International Research Journal of Applied Finance ISSN 2229 – 6891
Vol. VII Issue – 9 September, 2016 www.irjaf.com
DOI: 10.0709/article-3

The Bivariate Component GARCH Approach to Investigating the Relation between VIX and VIX Futures

Yen-Hsien Lee Jer-Shiou Chiou* Cheng-I Lee

Abstract

This study investigates the cointegration and lead-lag relationships between VIX and VIX futures from March 26, 2004 to September 30, 2011. This study applied the Bivariate Error Correction Component GARCH model (BEC-GARCH) to examine the permanent and transitory volatility between VIX and VIX futures. Moreover, we investigate the permanent and transitory effects on VIX and VIX futures in the panic events. The empirical evidence shows the long-run and bidirectional causal relationships between VIX and VIX futures. The BEC-GARCH model has better explanatory power model between VIX and VIX futures. Moreover, we find the innovation volatility can be up about to 20 periods on VIX and VIX futures and the effect of a past innovation on the conditional variance on VIX futures is large than VIX. Finally, the result suggests that permanent response effects for whom want to get normal returns, risk aversion or long-term investment, and the transitory response effects for whom want to speculation or arbitrage.

Keyword: VIX futures, Bivariate Error Correction Component GARCH model, Cointegration, Lead-lag relationship, Transitory and permanent volatility

I. Introduction

The VIX is implied volatility reverse thrust obtained from the S&P 500 stock index option premium price. The implied volatilities reaction investors expected in the future. VIX not only represents the majority views for the future index volatility, but also reveal the change of market expectations, VIX is known as investors fear gauge. Because investors cannot trade of VIX, CBOE has successively established the VIX derivatives. VIX futures have been offered since 2004. The value for the futures is based on the VIX index. The table 1 shows VIX futures average daily volume from 2004 to 2011. VIX futures average daily volume was about 17,470 and 47,780 contracts in 2010 and 2011, 280 percent over 2009 and 173 percent over 2010. Through average daily volume, we can know that the VIX futures is more and more importance.

Table 1: VIX Futures Average Daily Volume (contracts)

Year	2004	2005	2006	2007	2008	2009	2010	2011
Average daily volume	470	705	1906	4527	4591	4587	17471	47778

Note. The data is from the CBOE database.

Many existing empirical studies explored about lead-lag relationship in the past. Some literatures showed that futures markets had a lead effect to the spot markets. Example of FTSE100 (see e.g., ap Gwilym and Buckle, 2001; Brooks, Rew and Ritson, 2001), of Nikkei

225 (Lien, Tse and Zhang, 2003). Some literatures showed that spot and futures markets existed bi-directional causal relationship. Example of natural gas (Gebre-Mariam, 2011), of FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 (Kavussanos, Visvikis and Alexakis, 2008), of FTSE/ASE-20 (Athanasios, 2010), of VIX (Shu and Zhang, 2012), of FTSE100 (Tao and Green, 2012), SET50 (Songyoo, 2012), TWSE (Lai and Li, 2012), KOSPI 200 (see e.g., Min and Najand, 1999; Kang, Cheong and Yoon, 2013). Some of the previous literature explored the factors of lead-lag relationship between spot and futures markets, such as market liquidity (Fleming, Ostdiek and Whaley, 1996)[1]. According to market liquidity[2], S&P 500 index option have lower transaction fees than VIX futures, and average daily volume in S&P 500 index option significantly have more liquidity than VIX futures.[3] However, VIX calculated from S&P 500 option prices, there is a factor of VIX lead VIX futures. The futures price discovery is a reason of VIX futures lead VIX. Maybe the market liquidity and price discovery are the factors of bidirectional causal relationship between VIX and VIX futures. The existing studies reported about VIX and VIX derivatives[4], but seldom studies about the reason of the lead-lag relationship between VIX and VIX futures.

In the former literatures, the component GARCH (C-GARCH) model distinguishes the transitory and permanent volatility components in volatility dynamics, which has been widely used recently in finance. There were literatures showing that the C-GARCH model better than GARCH model, example in international equity markets (see e.g., Adrian and Rosenberg, 2008; Guo and Neely, 2008), of European options (Christoffersen, Jacobs, Ornthanalai and Wang, 2008), in U.S. output and the unemployment rate (Sinclair, 2009), in exchange rates (see e.g., Li, Ghoshray and Morley, 2012; Black and McMillan, 2004; Byrne and Philip Davis, 2005), in currencies (Pramor and Tamirisa, 2006). We also consider the basis between spot and futures, there may be exist error correction term. There are many previous studies adopted error correction model (ECM) (see e.g., Brooks et al., 2001; Lanza, Manera and Giovannini, 2005; Westgaard, Estenstad, Seim and Frydenberg, 2011). Consequently, maybe it exist cointegration relationship between VIX and VIX futures, when C-GARCH model is combined with ECM it creates EC-GARCH model. Finally, the univariate GARCH model in the volatility study had a foundation of success, the main advantage of bivariate GARCH (B-GARCH) model, which is more flexible to represent the

[1] The higher trading volume should lead the lower trading volume in investment objects.
[2] The market liquidity means keeping prices stable situation, the speed of the deal or the possibility of the market price of the transaction. There are four factors will affect market liquidity, which are the market mechanism, transaction costs, market participants' behavior and product design.
[3] S&P 500 trading volume are significantly greater than the VIX futures from 2004 to 2011. S&P 500 total trading volume and open interest of contracts from 2004 (3,666,246) to 2011 (10,915,797).
[4] (Lin and Chang, 2010) identify relationships between S&P 500, VIX and derivatives on VIX. Find that jumps in volatility and jumps in returns implicit in VIX option data. (Konstantinidi and Skiadopoulos, 2011) investigate whether VIX futures prices can be forecasted. Find the most liquid volatility futures market has been considered.

dynamics of conditional covariance. Previous literatures found that the overall functions of the bivariate or multivariate GARCH model indeed better than the univariate GARCH model. Example in spot and futures market (Baillie and Myers, 1991), in exchange rates (Klaassen, 1999), in the currencies (Tai, 2001), energy market volatility (Wang and Wu, 2012). While the C-GARCH model, ECM and B-GARCH model were successful models in existing literatures, respectively. Thus, we consider the transitory and permanent volatility with C-GARCH and the advantages of the BE-GARCH model, when BE-GARCH model is combined with C-GARCH model it creates BEC-GARCH model. In addition to, existing empirical studies were rarely discussing the transitory and permanent relationship between VIX and VIX futures. To our best knowledge, we are the first study of used the BEC-GARCH model to examine VIX and VIX futures.

Although VIX and VIX futures are widely explored in lead-lag relationship, VIX and VIX futures in transitory and permanent volatility components are seldom attention in empirical studies. This study bridges the gap in the literatures and investigates VIX and VIX futures in the different situations. There are four contributions in this study. First, we probe the Granger causality and Johansen cointegration test between VIX and VIX futures. There existing the causality and cointegration relationship between VIX and VIX futures. Second, we find the BEC-GARCH model provides more suitable model in VIX and VIX futures. Third, we compare the transitory and permanent volatility impact of an innovation volatility and sustained effect between VIX and VIX futures. The innovation volatility has relatively low and slow decay rate on VIX than VIX futures. The permanent impact expected value of VIX and VIX futures is 39.65 and 5.52, respectively. Fourth, we analyze transitory innovation volatility over total innovation volatility in VIX and VIX futures during the panic events period. The mean of transitory volatility of total volatility with VIX and VIX futures in the panic events is much two times higher than total estimate period. Obviously, the market panic is mainly from the transitory volatility rather than permanent volatility. The previous studies are rarely exploring the component analysis, but it is indispensable part to give component analysis to different investors. We also classify the mentality in the investment to offer to different investors. Permanent volatility is a basis indicator for investors, who want to get normal returns or risk aversion. Transitory volatility provides an indicator to investors, who want to obtain excess returns and profiteering.

The remainder of this study is organized as follows. The next section describes data and research methods, which includes the BE-GARCH and BEC-GARCH. Section III presents empirical results analysis and conclusions and suggestions in Section IV.

DOI: 10.0709/article-3

II. Data and Research methods

II.1 Data

The data set consists of daily data for VIX and VIX futures. All the data are collected from Datastream and cover the period from Mar 26, 2004 to Sep 30, 2011, which totals 1961 observations. There are 1961 daily data in our study. And $R_{i,t} = (lnP_{i,t} - lnP_{i,t-1}) \times 100$, where $R_{vix,t}$ and $R_{vixf,t}$ are the returns on the VIX and VIX futures. $P_{i,t}$ and $P_{i,t-1}$ are the VIX spot and futures at time t and time t-1.

II.2 BE-GARCH Model

We first discuss the bivariate, which has more explanatory variables than the univariate test. It could get more accurate forecasts than the univariate, and provide investors with more explanation. Conditional mean equation of BE-GARCH model can be represented as follows:

$$R_{s,t} = \mu_s + \sum_{i=1}^{m} \theta_{si} R_{s,t-i} + \sum_{j=1}^{n} \pi_{sj} R_{f,t-j} + \gamma_s Z_{t-1} + \varepsilon_{s,t} \tag{1}$$

$$R_{f,t} = \mu_f + \sum_{i=1}^{m} \theta_{fi} R_{f,t-i} + \sum_{j=1}^{n} \pi_{fj} R_{s,t-j} + \gamma_f Z_{t-1} + \varepsilon_{f,t} \tag{2}$$

where $R_{s,t}$ and $R_{f,t}$ are the VIX and VIX futures returns at time t. $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$ are the VIX and VIX futures error term at time t. Z_{t-1} is error correction term. Conditional variance and covariance equation can be represented as follows:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{3}$$

$$h_{sf,t} = \omega_{sf} \sqrt{h_{s,t} h_{f,t}} \tag{4}$$

where i=s and f in the equation (3), s and f are the VIX and VIX futures. $h_{s,t}$, $h_{f,t}$ and $h_{sf,t}$ are the VIX and VIX futures conditional variance and covariance. ω_{sf} is the correlation coefficient.

II.3 BEC-GARCH Model

Bivariate could get more accurate forecasts than the univariate, and provide investors with more explanation. Conditional mean equation of BEC-GARCH model can be represented as follows:

$$R_{s,t} = \mu_s + \sum_{i=1}^{m} \theta_{si} R_{s,t-i} + \sum_{j=1}^{n} \pi_{sj} R_{f,t-j} + \gamma_s Z_{t-1} + \varepsilon_{s,t}$$

$$R_{f,t} = \mu_f + \sum_{i=1}^{m} \theta_{fi} R_{f,t-i} + \sum_{j=1}^{n} \pi_{fj} R_{s,t-j} + \gamma_f Z_{t-1} + \varepsilon_{f,t}$$

Total volatility is sum of temporary Volatility and permanent volatility. Conditional variance and covariance equation can be represented as follows:

$$H_{i,t} = L_{i,t} + S_{i,t} \tag{5}$$

$$L_{i,t} = \omega_i + \rho_{1,i} L_{i,t-1} + \alpha_{1,i}(\varepsilon_{i,t-1}^2 - H_{i,t-1}) \tag{6}$$

$$S_{i,t} = \rho_{2,i} S_{i,t-1} + \alpha_{2,i}(\varepsilon_{i,t-1}^2 - H_{i,t-1}) \tag{7}$$

$$H_{sf,t} = \varpi_{sf} \sqrt{H_{s,t} H_{f,t}} \tag{8}$$

where i=s and f in the equation (5) to (7), s is the VIX and f is the VIX futures. Where $L_{i,t-1}$ is permanent volatility factor at time t-1. $\rho_{1,i}$ and $\rho_{2,i}$ are the estimated coefficients of the permanent and transitory effects to the market conditional variance, respectively. $\alpha_{1,i}$ and $\alpha_{2,i}$ are the unexpected message of pre-market impact on the conditional variance. ω_{sf} is the correlation coefficient.

There are two components contribute to the overall conditional variance at time t. One is capturing the permanent impact of an innovation; the other is capturing the transitory effect from a variance innovation. For each permanent and transitory react to recent innovation with the different rate of decay and innovation volatility. The equation represented as follows:

$$L_{i,t} = \sum_{k=1} \rho_{1,i}^{k-1} \omega_i + \rho_{1,i}^{k} L_{i,t-k} + \alpha_{1,i}(\eta_{i,t-1} + \rho_{1,i}\eta_{i,t-2} + \dots + \rho_{1,i}^{k-1}\eta_{i,t-k}) \tag{9}$$

$$S_{i,t} = \rho_{2,i}^{k} S_{i,t-k} + \alpha_{2,i}(\eta_{i,t-1} + \rho_{2,i}\eta_{i,t-2} + \dots + \rho_{2,i}^{k-1}\eta_{i,t-k}) \tag{10}$$

where $\eta_{i,t-1} = (\varepsilon_{i,t-1}^2 - h_{i,t-1})$ and assuming $0 < \rho_{1,i} < 1$ and $0 < \rho_{2,i} < 1$, then, the equation (11) and (12) can rewrite as:

$$L_{i,t} = \frac{\omega_i}{1-\rho_{1,i}} + \alpha_{1,i}(\eta_{i,t-1} + \rho_{1,i}\eta_{i,t-2} + \dots + \rho_{1,i}^{k-1}\eta_{i,t-k}) \tag{11}$$

$$S_{i,t} = \alpha_{2,i}(\eta_{i,t-1} + \rho_{2,i}\eta_{i,t-2} + \dots + \rho_{2,i}^{k-1}\eta_{i,t-k}) \tag{12}$$

Thus, the past innovation volatility on the conditional variance can be written as:

$$\frac{\partial h_{i,t}}{\partial \eta_{i,t-k}} = \alpha_{1,i}\rho_{1,i}^{k-1} + \alpha_{2,i}\rho_{2,i}^{k-1} \tag{13}$$

Moreover, the expected values of the transitory and permanent impact are as follows,

$$E(L_{i,t}) = \frac{\omega_i}{1-\rho_{1,i}}, \text{ and } E(S_{i,t}) = 0. \tag{14}$$

III. Empirical Results Analysis

The summary statistics of daily VIX and VIX futures are reported in Table 2. The means are positive for daily returns in the entire sample period. VIX standard deviations are greater than VIX futures of both daily levels and daily returns, represent that changes in the VIX futures is relatively more stable than VIX. According to skewness coefficient 0 and a kurtosis coefficient of 3, VIX and VIX futures are right-skewed distribution and leptokurtic distribution. VIX and VIX futures are pass 1% significance level in the Jarque-Bera normality test, obviously rejects the null hypothesis of normal distribution. Figure 1 and 2 shown the change of the VIX data is more dramatic than the VIX futures data.

Table 2: Descriptive Statistics

Items	Daily levels		Daily returns	
	VIX	VIX futures	VIX	VIX futures
Mean	21.01126	21.70465	0.046318	0.037226
Standard deviation	10.84586	9.274269	6.674115	3.558011
Maximum	80.86	66.23	49.60079	25.81866
Minimum	9.89	11.15	-35.0589	-19.9287
Skewness	2.064761	1.545625	0.737165	0.943748
Kurtosis	8.235438	5.67138	8.014333	8.064068
Jarque-Bera	3632.978***	1363.883***	2230.904***	2385.273***

Note. *** is significant at 1%.

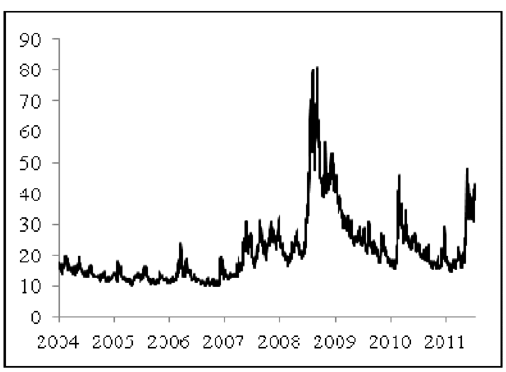

Figure 1：VIX daily chart

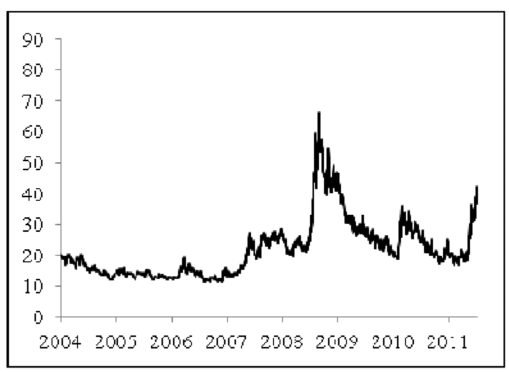

Figure 2：VIX futures daily chart

Table 3 shows the results of Augmented Dickey-Fuller (ADF) tests and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests of unit root tests for the stationary of VIX and VIX futures. These two types of ADF in level and KPSS in first order difference test

DOI: 10.0709/article-3

results are accept the null hypothesis at 1% levels of significance, represent that the investors can't forecast future prices from the past in the long period. Whereas ADF in first order difference and KPSS in level test are reject the null hypothesis of exist unit root at 1% levels of significance. The sequences after the first order difference are steady state of time series, I(0) time series, which can conduct the regression analysis.

Table 3: Unit Root Test

Items	ADF test				KPSS test			
	Level		1st		Level		1st	
	C	C&T	C	C&T	C	C&T	C	C&T
VIX	-1.975	-2.498	-21.481***	-21.483***	1.841***	0.415***	0.068	0.051
VIX futures	-1.817	-2.6	-43.284***	-43.285***	2.265***	0.460***	0.097	0.061

Note. 1. *** is significant at 1%.

2. C, C&T respective represent the Intercept and Trend model and the Intercept model.

Table 4 provides two types of Akaike info criterion (AIC) and Schwarz criterion (SC) model for Johansen cointegration test results between VIX and VIX futures. These two types' model test results of trace statistic and the max-eigenvalue statistic are higher than 1% critical value, respectively. The statistics results represent reject the null hypothesis $r=0$ at 1% levels of significance. There are exist long-term equilibrium relationship between VIX and VIX futures. However, the trace and max-eigenvalue statistic show that accept the null hypothesis of $r \leq 1$, respectively. Thus, VIX and VIX futures series have cointegration vectors. In other words, there is a long-term relationship between VIX and VIX futures.

Table 4: Johansen Cointegration Test

Lags	Null hypothesis	Trace	5%	1%	Max-Eigenvalue	5%	1%
AIC (4)	$(r=0)$	100.904***	25.32	30.45	91.038***	18.96	23.65
	$(r \leq 1)$	9.866	12.25	16.26	9.866	12.25	16.26
SC (4)	$(r=0)$	76.096***	12.53	16.31	76.046***	11.44	15.69
	$(r \leq 1)$	0.05	3.84	6.51	0.05	3.84	6.51

Note. 1. *** is significant at 1%.

2. Optimal lag behind through the VAR model, the selection of the lowest AIC and SC values.

We explore the VIX and VIX futures in BE-GARCH and BEC-GARCH model in table 5. Q(4) and $Q^2(4)$ are lag behind four periods for the Q and Q^2 statistic and P values were not significant, represent that the standardized residuals of VIX and VIX futures does not exist autocorrelation before four periods. ARCH(4) for VIX and VIX futures are not significant, show that the standardized residuals of VIX and VIX futures does not exist heteroskedasticity before four periods. Table 5 suggests that estimate the parameters and the

DOI: 10.0709/article-3

appropriate results in the BE-GARCH and BEC-GARCH model. The AIC of the BEC-GARCH model is 10.907, which is smallest one between AIC and SC in the both of BEC-GARCH and BE-GARCH model. Therefore, the BEC-GARCH model has more explanatory power than BE-GARCH model.

In the BEC-GARCH model, we found that transitory effects of VIX and VIX futures (ρ_2) were 0.919 and 0.722, permanent effects (ρ_1) were 0.553 and 0.859. Permanent effects of the volatility have greater mean-reverting than transitory effects of the volatility in VIX futures, but contrary in VIX. The VIX and VIX futures correlation coefficient are 0.769 and pass the 1% level of significance. In the BEC-GARCH model, an error correction term is passing the 1% level of significance. γ_s is -6.531 and γ_f is 2.816, it represents the VIX has quicker response than VIX futures. The S&P 500 index option significantly has more liquidity than VIX futures is the reason of different response rate. Moreover, the result expresses futures price is greater than the spot price for the long time. In the case of spread expanding, we propose to sell VIX futures and buy S&P 500 option to arbitrage for the investors.

Table 5: The estimated result of BE-GARCH with BEC-GARCH models

Models	BE-GARCH				BEC-GARCH			
	VIX		VIX futures		VIX		VIX futures	
Items	Coefficients	SD	Coefficients	SD	Coefficients	SD	Coefficients	SD
μ	-0.111***	0.143	-0.006***	0.086	-0.112***	0.085	-0.006***	0.044
γ	-6.521***	1.557	2.792***	0.830	-6.531***	1.010	2.816***	0.500
θ_1	-0.035***	0.037	0.045***	0.021	-0.032***	0.016	0.047***	0.008
θ_2	-0.038***	0.034	0.023***	0.021	-0.040***	0.014	0.021***	0.007
π_1	-0.091***	0.069	-0.085***	0.042	-0.093***	0.030	-0.088***	0.015
π_2	-0.062***	0.065	-0.082***	0.041	-0.057**	0.027	-0.078***	0.014
ω	5.623***	0.670	1.628***	0.257	17.724***	0.399	0.778***	0.012
α	0.858***	0.017	0.865***	0.021				
β	0.082***	0.009	0.051***	0.008				
ρ_1					0.553***	0.010	0.859***	0.013
ρ_2					0.919***	0.001	0.722***	0.038
α_1					0.001**	0.017	0.081***	0.007
α_2					0.016***	0.001	0.040***	0.006
ω_{sf}	0.769***	0.006			0.769***	0.003		

	BE-GARCH		BEC-GARCH	
Q(4) for VIX	1.674	0.643	1.714	0.634
$Q^2(4)$ for VIX	2.689	0.442	2.720	0.437
Q(4) for VIXF	4.962	0.175	4.866	0.182
$Q^2(4)$ for VIXF	2.178	0.536	2.243	0.524
ARCH(4) for VIX	2.640	0.620	2.670	0.614

DOI: 10.0709/article-3

ARCH(4) for VIXF	2.120	0.714	2.179	0.703
AIC	10.908		10.907	
SC	10.962		10.973	

Note. 1. AIC and SC are Akaike info criterion and Schwarz criterion.
2. ***, ** and * are significant at 1%, 5% and 10%.
3. Q(n) and $Q^2(n)$ are lag behind n period of the Ljung-Box test statistic.

The results of the causality tests report in Table 6. We find the causality relationship from VIX to VIX futures in BE-GARCH model at 10% significance level, but the bidirectional causal relationship between VIX and VIX futures in BEC-GARCH model at 1% significance level. The impacts of the VIX market on the VIX futures market being stronger than the impacts of the VIX futures market on the VIX market, indicating this finding is the consist with their result (Shu et al., 2012).

Table 6: The Granger Causality Test

Granger causality	BE-GARCH	BEC-GARCH
	F-statistic	F-statistic
VIXF impact on VIX	2.648	14.371***
VIX impact on VIXF	5.742*	46.321***

Note. *** and * are significant at 1% and 10%.

Figure 3 shows the past innovation volatility on the conditional variance in VIX and VIX futures in BEC-GARCH model. The innovation volatility can be up about to 30 periods on VIX and VIX futures. This conclusion in concert with the market expect of 30-day volatility in VIX.

The innovation volatility has relatively low and slow decay rate on VIX than VIX futures, which are gradually decreasing from about 0.2 to 0 and from near 0.14 to approaches 0, respectively. This evidence indicates that the new information could affect continue to 30 periods in the future. The permanent impact expected value[5] of VIX and VIX futures are 39.65 and 5.52, respectively. The permanent impact of VIX is higher than VIX futures, it represents the innovation volatility in VIX is more dramatic than the VIX futures.

[5] The expected values of the permanent impact is $E(L_{i,t}) = \omega_i / 1 - \rho_{1,i}$.

DOI: 10.0709/article-3

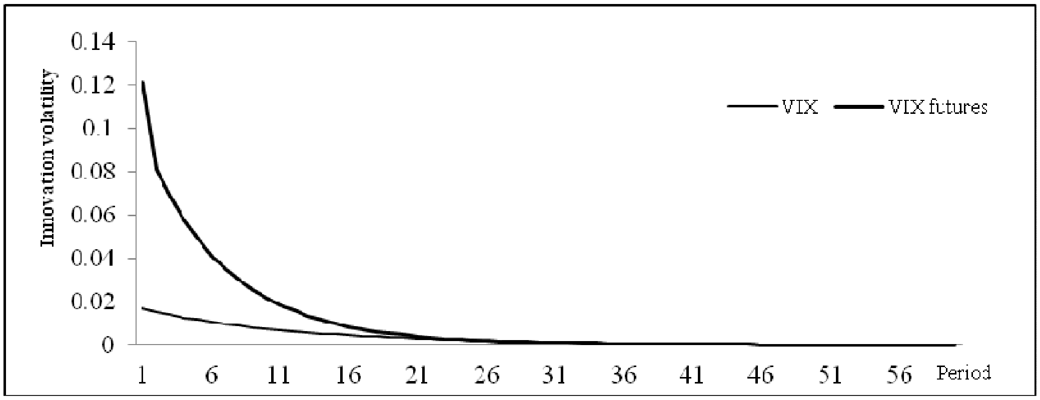

Figure 3：Impact on the conditional variance from the past innovation in BEC-GARCH model[6]

Figure 4 discusses transitory innovation volatility over total innovation volatility with VIX (S-S/H) and VIX futures (F-S/H).[7] Owing to VIX has more dramatic reaction than VIX futures, we find the VIX's proportion of transitory innovation volatility to permanent innovation volatility over than 50 percent and last 10 days or more in the panic events. Obviously, there are many periods accord testing. First is the beginning of subprime coupled with the bubble and overdraft in China, which cause heavy volume plummeted in Shanghai Stock Exchange and Shenzhen Stock Exchange on Feb 27, 2007. By the Chinese stock market crash, the U.S. and European markets also plunged. Second is U.S. hangs over of bankruptcy in the Lehman Brothers Holdings Inc. and the problems arising from the subprime mortgage crisis on Sep, 2008. In addition, The U.S. House of Representatives vetoes the proposed relief of the U.S. financial system. Third is Standard & Poor's credit rating agency downgrade the long-term sovereign credit rating of Greece to junk on Apr 27, 2010. U.S. and European financial markets have tumbled affected. Last is the Standard & Poor's downgrades U.S. long-term sovereign credit rating from AAA to AA+ with a negative outlook on Aug 5, 2011. The global stock markets tumbled in a few days.

Table 7 represents the mean of transitory volatility of total volatility with VIX is much higher than VIX futures in the mentioned events. There may be existing overreaction in VIX, which is obtained from the S&P 500 index option. Moreover, the mean of transitory volatility of total volatility with VIX and VIX futures in the panic events is much two times higher than total estimate period. Therefore, the panic events influence the S&P 500 index option is greater than the VIX futures. After exploring the past panics events between VIX and VIX

---

[6] The value of the past innovation volatility on the conditional variance is calculated from the equation of $\partial h_{i,t}^2 / \partial v_{i,t-k} = \alpha_1 \rho_1^{k-1} + \alpha_2 \rho_2^{k-1}$.

[7] In the sample periods, the transitory effects explain of the movements about 19% in VIX and about 7% in VIX futures.

DOI: 10.0709/article-3

futures. Obviously, the market panic is mainly from the transitory volatility rather than permanent volatility. Our results suggest the short-term investors to conduct for investment and arbitrage in S&P 500 options during the market panic. Moreover, the long-term investors have not concerned about the innovation impact, because the permanent volatility is relatively stabilized.

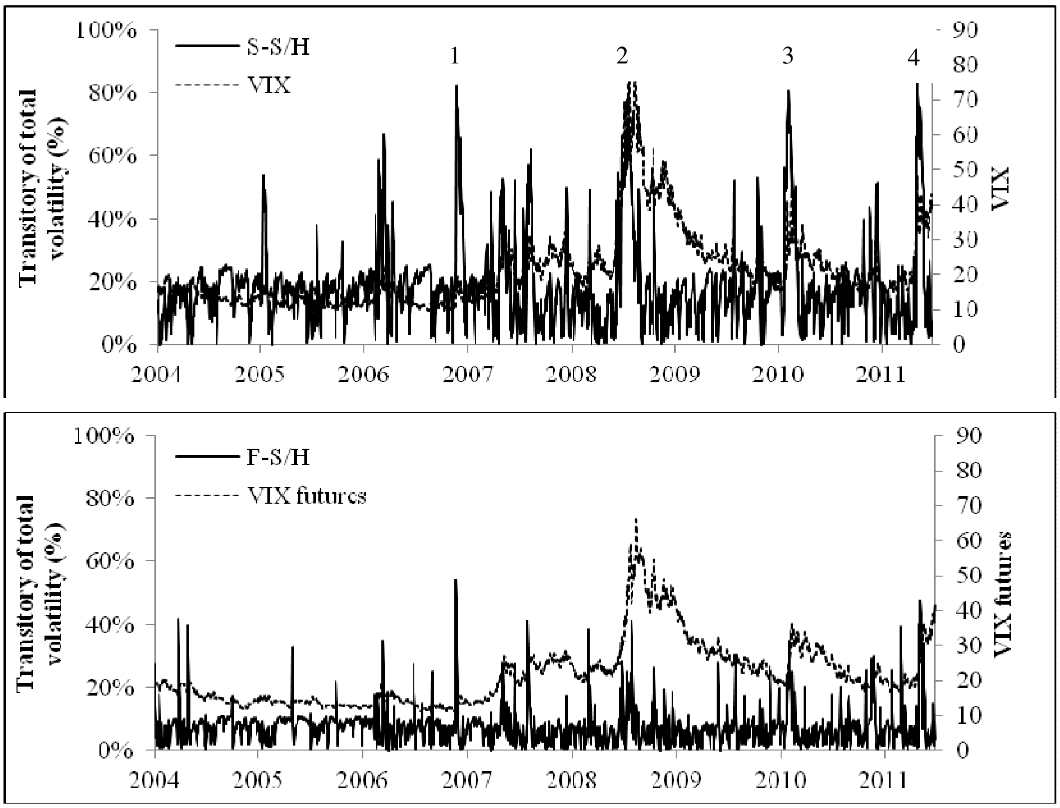

Figure 4：Compare transitory volatility of total volatility with VIX and VIX futures

Table 7: Component Analysis

Panic Events	Volatility Periods	The mean of S/H	
		VIX	VIX futures
Chinese stock market crash	Feb. 28, 2007 to Mar. 16, 2007	65%	19%
Subprime mortgage crisis	Sep. 30, 2008 to Oct. 31, 2008	60%	15%
Lowered credit rating of Greece	Apr. 28, 2010 to May 28, 2010	61%	19%
Lowered credit rating of U.S.	Aug. 5, 2011 to Aug. 26, 2011	69%	26%
Total	Mar. 26, 2004 to Sep. 30, 2011	19%	7%

Note. The mean of S/H is the mean of transitory innovation volatility over total innovation volatility.

IV. Conclusion

This study examines the Johansen cointegration, lead-lag relationships and Granger causality relationship between VIX and VIX futures from March 26, 2004 to September 30, 2011. This study applied the BEC-GARCH model to investigate the permanent and transitory volatility between VIX and VIX futures. Moreover, we further investigate the transitory and permanent volatility impact of an innovation volatility and sustained effect between VIX and VIX futures. Finally, we analyze transitory innovation volatility over total innovation volatility in VIX and VIX futures during the panic events period.

This study finds the change in the VIX futures is relatively stable. The VIX and VIX futures series have a long-term relationship between VIX and VIX futures. We discovered that the explanatory variables significantly increase the explanatory power in BEC-GARCH model. Therefore, BEC-GARCH model provides a more adequate description of VIX and VIX futures volatility than BE-GARCH model. In BEC-GARCH model, there is a bidirectional causal relationship between VIX and VIX futures. We offer transitory and permanent effects to help investors understand the volatility between VIX and VIX futures. The effect of a past innovation on the conditional variance on VIX futures is large than VIX. VIX mean volatility is much higher than VIX futures in the mentioned events. There may be existing overreaction in VIX, which is obtained from the S&P 500 index option. Finally, we suggest transitory response effects for investors, who want to speculation or arbitrage. The short-term investors can conduct for investment and arbitrage in S&P 500 options during the market panic. On the other hand, the permanent response effects for investors, who want to get normal returns, risk aversion or long-term investment. The long-term investors have not concerned about the innovation impact, because the permanent volatility is relatively stabilized.

References

Adrian, T., Rosenberg, J., 2008, "Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk", The Journal of Finance, vol. 63, no. 6, pp. 2997-3030.

ap Gwilym, O., Buckle, M., 2001, "The Lead-Lag Relationship between the FTSE100 Stock Index and Its Derivative Contracts", Applied Financial Economics, vol. 11, no. 4, pp. 385-393.

Athanasios, V., 2010, "Lead-Lag Relationship between Futures Market and Spot Market: Evidence from the Greek Stock and Derivative Market", International Research Journal of Finance and Economics, vol. no. 41, pp. 163-176.

Baillie, R. T., Myers, R. J., 1991, "Bivariate garch estimation of the optimal commodity futures Hedge", Journal of Applied Econometrics, vol. 6, no. 2, pp. 109-124.

Black, A. J., McMillan, D. G., 2004, "Long run trends and volatility spillovers in daily exchange rates", Applied Financial Economics, vol. 14, no. 12, pp. 895-907.

Brooks, C., Rew, A. G., Ritson, S., 2001, "A Trading Strategy Based on the Lead-Lag Relationship between the Spot Index and Futures Contract for the FTSE 100", International Journal of Forecasting, vol. 17, no. 1, pp. 31-44.

Byrne, J. P., Philip Davis, E., 2005, "The Impact of Short- and Long-run Exchange Rate Uncertainty on Investment: A Panel Study of Industrial Countries", Oxford Bulletin of Economics and Statistics, vol. 67, no. 3, pp. 307-329.

Chiang, S.-M., 2012, "The Relationships between Implied Volatility Indexes and Spot Indexes", Procedia - Social and Behavioral Sciences, vol. 57, no. 0, pp. 231-235.

Christoffersen, P., Jacobs, K., Ornthanalai, C., Wang, Y., 2008, "Option valuation with long-run and short-run volatility components", Journal of Financial Economics, vol. 90, no. 3, pp. 272-297.

Fleming, J., Ostdiek, B., Whaley, R. E., 1996, "Trading costs and the relative rates of price discovery in stock, futures, and option markets", Journal of Futures Markets, vol. 16, no. 4, pp. 353-387.

Gebre-Mariam, Y. K., 2011, "Testing for unit roots, causality, cointegration, and efficiency: The case of the northwest US natural gas market", Energy, vol. 36, no. 5, pp. 3489-3500.

Guo, H., Neely, C. J., 2008, "Investigating the intertemporal risk–return relation in international stock markets with the component GARCH model", Economics Letters, vol. 99, no. 2, pp. 371-374.

Kang, S. H., Cheong, C., Yoon, S.-M., "Intraday volatility spillovers between spot and futures indices: Evidence from the Korean stock market", Physica A: Statistical Mechanics and its Applications, vol. no. 0, pp.

Kavussanos, M. G., Visvikis, I. D., Alexakis, P. D., 2008, "The Lead-Lag Relationship between Cash and Stock Index Futures in a New Market", European Financial Management, vol. 14, no. 5, pp. 1007-1025.

Klaassen, F. J. G. M., Have Exchange Rates Become More Closely Tied? Evidence from a New Multivariate GARCH Model, in Discussion Paper, Editor^Editors. 1999, Tilburg University, Center for Economic Research. p.

Konstantinidi, E., Skiadopoulos, G., 2011, "Are VIX futures prices predictable? An empirical investigation", International Journal of Forecasting, vol. 27, no. 2, pp. 543-560.

Lai, L.-H., Li, S.-L., 2012, "A Trading Strategy Based on the Lead -- Lag Relationship between Futures and Spot Markets and Investor Sentiment", International Research Journal of Finance & Economics, vol. no. 96, pp. 63-79.

Lanza, A., Manera, M., Giovannini, M., 2005, "Modeling and forecasting cointegrated relationships among heavy oil and product prices", Energy Economics, vol. 27, no. 6, pp. 831-848.

Lien, D., Tse, Y. K., Zhang, X., 2003, "Structural Change and Lead-Lag Relationship between the Nikkei Spot Index and Futures Price: A Genetic Programming Approach", Quantitative Finance, vol. 3, no. 2, pp. 136-144.

Li, D., Ghoshray, A., Morley, B., 2012, "Measuring the risk premium in uncovered interest parity using the component GARCH-M model", International Review of Economics & Finance, vol. 24, no. 0, pp. 167-176.

Lin, Y.-N., Chang, C.-H., 2010, "Consistent modeling of S&P 500 and VIX derivatives", Journal of Economic Dynamics and Control, vol. 34, no. 11, pp. 2302-2319.

Min, J. H., Najand, M., 1999, "A Further Investigation of The Lead-Lag Relationship between the Spot Market and Stock Index Futures: Early evidence from Korea", Journal of Futures Markets, vol. 19, no. 2, pp. 217-232.

Pramor, M., Tamirisa, N. T., 2006, "Common Volatility Trends in the Central and Eastern European Currencies and the Euro", IMF Working Paper, vol. no. pp. 1-31.

Qiao, Z., Li, Y., Wong, W.-K., 2008, "Policy change and lead–lag relations among China's segmented stock markets", Journal of Multinational Financial Management, vol. 18, no. 3, pp. 276-289.

Sarwar, G., 2012, "Is VIX an investor fear gauge in BRIC equity markets?", Journal of Multinational Financial Management, vol. 22, no. 3, pp. 55-65.

Shu, J., Zhang, J. E., 2012, "Causality in the VIX futures market", Journal of Futures Markets, vol. 32, no. 1, pp. 24-46.

Sinclair, T. M., 2009, "The Relationships between Permanent and Transitory Movements in

DOI: 10.0709/article-3
U.S. Output and the Unemployment Rate", Journal of Money, Credit and Banking, vol. 41, no. 2-3, pp. 529-542.
Songyoo, K., 2012, "Optimal Positioning in Thailand's Spot and Future Market", Procedia - Social and Behavioral Sciences, vol. 40, no. 0, pp. 741-745.
Tai, C.-S., 2001, "A multivariate GARCH in mean approach to testing uncovered interest parity: evidence from Asia-Pacific foreign exchange markets", The Quarterly Review of Economics and Finance, vol. 41, no. 4, pp. 441-460.
Tao, J., Green, C. J., 2012, "Asymmetries, causality and correlation between FTSE100 spot and futures: A DCC-TGARCH-M analysis", International Review of Financial Analysis, vol. 24, no. 0, pp. 26-37.
Wang, Y., Wu, C., 2012, "Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models?", Energy Economics, vol. 34, no. 6, pp. 2167-2181.
Westgaard, S., Estenstad, M., Seim, M., Frydenberg, S., 2011, "Co-integration of ICE Gas oil and Crude oil futures", Energy Economics, vol. 33, no. 2, pp. 311-320.

Authors

Yen-Hsien Lee

Department of Finance, Chung Yuan Christian University, Taiwan, R.O.C. yh@cycu.edu.tw

Jer-Shiou Chiou*

Department of Finance and Banking, Shih-Chien University, Taiwan, R.O.C, jschiou@mail.usc.edu.tw

Cheng-I Lee

Department of Business Administration, Chung Yuan Christian University, Taiwan, R.O.C.

*corresponding author