"A study of dynamics in market volatility indices between US and Taiwan"

| AUTHORS | Yen-Hsien Lee
Jui-Cheng Hung
Yi-Hsien Wang
Chin-Yen Huang |

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Yen-Hsien Lee (Taiwan), Jui-Cheng Hung (Taiwan), Yi-Hsien Wang (Taiwan), Chin-Yen Huang (Taiwan)

A study of dynamics in market volatility indices between the US and Taiwan

Abstract

This study first investigates the long-run equilibrium by cointegration test and also explores the causality, asymmetry and jump intensity relationship by Correlated Bivariate Poisson Jump (hereafter CBPJ) model between the US and Taiwan volatility index (hereafter VIX and TVIX). The empirical results found the long-run equilibrium relationship between VIX and TVIX. The volatility persistence of the changes in VIX is greater than TVIX and the changes in VIX have the volatility asymmetry. The two volatility indices have the individual jump and the joint jump behavior, and then the change in the TVIX has highly jump risk.

Keywords: volatility index, causality test, CBPJ model.
JEL Classification: C21, G15.

Introduction

In recent years, the volatility index, which represents the investor's expectations with respect to price changes in the future as observed by Whaley (2000), has played an important role in financial markets and has been viewed as an indicator of investor sentiment; therefore, the volatility index is regarded as the investor fear gauge. As far back as 1993, the Chicago Board Options Exchange (CBOE) launched a volatility index which was published based on the S&P100 index, and then the CBOE in 2003 introduced a new volatility index (hereafter referred to as the VIX) which was based on options on the S&P500 index. In 2008, Futures Industry Association statistics revealed that TAIEX Options (TXO) amounted to 92,757,254 contracts thereby ranking the TXO as the 15th largest commodity contract market in the world. The Taiwan Futures Exchange (TAIFEX) also created the Taiwan volatility index (TVIX) that enabled investors to verify the accuracy and reliability of the information[1]. Whaley (2000) noted that investigating the issue of the volatility indices in different countries would become a major topic for research, and it is for this reason that this study examines the market volatility indices between the US and Taiwan.

Most existing studies focus on whether the US stock dominates the Taiwan stock market based on the Granger causality test and whether there exists a long-run relationship between the two markets based on the cointegration test. This would imply that this relationship is an important producer of information affecting their markets and that the international diversification between the two markets

is effective[2]. Various studies (Kwan et al., 1995; Cha and Cheung, 1998; Ding, 2010 and Baharumshah et al., 2003) have found that, in terms of the US stock market's impact on the Taiwan stock market, there is evidence of market integration between the US and Taiwan. However, other studies point out that the Taiwan stock market is not influenced by the US stock market (Cheung and Mak, 1992; Ghosh et al., 1999; Sheng and Tu, 2000) and there is a lack of cointegration between the two stock markets (Chan et al., 1992; Cheung and Mak, 1992; Dunis and Shannon, 2005; Jeyanthi and Pandian, 2008). Therefore, different opinions exist over the extent of the linkages between the US and Taiwan markets. On the other hand, we find few studies have suggested that the VIX will affect other countries' volatility indices[3], although it has been found that the VIX Granger causes the VXN (Badshah, 2009), and that the VDAX Granger causes both the VSMI and VSTOXX (Äijö, 2008). Based on the above findings, different conclusions are reached regarding the causality and long-run relationships between the US and Taiwan stock markets. According to the above discussions and the need to respond to the dearth of research on the volatility indices between the US and Taiwan, the purpose of the present study is to explore the causality and long-run relationship between the VIX and TVIX.

Wagner and Szimayer (2004), Dotsis et al. (2007), Becker et al. (2009) and Lin and Lee (2010) have confirmed that the jump behavior of the volatility index is an important indicator, thereby implying that the jump-diffusion model can measure the capacity of the volatility index. While most other studies have researched the impact of jump behavior on the volatility index using the univariate jump model, this article by contrast considers issues related to the

[1] Wong and Tu (2009) and Tzang et al. (2011) found that the VIX is superior to the VXO in Taiwan and that the Taiwan volatility index contains most of the information; hence, the new volatility index is more precise and reliable than the old volatility index.

[2] For example, Eun and Shim (1989), Cheung and Mak (1992), Cha and Cheung (1998), Liu et al. (1998), Sheng and Tu (2000) and Ding (2010).
[3] For example, Wagner and Szimayer (2004), Nikkinen and Sahlström (2004), Nikkinen et al. (2006), Äjiö (2008) and Badshah (2009).

jump activity between the VIX and TVIX. Many existing studies have indicated that the bi-variate jump model should be used to examine jump behavior in more than two markets, and Chan (2003) designed the Correlated Bivariate Poisson Jump (CBPJ) model to investigate both independent and joint jump behavior[1]. Lin and Lee (2010) investigated the S&P500 and changes in the VIX and found evidence of the jump-diffusion process and joint jump behavior. As far as the present writer is aware, there have been no studies on correlated jump behavior between volatility indices. The major advantage of this approach investigates jump behavior; moreover, the current research hopes to fill the existing gap in the literature. To the best of our knowledge, this study is the first to utilize the CBPJ model to explore the joint jump behavior between the VIX and TVIX and points out the advantages of such an approach for investors seeking to establish a jump dynamic strategy.

The remainder of this paper is organized as follows. In Section 1, we describe the data and discuss the CBPJ model. The empirical results are presented in Section 2. The final section concludes the paper.

1. Data and methodology

This paper adopts data from two sources. We obtain VIX and TVIX daily time series price data from the CBOE and TAIFEX. The TAIFEX originally adopted the approach of the CBOE, and it then launched the TVIX on December 18, 2006. The data used in this study cover the period from January 03, 2007 to September 30, 2010, providing a total of 896 observations.

This paper applies the CBPJ model by Chan (2003) to investigate the relationships between the VIX and TVIX. This model can adequately capture the diffusion and jump relationships between the changes in VIX ($r_{vix,t}$) and TVIX ($r_{tvix,t}$). The CBPJ model is described as follows:

$$r_{1,t} = \beta_{10} + \sum_{j=1}^{n} \alpha_j r_{1,t-j} + \sum_{j=1}^{m} \beta_j r_{2,t-j} +$$
$$+ \tau_1, Z_{t-1} + \varepsilon_{1,t} + J_{1,t}, \tag{1}$$

$$r_{2,t} = \beta_{20} + \sum_{j=1}^{n} c_j r_{2,t-j} + \sum_{j=1}^{m} d_j r_{1,t-j} +$$
$$+ \tau_2, Z_{t-1} + \varepsilon_{2,t} + J_{2,t}, \tag{2}$$

where $r_{1,t}$ ($r_{2,t}$) denotes the changes in the VIX (TVIX) at time t, given by $\ln(VI_t) - \ln(VI_{t-1})$, VI is the volatility index, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the error terms and $J_{1,t}$ and $J_{2,t}$ are the jump components for the

changes in the VIX and TVIX. Z_{t-1} is an error correction term. This paper applies the causality test of Granger (1969) to confer the causality between the VIX and TVIX. First of all, if $\beta \neq 0$ and $d_j = 0$ ($d_j \neq 0$ and $\beta = 0$), this means that the changes in the TVIX (VIX) will affect the changes in VIX (TVIX). Second, $\beta \neq 0$ and $d_j \neq 0$ refers to the feedback relationship between the changes in VIX and TVIX. Finally, if $\beta = 0$ and $d_j = 0$, this means that there is a non-causal relationship between the changes in VIX and TVIX.

The error term and the jump component are assumed to be independent, that is $E(\varepsilon_t, J_t) = 0$. The error term $\varepsilon_{1,t}$ ($\varepsilon_{2,t}$) has a bivariate normal distribution with zero mean and conditional covariance matrix $\tilde{H}_t$; besides, the jump component $J_{1,t}(J_{2,t})$ also has a bivariate normal distribution with zero mean and conditional covariance matrix Δt. In a bivariate framework, the jump component (J_t) is defined as:

$$J_t = \begin{bmatrix} \sum_{i=1}^{n_{1t}} Y_{1t,i} - E_{t-1}(\sum_{i=1}^{n_{1t}} Y_{1t,i}) \\ \sum_{i=1}^{n_{2t}} Y_{1t,i} - E_{t-1}(\sum_{i=1}^{n_{2t}} Y_{2t,i}) \end{bmatrix}, \tag{3}$$

where $\sum_{i=1}^{n_t} Y_{1t,i}(\sum_{i=1}^{n_t} Y_{2t,i})$ denotes the summation of n jumps or the jump intensity for $r_{1,t}(r_{2,t})$ over any period t. In addition, each stochastic variable Y_i follows a normal distribution with mean θ for its intercept term and variance δ^2; in other words, the bivariate jump intensities can be described as:

$$Y_{1t,i} \sim N(\theta_1, \delta_1^2) \text{ and } Y_{2t,i} \sim N(\theta_2, \delta_2^2). \tag{4}$$

In equation (3) the variables n_{1t} and n_{2t} both denote individual counting variables of jump intensity in that the two variables are constructed by the independent Poisson variables. Each one of these variables has a probability density function given by:

$$P(n_{it}^* = j | \Phi_{t-1}) = \frac{e^{-\lambda i_{\lambda_i^j}}}{j!}. \tag{5}$$

According to Chan (2003), the jump intensity parameter is the time-varying jump intensity, $i = 1, 2, 3$, and is defined as:

$$\lambda_{1,t} = \lambda_1^2 + \eta_1^2 r_{1,t-1}^2, \tag{6}$$

$$\lambda_{2,t} = \lambda_2^2 + \eta_2^2 r_{2,t-1}^2, \tag{7}$$

$$\lambda_{3,t} = \lambda_3^2 + \eta_3^2 r_{1,t-1}^2 + \eta_4^2 r_{2,t-1}^2, \tag{8}$$

where $r_{1,t-1}$ and $r_{2,t-1}$ denote the changes in the US's and Taiwan's VIX at time $t - 1$, respectively. The individual jump intensities $\lambda_{1,t}$ ($\lambda_{2,t}$) are assumed to

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[1] For example, Chan (2003), Chan and Young (2006), Chiu and Hung (2007), Lee and Cheng (2007), Chiu and Lee (2007), Cheng (2008) and Lin and Lee (2010).

be related to market conditions which are reflected in $r_{1,t-1}^2 (r_{2,t-1}^2)$ as an approximation of the last period's volatility. Similarly, the covariance $\lambda_{3,t}$ is governed by the variations in the last period's volatilities from both series.

By combining the GARCH model with the CBP function, the probability density functions both for $r_{1,t-1}$ and $r_{2,t-1}$ are defined by:

$$f(X_t | n_{1t} = i, n_{2t} = j, \Phi_{t-1}) =$$

$$= \frac{1}{2\pi^{N/2}} |H_{ij,t}|^{-1/2} \exp\left[- u'_{IJ,t} H_{ij,t}^{-1} u_{ij,t}\right], \qquad (9)$$

$$u_{ij,t} = \begin{bmatrix} r_{1,t} - E_{t-1}(r_{1,t}) - i\theta_1 + (\lambda_1 + \lambda_3)\theta_1 \\ r_{2,t} - E_{t-1}(r_{2,t}) - i\theta_2 + (\lambda_2 + \lambda_3)\theta_2 \end{bmatrix}, \qquad (10)$$

where X_t denotes $r_{1,t}$ and $r_{2,t}$, and $u_{ij,t}$ is the error term. $H_{ij,t}$ is the covariance matrix of $r_{1,t}$ and $r_{2,t}$. $H_{ij,t}$ is the summation of the covariance matrix for the normal disturbance $\tilde{H}_t$ component and the jump $\Delta ij,t$. The covariance matrix for the normal disturbance $\tilde{H}_t$ is defined as:

$$\tilde{H}_t = \begin{bmatrix} \sigma_{1,t}^2 & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{2,t}^2 \end{bmatrix}, \qquad (11)$$

where $\sigma_{1,t}^2 (r_{2,t}^2)$ and $\sigma_{12,t}$ are defined as:

$$\sigma_{1,t}^2 = \omega_1 + \varphi_1 \varepsilon_{1,t-1}^2 + \phi_1 \sigma_{1,t-1}^2 + \psi_1 \varepsilon_{1,t-1}^2 I_{1,t-1}, \qquad (12)$$

$$\sigma_{2,t}^2 = \omega_2 + \varphi_2 \varepsilon_{2,t-1}^2 + \phi_2 \sigma_{2,t-1}^2 + \psi_2 \varepsilon_{2,t-1}^2 I_{2,t-1}, \qquad (13)$$

where $\begin{cases} I_{1,t-1} = 1, \text{ if } \varepsilon_{1,t-1} > 0 \\ I_{1,t-1} = 0, \text{ if } \varepsilon_{1,t-1} \le 0 \end{cases}$ and

$$\begin{cases} I_{2,t-1} = 1, \text{ if } \varepsilon_{2,t-1} > 0 \\ I_{2,t-1} = 0, \text{ if } \varepsilon_{2,t-1} \le 0, \end{cases}$$

$$\sigma_{12,t} = \omega_{12} \sqrt{\sigma_{1,t}^2 \sigma_{2,t}^2}. \qquad (14)$$

Here $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the error terms of the changes in the VIX and TVIX. If the error terms are greater, imply actual fear volailtiy large than expected volaility so as this is bad news to the market. Conversely, if the the error terms are smaller, this is also good news to the market. ω_{12} denotes the diffusion correlation coefficient. Therefore, the covariance matrix for the jump component $\Delta_{ij,t}$ can be presented as:

$$\Delta_{ij,t} = \begin{bmatrix} i\delta_1^2 & \rho_{12}\sqrt{ij\delta_1\delta_2} \\ \rho_{12}\sqrt{ij\delta_1\delta_2} & i\delta_2^2 \end{bmatrix}, \qquad (15)$$

where the parameter ρ_{12} denotes the jump correlation coefficient of Y_{1t} and Y_{2t}. The covariance matrix of the CBP GARCH model is denoted by the summation of $\tilde{H}_t$ and $\Delta_{ij,t}$. Finally, the conditional density function is defined as:

$$P(X_t | \Phi_{t-1}) = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} f(X_t | n_{1t} = i, n_{2t} = j, \Phi_{t-1}). \qquad (16)$$

The log likelihood function is the sum of the log conditional densities:

$$\ln L = \sum_{t=1}^{N} \ln P(X_t | \Phi_{t-1}). \qquad (17)$$

The CBPJ model would reduce to a bivariate GARCH (BGARCH) model if one set $\theta_1 = \theta_2 = \delta_1 = \delta_2 = \rho_{12} = \lambda_1 = \lambda_2 = \lambda_3 = \eta_1 = \eta_2 = \eta_3 = \eta_4 = 0$.

2. Empirical results

Table 1 presents the basic statistics of the changes in the VIX and TVIX (Figure 1). The means (standard errors) of the changes in the VIX and TVIX are 0.0757 and 0.0106 (7.4756 and 5.6556). The investor fear gauge in the US market exhibits a larger variation than that in Taiwan, implying that the change in the VIX involves greater risk. In terms of skewness and kurtosis, the changes in the VIX and TVIX are significantly reflected by right skewed and leptokurtic distributions. Moreover, the Jarque-Bera test results are 658.1634 and 3281.003 for the changes in two indices and the null hypothesis of the normal distribution is rejected, implying that the changes in the VIX and TVIX are non-normally distributed. The Ljung-Box Q and Q^2 statistics for the changes in VIX and TVIX are significant at the 1% level, indicating that the changes in VIX and TVIX exhibit autocorrelation and linear dependence. We can see that the VIX and TVIX move together in Figure 1 and the changes in the VIX and TVIX are consistent with the steady-state phenomenon in Figure 2.

Table 1. Basic statistics of the changes in VIX and TVIX

Index	VIX	TVIX
Mean	0.07567	0.0106
Standard error	7.4756	5.6556
Skewness	0.6437**	0.6288 **
Kurtosis (excess)	6.9989**	12.2952 **
JB	658.1634**	3281.0030**
Q(25)	55.9560**	45.2030**
Q^2(25)	117.6000**	95.2320**

Notes: ** denotes significance at the 1% level. The Jarque-Bera statistic is used to determine whether the data come from a normal distribution. Q (25) and Q^2 (25) are Ljung-Box Q test statistics for serial correlation in the standardized residuals and in the squared standardized residuals.
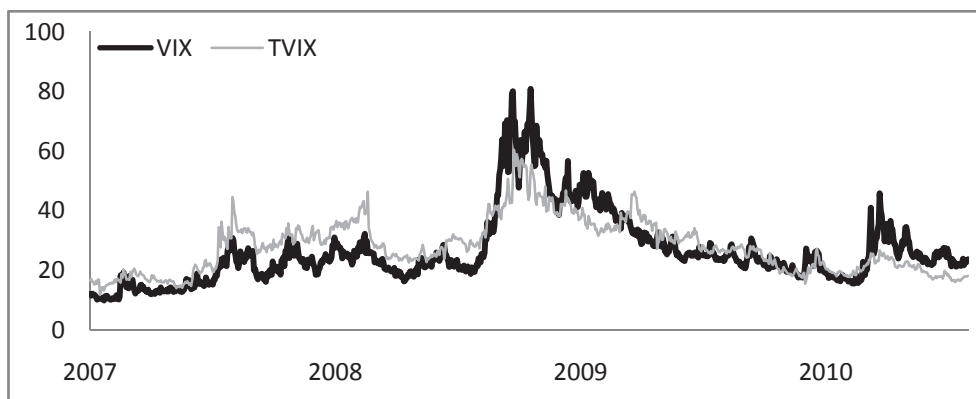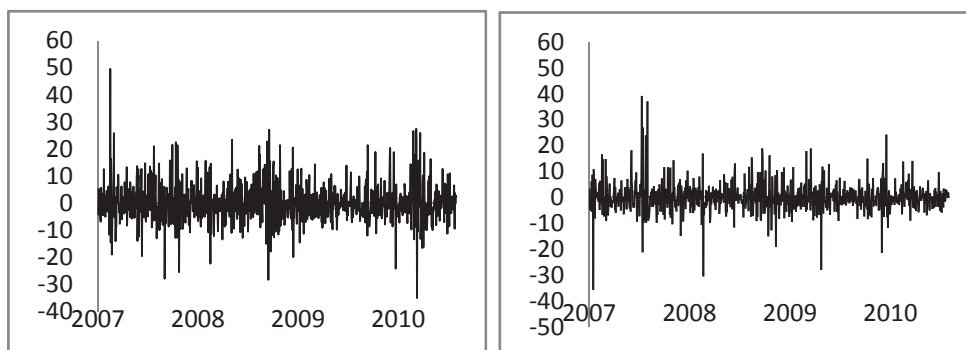
Fig. 1. VIX and TVIX

Fig. 2. The change in VIX (left) and TVIX (right)

This paper uses the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) methods of unit root tests to determine the series is stationary or not. In Table 2, ADF and PP tests are unable to reject the null hypothesis of unit root on the VIX and TVIX, and the KPSS test is significant rejected the null hypothesis of stationary at the 5% significance level. We find the VIX and TVIX are non-stationary; therefore, we take first differences on the series and then repeat the unit root tests. The ADF and PP tests of the changes in VIX and TVIX are significant rejected unit root at 1% level but

KPSS test is unable to reject the null hypothesis of stationary. From the above, the VIX and TVIX are $I(1)$ and stationary after first order difference. Hence, we further analyze long-run relationship between VIX and TVIX. The results of Johansen cointegration test are showed in Table 3. An empirical result of Trace and Max-Eigen statistics are 29.38476 and 23.67614 at the 5% level of significance. Hence, in the remainder of the paper we further analyze the long-run relationship between changes in the VIX and changes in the TVIX − τ_1 and τ_2 in equations (1) and (2) above.

Table 2. Unit root test of VIX and TVIX

Model		VIX				TVIX			
		Index level		First differences		Index level		First differences	
ADF	None	-0.7151	(4)	-16.8240**	(3)	-0.6127	(3)	-21.9004**	(2)
	Intercept	-2.2646	(4)	-18.5234**	(3)	-2.1827	(3)	-21.8882**	(2)
	Trend & intercept	-2.1767	(4)	-18.5275**	(3)	-2.2268	(3)	-21.9102**	(2)
PP	None	-0.8038	(20)	-36.3268**	(20)	0.6078	(37)	-35.2383**	(35)
	Intercept	-2.6004	(14)	-36.3113**	(20)	-2.5244	(26)	-35.2139**	(35)
	Trend & intercept	-2.5603	(13)	-36.3508**	(20)	-2.5316	(26)	-35.5745**	(36)
KPSS	Intercept	0.6914*	(23)	0.0771	(22)	0.6664*	(23)	0.1504	(38)
	Trend & intercept	0.4930**	(23)	0.0372	(22)	0.6565**	(23)	0.0333	(39)

Notes: * and ** denote significance at the 5% and 1% levels, respectively. Figures in parentheses denote the lag length.

Table 3. Cointegration test of VIX and TVIX

Null hypothesis	Trace statistic	5% critical value	Null hypothesis	Max-Eigen statistic	5% critical value
$r = 0$	29.3847**	25.8721	$r = 0$	23.6761**	19.3870
$r \leqq 1$	5.7086	12.5179	$r = 1$	5.7086	12.5179

Note: ** denotes significance at the 1% level.

Table 4 reports the results of a comparison between the BGARCH and CBPJ models. The Ljung-Box Q and Q^2 tests are not statistically significant in the BGARCH and CBPJ models, implying that standardized residual and square residual series do not exhibit serial correlation of linear intertemporal dependence. Therefore, the two models are good at measuring fitness capacity. Owing to the ability of the CBPJ model to analyze the jump relationship between the changes in the VIX and TVIX, we apply the LR test to compare the BGARCH and CBPJ models. The result of the LR test is significant, indicating that the CBPJ model is better than the BGARCH model. As a consequence, we further analyze the causality, asymmetry and jump intensity relationship between the changes in the VIX and TVIX using the CBPJ model.

Table 4. A comparison between the BGARCH and CBPJ models

Items	BGARCH		CBPJ	
	VIX	TVIX	VIX	TVIX
L-B Q(25)	24.127	34.376	20.641	36.442
L-B Q²(25)	17.715	30.720	14.996	31.072
Log likelihood	-5714.05		-5372.4572	
LR test	683.185**			

Notes: ** denotes significance at the 1% level. The LR test is the likelihood-ratio test.

Table 5 presents the estimated results for the CBPJ model. In Panel A of Table 5, α_1 and α_2 are -0.1444 and -0.0550 and are respectively significant at the 5% level, indicating that the lagged-one and lagged-two changes in the VIX have a negative influence on the current change in the VIX. The β_1 and β_2 are insignificant, indicating that the change in the current VIX is not affected by the lagged changes in the TVIX. d_1 is 0.18531 and is significant at the 1% level, also indicating that the change in the current TVIX is positively influenced by the lagged-one changes in the VIX. However, it is not affected by the lagged-one and lagged-two changes in the TVIX (c_2) or by the lagged-two change in the VIX (d_2). Hence, we further investigate the lead-lag relationship between the changes in the VIX and TVIX by performing the Granger causality test in the CBJ model. In Panel B of Table 5, the change in the TVIX has an insignificant impact on the change in the VIX; however, the change in the VIX has a significant impact on the change in the TVIX. This implies that the change in the VIX exerts an influence on the TVIX.

The coefficients τ_1 and τ_2 capture the speed of adjustment back towards the long-run equilibrium. We find that the parameters of τ_1 and τ_2 are significant at the 5% level, and that the signs of the coefficients are also both negative and positive, implying that there will be a tendency to move toward the equili-

brium in the long-run relationship[1]. Then, the estimated coefficient of the error correction term measures the speed of adjustment to restore equilibrium in the dynamic model. Through the error correction term, the changes in the VIX and TVIX will finally revert back to the equilibrium.

Table 5. Results for the models and the Granger causality test

Panel A. Estimation results for the BGARCH and CBPJ models				
Parameter	BGARCH model		CBPJ model	
	Coefficient	Standard error	Coefficient	Standard error
β_{10}	0.0686	0.2312	0.1977	0.1773
α_1	-0.1533**	0.0388	-0.1444**	0.0294
α_2	-0.0280	0.0413	-0.0550*	0.0280
β_1	-0.0619	0.0489	-0.0563	0.0405
β_2	0.0115	0.0456	0.0052	0.0359
τ_1	-1.3952	1.1576	-2.1875 *	0.8682
β_{20}	0.0088	0.1755	-0.0957	0.1345
c_1	-0.0996*	0.0446	-0.0342	0.0304
c_2	-0.0059	0.0417	-0.0163	0.0245
d_1	0.1853**	0.0257	0.1440 **	0.0237
d_2	0.0066	0.0258	0.0079	0.0201
τ_2	2.0104**	0.6703	1.2102 *	0.6005
ω_1	4.3318**	1.0658	1.0071 *	0.4552
ω_2	4.1436**	1.1012	6.6875 **	1.2636
φ_1	0.1547**	0.0401	0.0045	0.0112
φ_2	0.2826**	0.0702	0.0176	0.0152
Φ_1	0.8349**	0.0359	0.8568**	0.0269
Φ_2	0.6957**	0.0561	0.1340 *	0.0545
ψ_1	0.1616**	0.0449	0.0810 **	0.0234
ψ_2	0.2139**	0.0713	-0.0021	0.0106
ω_{12}	0.0271	0.0354	0.1087 *	0.0459
θ_1			5.5976 **	1.0133
θ_2			2.6972 *	1.1648
δ_1			7.8967 **	0.7764
δ_2			10.5574**	1.2297
ρ_{12}			-0.2535	0.2093
λ_1			-0.4395**	0.0535
λ_2			0.2183**	0.0615
λ_3			0.1968**	0.0535
η_1			0.0000	0.0124
η_2			0.0204	0.0107
η_3			-0.0000	0.0110
η_4			0.0167	0.0178
Panel B. Granger causality test				
TVIX ≥ VIX	0.8709		0.9900	
VIX ≥ TVIX	27.1869**		18.40933**	

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

As to the parameters of the conditional variance between the VIX and TVIX (ω_1, ω_2, ϕ_1, ϕ_2, and ψ_1), these are significant at the 1% or 5% levels. The

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[1] The estimated coefficient of the error correction term will be corrected by a negative τ_1 = -2.1875 and a positive τ_2 = 1.2102 when there is a positive departure from the equilibrium between the VIX and TVIX in the previous period, and vice versa.

volatility persistence of the changes in the VIX is $\varphi_1 + \phi_1 = 0.8613$ and in the TVIX is $\varphi_2 + \phi_2 = 0.1516$, clearly revealing that the volatility persistence of the changes in the VIX is greater than that of the changes in the TVIX. The volatility persistence of the changes in the VIX is close to 1, indicating the existence of a high volatility clustering phenomenon. On the contrary, the change in the TVIX exhibits a low volatility clustering phenomenon. Then, the correlation coefficient of volatility ($\omega_{12} = 0.1087$) shows that there is significant positive correlation at the 5% level. In the case of volatility asymmetry ($\psi_1 = 0.0810$; $\psi_2 = -0.0021$), only the negative information regarding the changes in the VIX (ψ_1) exhibits significant evidence of enhancement compared to the changes in current volatility. Therefore, the US volatility index exhibits asymmetry.

In terms of the jump parameters, both of the means of the jumps are $\theta_1 = 5.5976$ and $\theta_2 = 2.6972$, which are significant at the 1% and 5% levels, respectively. That is, when there is abnormal information, the changes in the VIX and TVIX exhibit jump behavior. As for the variances in the jumps, the parameters are $\delta_1 = 7.8967$ and $\delta_2 = 10.5574$ and are significant at the 1% level, implying that the variances of the jumps will obviously be enhanced when the jump behavior occurs. Moreover, the jump variance of the change in the TVIX is greater than that of the change in the VIX.

As to the jump intensity, $\lambda_1 = -0.4395$ and $\lambda_2 = 0.2183$ are significant at the 1% level, indicating that the changes in the VIX and TVIX exhibit the jump intensity. In the case of η_1 (η_2), the jump intensity of the change in the VIX (TVIX) is insignificant at the 5% level and, moreover, the square of the prior returns does not have an impact on the individual jump intensity in the VIX (TVIX) of the change. The joint jump intensity parameter $\lambda_3 = 0.1968$ is significant at the 1% level, indicating that the changes between the VIX and TVIX exhibit joint jump behavior. However, the parameters $\eta_3 + \eta_4$ are insignificant at the 5% level, revealing that the joint jump intensity ($\lambda_{3,t}$) is not affected by the changes in the VIX and TVIX of the squared prior returns. This finding indicates that there is no time-varying joint jump intensity as the relationship changes with time between the changes in the VIX and those in the TVIX.

Conclusions

This study investigates the long-run equilibrium between volatility indices. By comparing the BGARCH model with the CBPJ model by performing the LR test, the model is found to have a good fitness capacity. In addition, this study also explores the causality, asymmetry and jump intensity relationship using the Correlated Bivariate Poisson Jump model of Chan (2003) between the US and Taiwan volatility indices.

The empirical results show that the volatility persistence of the change in the VIX is greater than that of the TVIX, and the change in the VIX exhibits volatility asymmetry. Moreover, the correlation coefficient of the volatility between the VIX and the TVIX is found to be positive. The changes in the VIX and TVIX exhibit an individual jump relationship, whereas the changes in the TVIX exhibit high jump risk. Although the changes in the two countries exhibit joint jump behavior, the results shows that the jump behavior does not change over time. Finally, the changes in the TVIX are deeply affected by the past information on the changes in the VIX by the Granger causality test in the CBJ model. Therefore, the investor fear gauge for the US will affect the investor fear gauge for Taiwan.

The results of this study also indicate that the jump dynamics in market volatility indices are strong phenomenon. Clarification of the roles of the jump dynamics in market volatility indices is helpful in clarifying the risks and is helpful in improving investment performance.

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