Returns, Volatility spillover effect.
JEL Classification: O53, O57.

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Contribution/ Originality

This study is one of very few studies which adopt Bi-EGARCH model to explore the returns and the volatility spillover effect in Taiwan and Japan stock markets. Moreover, this study contributes to an understanding of the short-term returns and the volatility spillover effect relationship between these two stock markets.

1. INTRODUCTION

The vigorous development of information science and technology has led to an extraordinary increase in the pace of current information transfer. The world is moving towards an era in which it would become a "global village," such that the influence of an event in one country would be closely correlated with those in other countries. Economic

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and trade exchange and mutual financial investment have resulted in increasingly apparent interdependent relationships between countries.

Several Asian countries have excelled in economic development. Despite the outbreak of two financial crises in Asia, the region, in general, has experienced vigorous economic growth. Taiwan and Japan are among the most sophisticated economic and trade markets in Asia. Additionally, the two countries are important partners that share a close bilateral economic and trade relationship, as well as frequent interaction.

As indicators of a country's economic development, stock markets showcase a country's economic status. Therefore, by adopting a bivariate exponential generalized autoregressive conditional heteroskedasticity model (Bi-EGARCH model), this study intends to examine the returns on TAIEX and NIKKEI and thereby explore the volatility spillover effects between the Taiwanese and Japanese stock markets.

2. LITERATURE REVIEW

In the present financial markets, the flow of information is rapid. As a result, spillover effects can be generated by changes in transaction price, volume, and returns of the stock index in any given market. In addition, such effects are usually interactive. However, statistically, the returns on stock indices in financial reports are usually not normally distributed, but rather presented in a fat-tailed leptokurtic distribution with heteroskedasticity and volatility clustering. Hence, normal regression models can not be used to interpret actual market conditions fully, as estimations based on normal distribution may lead to biased results.

To handle such high-frequency financial data, Engle (1982) proposed an autoregressive conditional heteroskedasticity (ARCH) model. The ARCH model introduced squared error terms of the previous time period as conditional variance of returns to demonstrate that conditional variance tends to change over time. The purpose of this model is to resolve the problems of autocorrelation and heteroskedasticity, and correct the unreasonable assumption of conventional time series models, which regards variance as a constant.

Bollerslev (1986) found that the current conditional variance tends to be affected by squared error terms and conditional variance of the previous time-period, and hence he generalized the ARCH model, which is referred to as the GARCH model. The GARCH model took into consideration the influence of lagged squared residuals and conditional variation, allowing for a more flexible, dynamic structure of conditional variance and a more streamlined estimation of parameters. Bollerslev *et al.* (1992) proved that the GARCH (1,1) model can achieve good performance in capturing the dynamic processes of volatility for most financial time series.

However, the GARCH model was found to be unable to capture the asymmetric effect of volatility. Hence, Nelson (1991) further modified the GARCH model and proposed an exponential GARCH model (EGARCH). Hafner (1998) confirmed that the EGARCH model has a better explanatory power in estimating the volatility of high-frequency foreign exchange rate.

Bhar (2001) adopted a Bi-EGARCH model to investigate the volatility spillover effect between the returns on the Australian All-Ordinaries Index (AOI) of the spot market and the Share Price Index (SPI) of the Sydney Futures Exchange, and discovered that cross-market hedging tends to cause information spillover. Additionally, the inflow of such information into other markets is likely to generate a spillover effect that leads to volatility of returns. Likewise, the outflow of information from any given market may also trigger volatility of returns in other markets. Lee and Tsai (2014) employed the Bi-EGARCH model to examine the mutual influential relationships between the rate of return and volatility of the stock markets in Taiwan, the United States, and China. The study discovered a mutual spillover effect between the Taiwanese and US stock markets, but found no spillover effect between the US and Chinese stock markets. Additionally, a spillover effect from the Taiwan stock market to the Chinese stock market was observed; however, the findings did not reveal any effect of the Chinese stock market on the Taiwanese stock market. Applying a Bi-EGARCH model, Hsu and Tsai (2016) explored the long- and short-term relationships between the international crude oil prices and gold prices and found a cross-market volatility spillover effect between the two markets.

Booth *et al.* (1997) utilized an EGARCH model to study the impact of good news (market advances) and bad news (market retreats) in the stock markets from four Nordic countries (Denmark, Norway, Sweden, and Finland), and discovered an asymmetric volatility spillover effect between the two types of news. The results showed a greater spillover effect for the bad news than for the good news.

Given that the purpose of this study is to investigate the returns on TAIEX and Nikkei and their volatility spillover effect between the two stock markets, we adopted the Bi- EGARCH (1, 1) model for the analysis.

3. METHODOLOGY

3.1. Data and Computing

A sample of 3,777 returns was collected from both indices over the period of January 1, 2000 to March 31, 2016. In research, economic sequences should depict variations in percentage in order to be meaningful, such as the changes in economic growth rate, interest rates, or unemployment rate. Moreover, extracting the differentiation of logarithmized series variables ($\ln y_t - \ln y_{t-1}$) yields a good approximation to the percent variation $(y_t - y_{t-1})/y_{t-1}$. To retain the validity of the series, this study adopted this calculation method by taking the natural logarithm of all the stock indices and calculating the first order difference of the logarithmized values, before conducting further analysis. The equation is as follows:

$$R_{i,t} = (lnP_{i,t} - lnP_{i,t-1}) \times 100 \qquad (1)$$

Where, $R_{i,t}$ refers to the ith country's daily return of stock index of the tth period, and $P_{i,t}$ represents the ith country's closing price of the tth period. $lnP_{i,t}$ and $lnP_{i,t-1}$ are the natural logarithms of closing prices of the tth and $(t-1)$th periods, respectively.

3.2. Unit-Root Test

Unit-root test aims at determining whether a given time series variable is stationary. If the time series manifests a non-stationary state, spurious regression is likely to be generated. The more commonly used unit-root tests include the Dickey–Fuller test and the augmented Dickey–Fuller test (ADF), proposed by Dickey and Fuller (1979;1981) respectively. Due to the existence of autocorrelation of the residuals in the Dickey-Fuller test, the ADF includes the change of lag in the time series. By applying the AR (p) model to the unit-root test, the model is able to resolve the problem of apparent autocorrelation of the residuals in the Dickey-Fuller test. Hence, this study utilized ADF in the unit-root test.

3.3. Cointegration Test

Cointegration is a statistical phenomenon proposed by Engle and Granger (1987) which is defined as two non-stationary time series data $\{X_t\}$ and $\{Y_t\}$ that are formed into a stationary combination after being differenced d times, I (d). If there is a linear combination that allows $\varepsilon_t = Y_t - \beta X_t$ equals I (d-b), and b> 0, then $\{X_t\}$ and $\{Y_t\}$ are considered as cointegrated, or they have a long-run linear relationship.

Usually the Engle-Granger two-step estimator and Johansen's maximum likelihood estimator are used to test cointegration. However, a comparison of the two methods showed that although the conceptual and testing processes of the Engle-Granger two-step method are relatively easier to use, it has many defects. However, Johansen's maximum likelihood method can extract all the implicit time series data, estimate the cointegration vectors, and provide the test statistics with the correct limit distribution. After performing a comparative analysis of a multitude of methods for testing cointegration, Gonzalo (1994) found Johansen's maximum likelihood method to be the most convincing approach. Hence, this study applied the maximum likelihood estimation procedure to test the existence of cointegration between variables and the number of corresponding cointegration vectors.

3.4. Empirical Model

Lee (1994) states that the error correction term gains predictive power when two time series are cointegrated. Additionally, the square of lagged error correction term has potential predictive power on the conditional covariance matrix. Hence, Bi-EGARCH is adopted as a suitable research model for analyzing a cointegrated time series .Prior to investigating the interaction of variances, the Bi-EGARCH model analyzes the interaction of mean values. Its theoretical model is as follows:

3.4.1. Mean Equation of Returns

$$R_{1,t}= \beta_{10} + \beta_{11} R_{1,t-1} +\beta_{12} R_{2,t-1} + \varepsilon_{1,t} \qquad (2)$$

$$R_{2,t}= \beta_{20} + \beta_{21} R_{1,t-1} + \beta_{22} R_{2,t-1} + \varepsilon_{2,t} \qquad (3)$$

$$\begin{bmatrix}\varepsilon_{1,t}\\ \varepsilon_{2,t}\end{bmatrix} |\Omega_{t-1} \sim N(0,\Sigma_t)$$

In $R_{1,t}$,let$t$=1 and 2 be the return of time period t (where, “1” refers to the return of stock index before this item and “2” refers to the return of stock index after the item).$e_t$is the error correction term of cointegration, $\varepsilon_{i,t}$is the error term, and $\varepsilon_{i,t} = R_{i,t} - u_{i,t}$ is the residual term. The mean of residual terms is used to identify the interaction of returns.$u_{i,t}$ = conditional mean,Ω_{t-1} refers to the information set of the *(t-1)*th time period.

When estimating the mean of return, the present study took into consideration the past returns on the given market, the returns on the counterpart market, and the variances of error correction terms.

3.4.2. Variance Equation for Volatility

Under a regular distribution assumption, the Bi-EGARCH model adopted a maximum likelihood method. The model utilized the calculation processes of an iterative algorithm to obtain extreme values for the functions and estimated values for the parameters. We then applied the Berndt-Hall-Hall-Hausman (BHHH) algorithm to estimate the parametric vectors. The Bi-EGARCH (1,1) model is as follows:

$$\ln(\sigma^2_{1,t}) = \alpha_{10} + \alpha_{11}\lambda_{1,t-1} + \alpha_{12}\lambda_{2,t-1} + \gamma_1\ln(\sigma^2_{1,t-1}) \qquad (4)$$

$$\ln(\sigma^2_{2,t}) = \alpha_{20} + \alpha_{21}\lambda_{1,t-1} + \alpha_{22}\lambda_{2,t-1} + \gamma_2\ln(\sigma^2_{2,t-1}) \qquad (5)$$

$$\lambda_{1,t-1} = (|\varphi_{1,t-1}|-E|\varphi_{1,t-1}|) + \delta_1 \varphi_{1,t-1} \qquad (6)$$

$$\lambda_{2,t-1} = (|\varphi_{2,t-1}|-E|\varphi_{2,t-1}|) + \delta_2 \varphi_{2,t-1} \qquad (7)$$

$$\sigma_{i,j,t} = \rho_{ij}\sigma_{it}\sigma_{jt} \ (i \neq j) \qquad (8)$$

$\sigma^2_{i,t} = var(\varepsilon_{i,t}|\Omega_{t-1})$is the conditional variance Ω_{t-1} refers to the information set at the (t-1)th time period, and

$\sigma_{i,j,t}$ is the conditional covariance. The equations (4) and (5) are the key formulae for the variance equations in the

EGARCH model. These formulae explain variance while indicating that the variance has exponential autocorrelation, and the residuals tend to affect future variation. In the above equations, $\varphi_{1,t-1} \equiv/\varepsilon_t^2$ refers to standardized residuals.

Based on the coefficients α_{11} and α_{21} of $|\varphi_{1,t-1}|-E|\varphi_{1,t-1}|) + \delta_1 \varphi_{1,t-1}$ in (4) and (5), the influence of the past standardized residuals on current variance can be obtained. Positive $\alpha_{11}$and α_{21} indicates an increase in volatility caused by new information. Nevertheless, the degree of volatility enhancement caused by positive and negative information is different. Given that $\varphi_{1,t-1}$ of positive information has a positive value and the negative information has a negative value, when the coefficient $\delta_1$or δ_2 is a negative value, then the degree of volatility enhancement caused by negative information is greater than that caused by positive information. Likewise, if the coefficient $\delta_1$or δ_2 is a positive value, then the degree of volatility enhancement caused by positive information is greater than that caused by negative information.

$|\varphi_{i,t-1}| = \boldsymbol{\varepsilon}_{i,t}/\sigma_{i,t}$ represents standardized residuals and is subject to normal distribution. The purpose of taking the absolute value of the standardized residuals is to ensure that the enhancement effect of both positive and negative standardized residuals on conditional volatility generates a positive value.

$(|\varphi_{i,t-1}| - E|\varphi_{i,t-1}|) + \delta_i\varphi_{i,t-1}$ is a function of past standardized residuals.

$|\varphi_{i,t-1}| - E|\varphi_{i,t-1}|$ refers to the size effect, whereas $\delta_i\varphi_{i,t-1}$ stands for the sign effect.

The signs of coefficients, δ_i, can enhance or offset the size effect. Usually, δ_i should be smaller than zero, implying that the market volatility will increase after a negativeshock (bad news) and decrease after a positive shock (good news).

α_{11} and α_{22} describe the asymmetric volatility of a given market caused by the impact of standardized residuals on its own market price. For example, if $\alpha_{11} > 0$ and $-1 < \delta_i < 0$, then negative shock in a given market ($\varphi_{i,t-1}<0$) will lead to greater volatility than positive shock in this market. This phenomenon is commonly known asthe leverage effect. α_{12} and α_{21} describe the asymmetric volatility of the counterpart market caused by the impact of standardized residuals on the price of a given market, which is also known as the market volatility spillover effect. If coefficient α_{12} is a positive value and δ_1 is a negative value, then negative shock in a given market will lead to greater volatility than positive shock in the counterpart market.

Based on the coefficients γ_1 and γ_2 of $\ln(\sigma^2_{1,t-1})$ and $\ln(\sigma^2_{2,t-1})$, the influence of past residuals on current residuals, known as residual consistency, can be acquired. γ_1 And γ_2 describe the volatility autocorrelation in a given market. The necessary condition for the volatility process to be stable is that the values of γ_1 and γ_2 should be smaller than 1. This study adopted a half-life (HL) to measure the time needed between the occurrence of a shock and the end of its influence.

It can be concluded from the design of the conditional variance equation that equations (4) and (5) are functions of past shocks and volatility, which allow the emergence of the transfer effect, whereas $|\varphi_{i,t-1}| - E|\varphi_{i,t-1}|$ can capture the ARCH effects and measure the extent of the impact caused by a shock on conditional volatility. When $|\varphi_{i,t-1}| - E|\varphi_{i,t-1}| > 0$, then the shock of conditional variance of $\varphi_{i,t-1}$ is a positive value. In this case, parameters δ_1 and δ_2, which are used to estimate the transfer effect of returns on stock indices between markets, are bound to be positive values.

3.5. Information Transfer Effect

3.5.1. The Leverage Effect

There are two "[ ]" in each of the volatility variance equation (4) and (5). The functions in the "[ ]" can be replaced by the functions of standardized residuals $f_1 = (\varphi_{1,t-1})$ and $f_2 = (\varphi_{2,t-1})$, respectively. The inputs of the function, where the mean value is 0, represent *iid* and allow an asymmetric effect of the past standardized residuals. The first two standardized residual functions in the "[ ]" measure the size effect of the volatility and the third function measures the sign effect. The sign effect enhances or offsets the size effect by changing the direction of the sign of δ_i: if δ_i is a negative value, then the negative standardized residuals φ_t will have a greater impact on the volatility than the positive standardized residuals φ_t. If the absolute value of the past standardized residuals φ_t is greater than the estimated value of φ_t, then the current volatility will increase. However, the multiplication of coefficients α_{11} and α_{21}

in the standardized residual functions needs to be considered, as the sign of α_{11} and α_{21} (being positive or negative) may increase or reduce the size effect of volatility. If both α_{11} and α_{21} are positive values and δ_1 or δ_2 is negative, then the past negative residuals will lead to greater volatility effect than past positive residuals (two negatives make a positive), and thereby cause a greater conditional volatility in the current period.

3.5.2. The Spillover Effect

In the context of financial markets, the spillover effect refers to the situation wherein more powerful and efficient markets spill energy or information into weaker markets, thereby influencing the weaker markets. However, a mutual spillover effect is experienced, in certain circumstances, when the two markets have a similar level of power.

The cross-market correlation effect of volatility is subject to the control of parameters α_{12} and α_{21}. α_{12} and α_{21} capture the overall extent to which the two markets impact each other by their volatility that is caused because of the influence of standardized residuals on their stock indices returns. For example, let α_{21} be the impact of the standardized residuals of the returns from Market A upon the volatility of the returns from Market B, and let α_{12} be the impact of the standardized residuals of the returns from Market B upon the volatility of the returns from Market A. If the value of α_{21} is positive and the value of δ_1 is negative, then the negative residuals of Market A will cause a greater volatility effect in Market B than positive residuals.

3.5.3. Asymmetric Effect

It is necessary to test the presence of asymmetric effect for verifying the existence of the leverage effect. Let δ be asymmetric volatility; then, when $-1<\delta<0$, the impact of the shocks caused by both positive and negative information on the volatility is a positive value. However, if the degree of positive and negative information shocks is the same, then the positive impact on volatility caused by the positive information shock is smaller than the positive impact on volatility caused by the negative information shock. When $\delta < -1$, the impact on volatility caused by the negative information shock is a negative value, while the impact caused by the positive information shock is a positive value, and hence, $\delta< 0$ indicates the existence of an asymmetric effect.

The relative asymmetric effect can be calculated through $\frac{|-1+\delta_t|}{(1+\delta_t)}$. An outcome >1, =1, and <1 denotes negative asymmetry (the effect of a downward trend is greater than that of an upward trend), symmetry (the effect of a downward trend is equivalent to that of an upward trend), and positive asymmetry (the effect of an upward trend is greater than that of a downward trend), respectively.

3.5.4. Persistence of Volatility

Chou (1988) claimed that under different volatility dynamic structures, the speed of information transfer can be interpreted using the HL of volatility shocks as an indicator. Therefore, the present study applied the HL concept to the calculation of the time needed for the stabilization of conditional volatility.

The HL is calculated as follows:

$$HL = \frac{\ln(0.5)}{\ln|\gamma_t|} \tag{9}$$

where,

HL refers to the time needed for the size of the shocks to reduce to half of its original level.

γ is the impact of past conditional volatility on the current conditional volatility.

The requirement for the stabilization of the conditional volatility process is $|\gamma| < 1$.

The purpose of calculating HL is to know the time needed for a shock to reduce to half of its original impact level—when the shock is about to quickly recess to null influence.

4. RESULTS AND ANALYSES

4.1. Descriptive Statistics of the Sample

It can be observed from Figure 1 and 2 that the trend of the indices of the two stock markets is non-stationary; hence, it is necessary to test whether the stock price index series presents a stationary state before using the model for estimation. This study adopted the ADF method as the unit-root test.

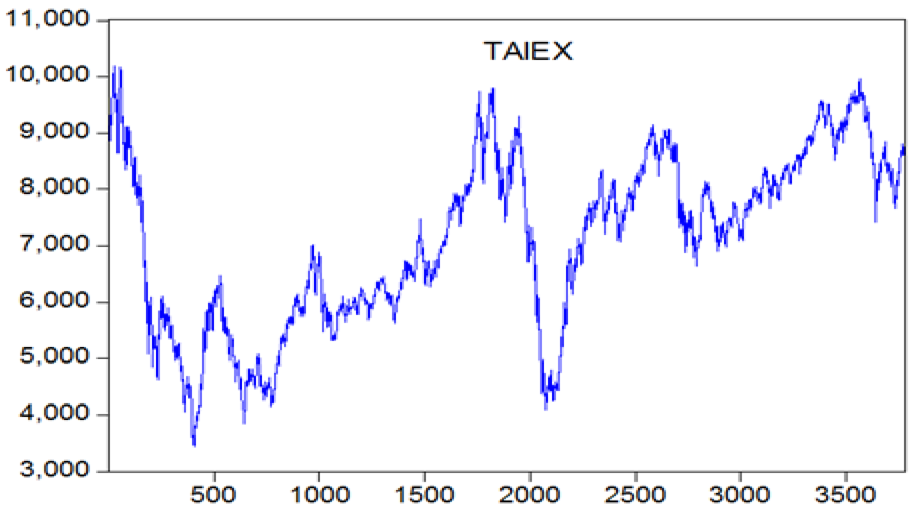

Figure-1. Trend of TAIEX

Source: Taiwan Economic Journal (TEJ) database

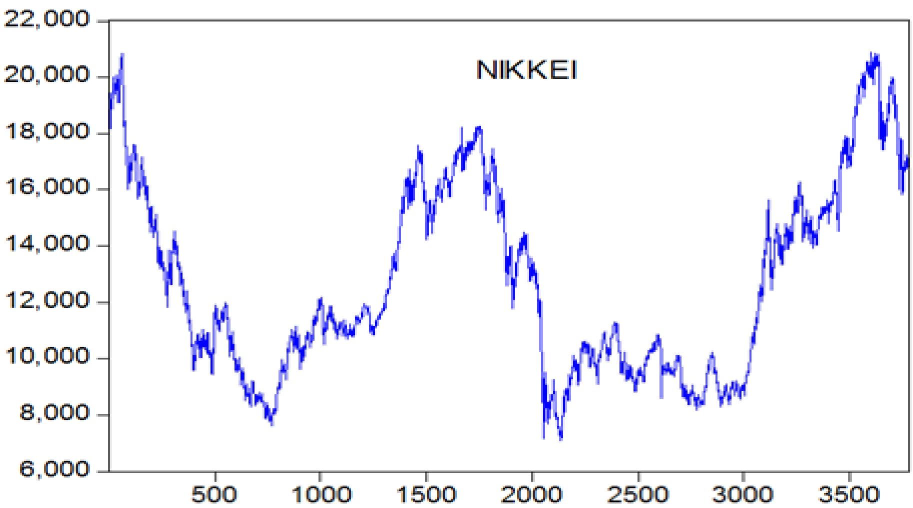

Figure-2. Trend of NIKKEI

Source: https://hk.finance.yahoo.com/q/hp?s=%5EN225&d=10&e=4&f=2016&g=d&a=0&b=4&c=1984&z=66&y=66

The results of the unit-root test are presented in Table 1. The *p* values of original series before differencing are both greater than 1% (the significant level).The null hypothesis of the presence of a unit-root is accepted, suggesting that the series are non-stationary, and hence not suitable for time series analysis. Additionally, first-order differential processing of the stock indices is necessary before further analysis.

The present study referred to the practice adopted by many securities market researchers, such as Bhar (2001) and applied first-order differential processing to the stock price indices, after taking the natural logarithm of each of the indices. After first-order differentiation, both series achieved *p* values of less than 1% (significant level), indicating that the series had reached a stationary state and were suitable for time series analysis (Table 1).

Table-1. ADF Test Results of Returns on TAIEX and NIKKEI

	TAIEX		**NIKKEI**	
	Before Differencing	**After Differencing**	**Before Differencing**	**After Differencing**
With Intercept and Trend	-3.49	-58.02*	-2.28	-62.85*
With Intercept and without Trend	-2.12	-58.02*	-2.05	-62.83*
Without Intercept or Trend	-0.45	-58.03*	-0.70	-62.84*

Remark: * indicates a significant level of less than 1%.

Given that each time series is the particular realization of a random process, it is necessary to observe the trend of the time series before analyzing them. The trends of the returns on TAIEX and NIKKEI are presented in Figures 3 and 4.

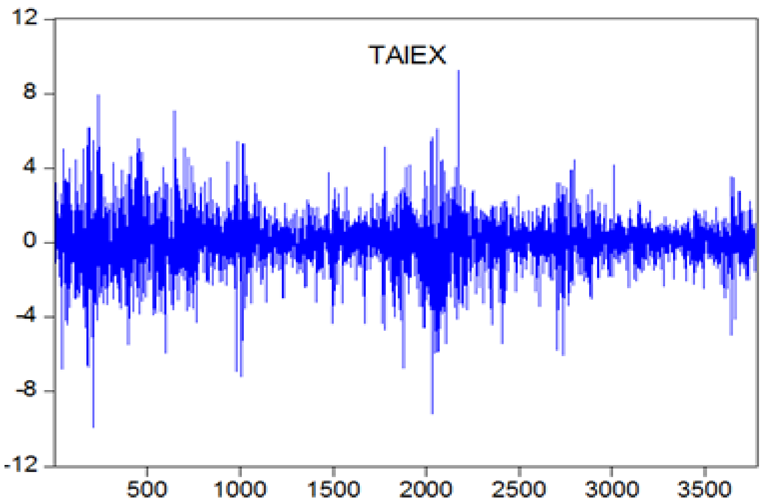

Figure-3. Returns on TAIEX

Source: Taiwan Economic Journal (TEJ) database

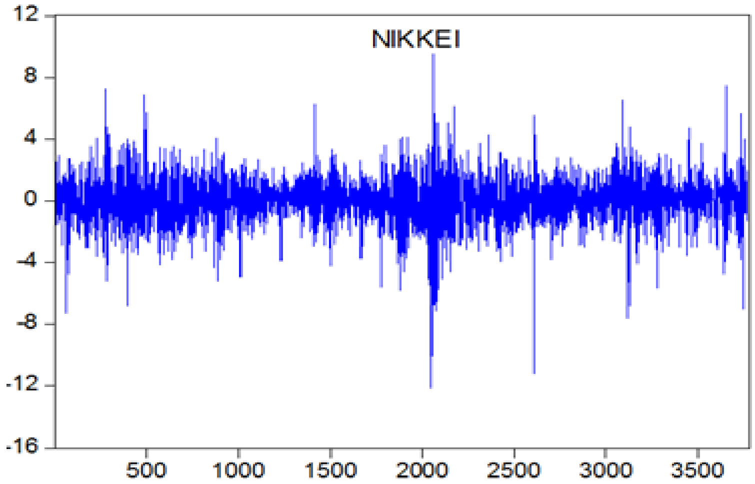

Figure-4. Returns on NIKKEI

Source:https://hk.finance.yahoo.com/q/hp?s=%5EN225&d=10&e=4&f=2016&g=d&a=0&b=4&c=1984&z=66&y=66

4.2. Cointegration Test Results

If the two series are of the same order, then there is a linear combination relationship, and if the linear relationship is *I* (1), then the two variance series are cointegrated. This cointegration relationship indicates a long-run equilibrium relationship between the two series (Engle and Granger, 1987). This study employed the maximum likelihood estimation procedure proposed by Johansen (1988) to test the existence of cointegrated relations between the two series. The results of the maximum eigenvalue statistics (Max-Eigen Statistic) and the sum of the diagonal elements (Trace Statistics) are exhibited in Table 2.

According to Table 2, the Trace Statistics of the two series at the 5% significant level are likelihood ratio (LR) (none) = 1490.804 > 29.79707 (the null hypothesis of no cointegration vector is rejected), LR (not more than 1) = 738.2564 > 15.49471 (the null hypothesis of at the most one cointegration vector is rejected), and LR (not more than 2) = 0.209096 < 3.841466 (the null hypothesis of at the most two cointegration vectors is not rejected), respectively. The above results suggest that at least two cointegration vectors exist between the two series.

The Max-Eigen Statistic of the two series at the 5% significance level are LR (none) = 752.5471 > 21.13162 (the null hypothesis of no cointegration vector is rejected), LR (not more than 1) = 738.0473 > 14.26460 (the null hypothesis of at the most one cointegration vector is rejected), and LR (not more than 2) = 0.209096 < 3.841466 (the null hypothesis of at the most two cointegration vectors is not rejected), respectively. The above results confirm that at least two cointegration vectors exist between the two series.

Both Trace Statistics and Max-Eigen Statistic have verified the existence of the cointegration vectors between the returns on stock indices of the two markets, indicating a long-run equilibrium relationship between the two stock markets.

Table-2. Cointegration Test of Returns on TAIEX and NIKKEI, Using Johansen's Approach

Panel -1. Trace Statistics

No.of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	Prob.
None	0.180867	1490.804	29.79707	0.0001
At the most 1*	0.177712	738.2564	15.49471	0.0001
At the most 2*	0.0005	0.209096	3.841466	0.6475

Panel-2. Maximum Eigenvalue (Max-Eigen Statistic)

No.of CE(s)	Eigenvalue	Max-Eigen Statistic	5% Critical Value	Prob.
None	0.180867	752.5471	21.13162	0.0001
At the most 1*	0.177712	738.0473	14.26460	0.0001
At the most 2*	0.00054	0.209096	3.841466	0.6475

Source: compiled by this study

4.3. Estimated Parameters of Bi-EGARCH Model

The study applied the BHHH method to estimate the parameters of the Bi-EGARCH model. The most significant feature of this method is that no restrictions are needed between the parameters. Table 3 Panel 1 shows the estimated parameters of equations (2) and (3), where error correction term is$\beta_{i,1}$ and i = 1,2 (1 = returns on TAIEX and 2 = returns on NIKKEI).

From an inner-market perspective, the estimated value of parameter $\beta_{1,1}$ is 0.03 (positive and reaches statistical significance), indicating a significant positive impact of the past returns of TAIEX on the current returns on TAIEX. The estimated value of parameter $\beta_{2,2}$ is 0.06 (positive and reaches statistical significance), suggesting that the past returns onNIKKEI has an apparent positive effect on the current returns onNIKKEI. From across-market perspective, the estimated value of parameter$\beta_{1,2}$ is 0.04 (positive and reaches statistical significance), indicating that the past returns onNIKKEI has a phenomenal influence over the current returns on TAIEX. The estimated value of parameter $\beta_{2,1}$is 0.03, and although it is a positive value, it did not reach statistical significance. This outcome suggests that the past returns onTAIEX have no obvious influence on the current returns onNIKKEI.

In summary, the returns on TAIEX and NIKKEI were found to be significantly affected by the past returns of indices of their own markets. While the past returns on NIKKEI were found to have a substantial impact on the current returns on TAIEX, noticeable influence of past returns on TAIEX on the current returns on NIKKEI was not revealed. These findings revealed the existence of a strong volatility clustering in major stock markets in Taiwan and Japan. Additionally, Taiwan's stock market is still shallow and vulnerable to the impact by the stock market in Japan.

Table-3. Parameter Estimation of the Returns on TAIEX and NIKKEI, Using BHHH Algorithm

Mean spillover parameters		TAIEX	NIKKEI
$\beta i1$		0.03* (2.04)	0.03 (1.58)
$\beta i2$		0.04* (2.70)	0.06* (-1.84)
Panel-2. Variance Equations for Volatility			
α_{i1}		0.11* (12.85)	-0.04* (-2.65)
α_{i2}		-0.04* (-9.08)	0.27* (10.84)
δ_i		-0.49* (-8.95)	-0.65* (-12.01)
Γ		0.98* (528.00)	0.90* (88.68)
HL = ln(0.5)/ln(γ_i)		46.44(days)	6.98 (days)
Relative asymmetry		2.98	4.86

Source: compiled by this study

Figures within () are the *t* value

*: P < 0.05

Table 3 Panel 2 exhibits the estimation results of the volatility variance equations. Parameter $\alpha_{1,1}$ represents the impact of the standardized residuals of the returns on TAIEX on the current conditional volatility of the Taiwanese stock market; estimated value is 0.11, with statistical significance. $\alpha_{2,2}$represents the standardized residuals of returns of NIKKEI on the current conditional volatility of the Japanese stock market; estimated value is 0.27, with statistical significance. The results suggest the existence of an inner-market leverage effect on the returns of indices in the two stock markets. The results also reveal that the past standardized residuals have a significant impact on the volatility of the current period.

The parameters$\alpha_{1,2}$ and$\alpha_{2,1}$ of the volatility equations reflect the cross-market spillover effect; the positive or negative standardized residuals of the previous period has an enhancing or reducing effect on conditional volatility. If $\alpha_{1,2}$ and$\delta_1$are negative values, then the influence of retreat of the returns on NIKKEI on the conditional volatility of the returns on TAIEX ($\alpha_{12}(-1+\delta_1)$) will be enhanced. However, if α12 is positive and $\delta_1$is negative, then the influence of advance of the returns of NIKKEI on the conditional volatility of the returns of TAIEX ($\alpha_{12}(-1+\delta_1)$) will be reduced. The result calculated based on a retreat market to be divided by an advancing market yields an asymmetric effect.

In the present study, $\alpha_{1,2}$ was -0.04 andδ_1 was -0.49 (both were negative values), indicating an enhanced impact of the returns onNIKKEI on the conditional volatility of the returns onTAIEX in context of a retreat market in Japan. Additionally, $\alpha_{2,1}$ was -0.04 andδ_2 -0.65, suggesting that the influence of falling returns of TAIEX will also enhance the conditional volatility of the returns of NIKKEI. These findings revealed negative cross-market spillover effects between the two stock markets; the two markets are vulnerable to the bad news from the counterpart market, which leads to a drop in stock indices. Moreover, this mutual influence is quite strong.

Both α_{ij} and δ_i have to be significant for the cross-market influence of volatility to have a price leading effect. According to Table 4-5 Panel 2,$\alpha_{1,2}$,δ_1, $\alpha_{2,1}$, andδ_2 are all significant, indicating a mutual price leading effect or a volatility feedback effect between the two markets.

The relative asymmetric effect is calculated based on $\frac{|-1+\delta_t|}{(1+\delta_t)}$. In the present study, the relative asymmetry values were 2.98 and 4.86, both greater than 1, suggesting that both markets are more affected by the declining than the rising trends of the counterpart market. Specifically, the two stock markets are likely to crash due to bad news from the counterpart market.

The value of γ is a necessary condition to determine whether volatility is moving towards stabilization. Table 4-5 showed that the values of γ of both markets are < 1, indicating that the volatility processes of both markets will stabilize in the long-run.

HL was used to measure the consistency of the volatility shock. The results showed that the influence of past volatility shock on the current volatility of TAIEX and NIKKEI was 46.44 and 6.98 days, respectively. This finding indicates that the impact of a shock in the stock markets of Taiwan and Japan tends to decline gradually after an average of 46.44 and 6.98 days, respectively. This may attribute to the fact that markup and markdown limits in Taiwan's stock market has increased from 7% to 10%, while that of the stock market in Japan vary by the tick size of stocks. Hence, the influence of past volatility shocks on the current volatility of Japan's stock market ends quickly. However, the response of the market to the shocks is relatively slow in Taiwan's stock market due to the markup and markdown limits.

5. CONCLUSION

This study mainly investigated the returns on TAIEX and NIKKEI, and the volatility spillover effect between the Taiwanese and Japanese stock markets. Through an empirical data examination based on the analysis of mean values, we explored inner and cross-market influence of the two markets. Subsequently, variance analysis was applied to explore the leverage and cross-market spillover effect within each market, asymmetric effects, price leading effect, and volatility shocks between the two markets.

The software Eviews was utilized to estimate the mean equation and the Regression Analysis of Time Series (RATS) software was utilized for the estimation of variance equation of the Bi-EGARCH model. The series test showed that both series were non-stationary before differencing. However, both the series presented stationary properties after first-order differential processing, a state suitable for time series analysis. Subsequently, the maximum likelihood estimation (MLE)procedure was adopted to test the existence of cointegrated relationships between variables. The results revealed that a cointegrated relationship existed between the two series, indicating a long-run equilibrium relationship between the two stock markets. Given that the two series were found to be cointegrated, the Bi-EGARCH model was utilized for further study by computing the interaction of mean values and then the interaction of variance. The results are described in the following sections.

5.1. Parameter Estimation of the Mean Equations

The returns on both TAIEX and NIKKEI were substantially influenced by their own returns of previous periods. Additionally, the past returns on NIKKEI were found to affect the current return of TAIEX significantly, while no obvious influence of the past returns of TAIEX on the current returns on NIKKEI was discovered.

5.2. Parameter Estimation of the Variance Equations

The returns of stock indices on both markets were found to have an inner-market leverage effect, as past standardized residuals had a significant impact on the volatility of the current period. There is a negative mutual volatility spillover effect between the two markets, indicating that both markets might undergo a drop in stock indices due to a bad news from the counterpart market, and this mutual influence is quite strong. The study also found a mutual price leading effect between the two markets. The relative asymmetry analysis showed that the two stock markets are more sensitive to falling rather than rising trends of the counterpart market, indicating that the two markets have a tendency to crash due to the retreat in the counterpart market. Moreover, the impact of previous volatility shocks on the current volatility of TAIEX and NIKKEI are 46.44 and 6.98 days, respectively.

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