

Contagion Effects and Volatility Impulse Responses between US and Asian Stock Markets*

Sang Hoon Kang^{**} · Hee-un Ko^{***} · Seong-Min Yoon^{****}

In this study, we investigated volatility transmission effects between the US and six Asian markets — China, Hong Kong, Japan, Korea, Singapore, and Taiwan — using a bivariate GARCH-BEKK model. We also assessed the impact of shocks on stock market volatility using the volatility impulse response function (VIRF). Our empirical findings extend several recent reports. First, the empirical results of this study show that the US and Asian stock markets are interrelated by their volatility. Second, we found that the 2008 global financial crisis intensified volatility transmission across the US and Asian stock markets. Third, we found that one large shock, the bankruptcy of Lehman Brothers, resulted in an increase in expected conditional volatilities in the post-bankruptcy era. Moreover, the magnitude and the persistence of the volatility impulse responses differed across Asian stock markets due to differing investor reactions to shocks in each market.

JEL Classification: C58, F36, F65, G15

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** Associate professor, Department of Business Administration, Pusan National University, Busan 609-735, Republic of Korea, E-mail: sanghoonkang@pusan.ac.kr

*** Ph.D. Candidate, Department of Business Administration, Pusan National University, Busan 609-735, Republic of Korea, E-mail: cloud3817@naver.com

**** Corresponding Author, Professor, Department of Economics, Pusan National University, Jangjeon2-dong, Geumjeong-gu, Busan 609-735, Republic of Korea, Tel: +82-51-510-2557, Fax: +82-51-581-3143, E-mail: smyoon@pusan.ac.kr

1. INTRODUCTION

“Volatility transmission” indicates that a large shock increases correlations not only in its own asset market but also in other asset markets, with reference to the “meteor shower” process of Engle *et al.* (1990). This effect can be intensified, particularly during financial crises, such as the global financial crisis (GFC) of 2008, further indicating that both stock volatility and correlations move consistently together over time. Thus, recent financial crises provide a unique opportunity for investigating dynamic relationships among global stock markets. Studies on the transmission of volatility shocks from one market to another are important in finance, and have many implications for international asset pricing, assessing investment and leverage decisions, and portfolio allocation, as well as for assisting policy makers in developing strategies to help insulate economies.

Many empirical studies have already analysed volatility transmission in stock markets during the recent financial crises (e.g., Dimitriou *et al.*, 2013; Gjika and Horváth, 2013; Kenourgios and Dimitriou, 2015; Kim *et al.*, 2015; Sensoy *et al.*, 2015). However, they do not explain how and to what extent the recent financial crises impacted the dynamic adjustment of volatility and the persistence of these transmission effects. That is, there are no confirmative findings about how a shock to one market influences the dynamic adjustment of volatility in another market, or the persistence of these transmission effects in specific market events.

Some studies have analysed the impact of volatility transmission across different markets using the volatility impulse response function (VIRF) of Hafner and Herwartz (2006). The VIRF approach allows quantification of the impact of large shocks on volatility by tracing the time pattern of the effects of independent shocks on volatility (Jin and An, 2016). Jin *et al.* (2012) investigated volatility transmission effects among three crude oil markets using a VAR-GARCH-BEKK model. They also analysed the size and persistence of the volatility connections with the VIRF method. They showed that the 2008 GFC had large and positive impacts on expected conditional variances in three crude

oil markets. Jin (2015) also explored the impact of volatility transmission in the Greater China stock markets using the VIRF method. This study showed that two financial crises — the 1997-1998 Asian financial crisis and the 2008 GFC — had large and positive impacts on expected conditional variances, but the size and dynamics of the impact were largely market-specific in the Greater China region.

In this study, we investigated contagion effects between the US and Asian stock markets via the extent of volatility transmission using the VIRF of Hafner and Herwartz (2006). In investigating the impact of recent financial crises on volatility transmission, we had two goals: (1) to investigate the volatility transmission mechanism, using a multivariate conditional variance model, within and across Asian and US stock markets, and (2) to apply the volatility impulse response function analysis to uncover the impact of historical innovations on conditional volatility using the transmission mechanism above and to quantify the risk on a future horizon.

This study considered the weekly closing Morgan Stanley Capital Index (MSCI) data of six Asian stock markets — China, Hong Kong, Japan, Korea, Singapore, and Taiwan — as well as the US stock market to examine volatility transmission and the impact of recent financial crises on volatility transmission across the US and Asian stock markets. Regarding the first goal, we estimate a bivariate GARCH-BEKK model and find evidence of volatility transmission between Asian and US stock markets. These empirical results have significant implications with regard to how volatility is transmitted among stock markets and, thus, how to detect the pattern of information flow and, to some extent, the relative strengths of the stock markets. For the second goal, we use the volatility impulse response function (VIRF) approach proposed by Hafner and Herwartz (2006) to investigate the spread and impact of a recent financial crisis — the 2008 GFC — to Asian stock markets and then establish the pattern of information transmission across these markets. Our analysis shows that during the global financial crisis, there were significant contagion effects from the US to the Asian stock markets. However, the degree of stock market response to such shocks differed from one market to another, depending on the level of

integration with the international economy in the Asian region.

The remainder of this study is organized as follows. Section 2 discusses the methodology used. Section 3 describes the preliminary data analysis. Section 4 reports the empirical results. Section 5 provides our concluding remarks.

2. ECONOMETRIC MODELING FRAMEWORK

2.1. The GARCH-BEKK Model

We analysed volatility spillover effects in stock markets using a bivariate GARCH framework of the BEKK parameterisation (Engle and Kroner, 1995) to model the behaviour of conditional variance-covariance matrix H_t :

$$r_{i,t} = \mu_{i,0} + \varepsilon_{i,t}, \quad i = 1, 2, \quad (1)$$

$$\varepsilon_t | \Omega_{t-1} \sim Student-t(0, H_t, \nu), \quad (2)$$

where $r_{i,t}$ is each stock returns i at time t , the 2×1 vector of random errors, ε_t , represents the innovation for each market at time t with its corresponding 2×2 conditional variance-covariance matrix H_t . The information set Ω_{t-1} represents the market information available at time $t-1$. ν denotes the degree of freedom for Student's t -distribution.

The conditional variance-covariance matrix H_t for a BEKK(1, 1) model can be written as:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + GH_{t-1}G', \quad (3)$$

$$\begin{aligned} \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} &= \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{21} \\ 0 & c_{22} \end{bmatrix} \\ &+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \end{aligned} \quad (4)$$

$$+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{21} \\ g_{12} & g_{22} \end{bmatrix},$$

where C is a 2×2 lower triangular matrix with three parameters, A is a 2×2 square matrix of parameters and measures the extent to which conditional variances are correlated past squared errors, and G is a 2×2 squared matrix of parameters and shows the extent to which current levels of conditional variances are related to past conditional variances. Engle and Kroner (1995) assumed that the BEKK model was second-order stationary if and only if all the eigenvalues of $(A \otimes A + G \otimes G)$ were less than unity in modulus. The model allowed us to measure the transmission channel of conditional variances in each stock market. It is also capable of capturing the effects of time-varying conditional correlations.

The conditional variance of the bivariate BEKK (1, 1) model can be expressed as:

$$h_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{12}^2 \varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{12} h_{12,t-1} + g_{12}^2 h_{22,t-1}, \quad (5)$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{21}^2 \varepsilon_{1,t-1}^2 + 2a_{21}a_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + g_{21}^2 h_{11,t-1} + 2g_{21}g_{22} h_{12,t-1} + g_{22}^2 h_{22,t-1}, \quad (6)$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{21} \varepsilon_{1,t-1}^2 + (a_{11}a_{22} + a_{12}a_{21}) \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{12}a_{22} \varepsilon_{2,t-1}^2 + g_{11}g_{21} h_{11,t-1} + (g_{11}g_{22} + g_{12}g_{21}) h_{12,t-1} + g_{12}g_{22} h_{22,t-1}, \quad (7)$$

where $h_{11,t}$ and $h_{22,t}$ denote the conditional variances for each stock market and $h_{12,t}$ denotes the conditional covariances between stock markets. The coefficients a_{12} , a_{21} , g_{12} , g_{21} of Eqs. (5)-(7) reveal how shock and volatility are transmitted over time and between two markets, such as shock spillover (a_{12} and a_{21}) and volatility spillover (g_{12} and g_{21}).

The parameters of the bivariate BEKK model can be estimated by the maximum likelihood of the probability density function of a bivariate Student's

t -distribution. The contribution of each observation at time t to the log-likelihood $l_t(\Theta)$ can be expressed as:

$$l_t(\Theta) = \log \left\{ \frac{\Gamma\left(\frac{\nu+2}{2}\right)^\nu}{(\nu\pi)\Gamma\left(\frac{\nu}{2}\right)(\nu-2)} \right\} - (1/2)\log|H_t| - (1/2)(\nu+2)\log\left\{1 + (\varepsilon_t H_t^{-1} \varepsilon_t) / (\nu-2)\right\}, \quad (8)$$

where $\Gamma(\cdot)$ is the gamma function and ν is the degree of freedom for Student's t -distribution. Θ is a parameter vector with all of the coefficients of the bivariate BEKK model.

2.2. Volatility Impulse Response Functions

To quantify the impacts of shocks on conditional variance, we used the volatility impulse response function (VIRF) of Hafner and Herwartz (2006), which allows tracking the effects of independent shocks on volatility through time. In the first step, we identified independent shocks in the VIRF methodology using a Jordan decomposition, which decomposes H_t such that identical and independent shocks can be retrieved from Eq. (3). The symmetric matrix of $H_t^{1/2}$ is decomposed as:

$$H_t^{1/2} = \Gamma_t \Lambda_t^{1/2} \Gamma_t', \quad (9)$$

where $\Lambda_t = \text{diag}(\lambda_{1t}, \lambda_{2t}, \dots, \lambda_{Nt})$ is the diagonal matrix the components of which, λ_{it} ($i=1, 2, \dots, N$), denote the eigenvalues of H_t . $\Gamma_t = (\gamma_{1t}, \gamma_{2t}, \dots, \gamma_{Nt})$ is a matrix $N \times N$ of the corresponding eigenvectors. Thus, the independent shocks are defined as $z_t = H_t^{-1/2} \varepsilon_t$. Hafner and Herwartz (2006) suggested that under the hypothesis of non-Gaussian distinction, z_t was uniquely defined, and may be treated as shocks from the past that could affect each of the markets in the future.

In the second step, we used the VIRF methodology described by Hafner and

Herwartz (2006), based on an alternative multivariate GARCH (1, 1) representation, specifically, the VEC model of Bollerslev *et al.* (1988), given by:

$$vech(H_t) = vech(C) + R_1 \times vech(\varepsilon_{t-1} \times \varepsilon'_{t-1}) + F_1 \times vech(H_{t-1}), \quad (10)$$

where $vech(\cdot)$ denotes the operator that stacks the lower fraction of a 2×2 matrix into an $N^* = N(N+1)/2$ dimensional vector. R_1 and F_1 are parameter matrices each containing $(N^*)^2$ parameters, whereas $vech(C)$ contains N^* coefficients.¹⁾

Hafner and Herwartz (2006) defined the VIRF as the expectation of volatility conditional on an initial shock and history, minus the baseline expectation that conditions on history alone, which is given by:

$$V_t(z_0) = E[vech(H_t) | z_0, \Omega_{t-1}] - E[vech(H_t) | \Omega_{t-1}], \quad (11)$$

in which z_0 is an initial specific shock hitting the system at time 0, Ω_{t-1} is the observed history up to time $(t-1)$, and $V_t(z_0)$ is the $N^* = N(N+1)/2$ vector of the impact of the identical and independent shock components of z_0 on the t -step ahead of conditional variance-covariance matrix components. For a BEKK (1, 1) model with the number of dimensions equal to 2, there will be three components in the $vech$ representation model of Eq. (10). Thus, the first and third elements of $V_t(z_0)$ ($v_{1,t}$ and $v_{2,t}$, respectively) represent the reaction of the conditional variance of the first and second variable, respectively, to the shock, z_0 , that occurred t periods ago.

Applied to a BEKK (1, 1) model and then the $vech$ representation, the one-step ahead VIRF is obtained as:

$$\begin{aligned} V_1(z_0) &= R_1 \times \left\{ vech(H_0^{1/2} z_0 z_0' H_0^{1/2}) - vech(H_0) \right\} \\ &= R_1 D_N^+ (H_0^{1/2} \otimes H_0^{1/2}) D_N vech(z_0 z_0' - I_N), \end{aligned} \quad (12)$$

¹⁾ It is assumed that the sum of the matrices R_1 and F_1 values is less than one, in which case the vector process ε_t is covariance stationary (Hafner and Herwartz, 2006, p. 724).

where H_0 is the conditional variance-covariance matrix at initial time 0, D_N is the duplication matrix defined by the property $vec(Z) = D_N vech(Z)$ for any symmetric $(N \times N)$ matrix Z , D_N^+ denotes the Moore-Penrose inverse of matrix Z , I_N is the identity matrix, \otimes is the Kronecker tensor product, and R is as specified in Eq. (10). For any $t \geq 2$, the VIRF is:

$$\begin{aligned} V_t(z_0) &= (R_1 + F_1)^{t-1} R D_N^+ (H_0^{1/2} \otimes H_0^{1/2}) D_N vech(z_0 z_0' - I_N) \\ &= (R + F) \times V_{t-1}(z_0). \end{aligned} \quad (13)$$

Le Pen and Sévi (2010) suggested three distinct characteristics of the VIRF, compared with the traditional impulse response function (IRF) in the conditional mean. First, the VIRF is a symmetric function of the shock: that is, $V_t(z_0) = V_t(-z_0)$, as opposed to an odd function of the initial shock in the IRF. Second, the VIRF is not a homogeneous function of any degree, in contrast to the traditional linear function of the IRF. Third, the VIRF depends on the history through the volatility state H_0 at the time when the initial chock occurs, whereas the IRF does not depend on the history of the process.

3. DATA AND SUMMARY STATISTICS

We considered the weekly Friday closing price index data for six Asian stock markets — China, Hong Kong, Japan, Korea, Singapore, and Taiwan — as well as for the US stock market.²⁾ The time period chosen for this study was from January 1, 2004, to May 5, 2016, covering recent times and extending sufficiently to account for regional and international economic events, allowing a better understanding of spillover effects between US and Asian stock

²⁾ Weekly data seemed to capture the dynamic interaction among stock prices better than daily and monthly data. The reason is that the use of daily data often induces potential biases arising from the non-synchronous trading days, and the effects of illiquidity on asset prices, while monthly data may miss some volatility transmission mechanisms due to time aggregation and compensation effects (Sadorsky, 2014; Batten *et al.*, 2015).

Table 1 Chow Breakpoint Test

Chow Breakpoint Test: 9/12/2008			
Null hypothesis: No breaks at specified breakpoints			
<i>F</i> -statistic	7.77	Prob. $F(7, 631)$	0.0000
Log likelihood ratio	53.30	Prob. $\chi^2(3)$	0.0000
Wald statistic	54.36	Prob. $\chi^2(3)$	0.0000

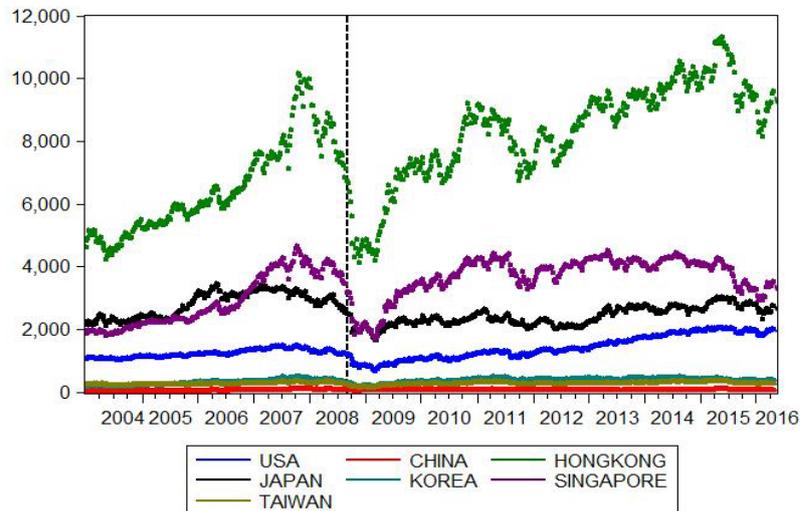
markets.³⁾

We use the Chow test (1960) to investigate the break point date as September 12, 2008, corresponding to the US Lehman Brothers collapse. Table 1 shows the results of Chow break point test. The Chow test statistics based on *F*-statistics reject the null hypothesis of no breaks, indicating that a break exists at this specific date. Thus, we determine the break point date as September 12, 2008.

Figure 1 illustrates the dynamics of the weekly US and Asian stock market indices over the study period. The vertical dotted line indicates the break date, September 12, 2008, corresponding to the Lehman Brothers collapse. The figure shows a significant decline in the US and in each Asian stock index since the bankruptcy of Lehman Brothers. This date was selected as the break point of the “global financial crisis” (GFC).

We calculate the continuously compounded weekly returns by taking the difference in the logarithms of two consecutive prices of a series: that is, $r_{i,t} = \ln(P_{i,t} / P_{i,t-1}) \times 100$, where $r_{i,t}$ denotes the continuously compounded percentage returns for index *i* at time *t* and $P_{i,t}$ denotes the price level of index *i* at time *t*. Descriptive statistics and the results of the statistical tests of the weekly returns for the US and the six Asian stock markets are presented in table 2.

³⁾ The data sets were extracted from the Morgan Stanley Capital Index (MSCI) database (www.msci.com). These indices are quoted in US dollars for conformity and to avoid effects of local inflation and national currency fluctuations on the indices, as indicated by Bekaert and Harvey (1995) and Dimitriou *et al.* (2013).

Figure 1 Price Dynamics of US and Six Asian Stock Market Indices**Table 2 Descriptive Statistics**

	US	China	Hong Kong	Japan	Korea	Singapore	Taiwan
Mean	0.097	0.111	0.108	0.031	0.123	0.088	0.024
Max.	11.52	17.94	9.823	7.876	28.63	18.51	9.609
Min.	-20.11	-22.12	-17.14	-16.40	-27.63	-19.80	-12.25
Std. dev.	2.425	3.817	2.834	2.572	4.068	2.995	3.111
Skewness	-0.982	-0.313	-0.371	-0.645	-0.475	-0.436	-0.627
Kurtosis	12.48	6.201	5.899	6.073	11.54	11.04	4.296
Jarque-Bera	2522.***	285.9***	240.7***	298.7***	1984.***	1755.***	94.73***
$Q^2(20)$	276.2***	201.5***	345.2***	48.88***	444.1***	246.9***	321.1***
ADF	-26.92***	-25.89***	-25.11***	-26.52***	-26.16***	-15.59***	-26.61***
PP	-26.94***	-25.89***	-25.19***	-26.54***	-26.16***	-25.03***	-26.73***
KPSS	0.113	0.144	0.062	0.077	0.128	0.159	0.035
ARCH(10)	15.04***	7.313***	16.60***	4.057***	29.10***	15.21***	14.10***

Notes: $Q^2(20)$ refers to the Ljung-Box test for the autocorrelation of squared residuals. This test is distributed as $\chi^2(10)$. ADF and PP are the empirical statistics of the augmented Dickey-Fuller (1979), and Phillips-Perron (1988) unit root tests which test the null hypothesis that the variable is non-stationary, $I(1)$, against the alternative that the variable is stationary $I(0)$. KPSS is the Kwiatkowski *et al.* (1992) stationarity test, which tests the null hypothesis is that the variable $I(0)$, against the alternative that the variable is $I(1)$. The ARCH(10) test of Engle (1982) is to check for the presence of ARCH effects based on the F -statistics. *** denotes rejection of the null hypotheses of normality, no autocorrelation, unit root, non-stationarity, and conditional homoscedasticity at the 1% significance level.

These results show that the Korean index had the highest average returns and standard deviation, indicating that investment in the Korean stock market may provide higher returns, but more risk, than in the other Asian markets. Conversely, the US market is found to have the lowest volatility. The skewness and kurtosis results, along with the Jarque-Bera test for normality, indicate that the weekly returns for both the Asian and the US markets are asymmetric, fat-tailed, and high-peaked versus a Gaussian distribution, implying the presence of extreme movements in either direction, thus supporting the use of the Student's t -distribution in the estimation process.⁴⁾ These results are consistent with the GARCH effects. According to the ARCH effects of Engle (1982), we reject the null hypothesis of no ARCH effect, based on F -statistics. As shown in table 2, the results of the Ljung-Box test statistic, $Q^2(20)$, also reject the null hypothesis of no serial correlation in the squared residuals. Moreover, the results of three types of unit root test: the standard parametric augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The values resulting from the ADF and PP tests are large and negative, rejecting the null hypothesis of a unit root; the KPSS test statistic did not reject the null hypothesis of stationarity at the 1% level of significance. Thus, all of the return series are stationary processes.

4. EMPIRICAL RESULTS AND IMPLICATIONS

4.1. Estimation Results with the Bivariate BEKK Model

We proceed, under a Student's t -distribution, with estimation of the bivariate GARCH-BEKK (1, 1) model between the US and six Asian stock markets. Use of the Student's t -distribution is more appropriate to fit the residuals, which were fat-tailed. The estimated coefficients of the conditional variances

⁴⁾ To capture the return distribution with higher peak and fatter characteristics, Hafner and Herwartz (2006) assumed a Student's t -distribution in multivariate GARCH models. Many subsequent studies have the same assumption of return process (Le Pen and Sévi, 2010; Jin, 2015; Jin *et al.*, 2016).

Table 3 Estimation Results for the BEKK Model with Student's t -Distribution

	US-China	US-Hong Kong	US-Japan	US-Korea	US-Singapore	US-Taiwan
c_{11}	0.3511*** (2.8968)	0.3154*** (3.4928)	0.0760 (0.6063)	0.4014*** (3.2267)	-0.0231 (-0.1076)	0.4792*** (3.6358)
c_{21}	0.5151** (2.0215)	0.5145*** (5.4676)	1.5054*** (20.555)	-0.8724 (-1.5378)	0.6786 (1.2090)	0.6619*** (6.1860)
c_{22}	0.4827*** (2.9415)	-0.0000 (-0.0000)	-0.000002 (0.0000)	1.6678*** (3.5874)	0.0637 (1.1731)	0.0000 (0.0000)
a_{11}	0.2371*** (3.6989)	0.2966*** (4.9269)	0.2746*** (5.5435)	0.1378*** (2.5566)	0.3084*** (3.4887)	0.4884*** (7.5839)
a_{12}	0.0343 (0.3720)	0.3951*** (6.9929)	-0.0859 (-0.9959)	-0.0502 (-0.4614)	0.3403*** (4.4954)	0.4580*** (6.0985)
a_{21}	0.0446 (1.2087)	-0.3369*** (-6.5039)	0.0580 (1.2842)	0.2467*** (5.5941)	0.1633** (2.4780)	-0.1585*** (-4.0025)
a_{22}	0.2840** (4.6942)	0.2237*** (4.3521)	0.3750*** (4.8641)	0.5861*** (6.8231)	0.3782*** (4.9181)	0.2738*** (6.2086)
g_{11}	0.9636*** (34.661)	0.9829*** (63.006)	0.9746*** (61.862)	0.8558*** (15.503)	0.6490*** (27.268)	0.9283*** (29.191)
g_{12}	0.0032 (0.0831)	0.0178 (0.8990)	0.1777 (1.8743)	0.3093 (1.0229)	0.3195*** (6.0397)	0.0023 (0.0742)
g_{21}	-0.0231 (-1.2762)	-0.0503*** (-4.2991)	-0.2302*** (-3.9889)	0.1995*** (3.8218)	-0.2541*** (-8.7320)	-0.0701*** (-5.5197)
g_{22}	0.9342*** (34.858)	0.9353*** (64.503)	-0.0033 (-0.0089)	0.5420*** (3.7955)	0.7261*** (26.213)	0.9280*** (58.364)
$d.f.$	8.8146*** (5.1787)	8.1233*** (5.3257)	5.0684*** (7.7615)	7.7832*** (5.4133)	6.3798*** (6.7618)	10.278*** (4.4745)
ρ_i	0.9835 0.9709 0.9457 0.8836	0.9524 0.9306 0.6681 0.4352	0.9579 0.9457 0.1309 0.1309	0.9166 0.6394 0.5237 0.3802	0.9638 0.8021 0.7627 0.7432	0.9754 0.8499 0.8321 0.8052

Notes: The t -statistics are in parentheses. The ρ_i values are the eigenvalues of the matrix $A \otimes A + G \otimes G$. $d.f.$ are the estimated degrees of freedom of the Student's t -distribution. *** and ** indicate significance at the 1% and 5% levels, respectively.

and covariances, with associated t -statistics in parentheses, the estimated degrees of freedom from the t -distribution, and the eigenvalues of the model are presented in table 3.

As shown in table 3, the diagonal elements in matrix A capture the own past shock effect, while the diagonal elements in matrix G measured the own past volatility effect. The estimated diagonal parameters were all significant,

indicating the presence of ARCH and GARCH effects.⁵⁾

Next, we turn to the off-diagonal elements of matrices A and G , which captured cross-market effects between US and Asian stock markets. Except for the US-China pair-wise comparison, some off-diagonal coefficients are statistically significant, indicating that volatility spill overs are transmitted through the cross product of innovations (a_{12}, a_{21}) as well as the squared innovations (g_{12}, g_{21}) . For example, we find bi-directional volatility spill over between the US and Singapore stock markets because of the significance of all off-diagonal coefficients $(a_{12}, a_{21}, g_{12}, g_{21})$. However, Hong Kong, Japan, Korea, and Taiwan show unidirectional volatility spill over from the US, indicated by the insignificance of the coefficients a_{12} and g_{12} . More specifically, the volatility shock of the US seems to spill over Korea positively, whereas the US volatility has a negatively impact on the volatiles of other countries including Japan. This finding suggests that the shocks of US volatility increase the volatility of Korean stock market, while the volatilities of other markets become smaller by the volatility transmission of US.

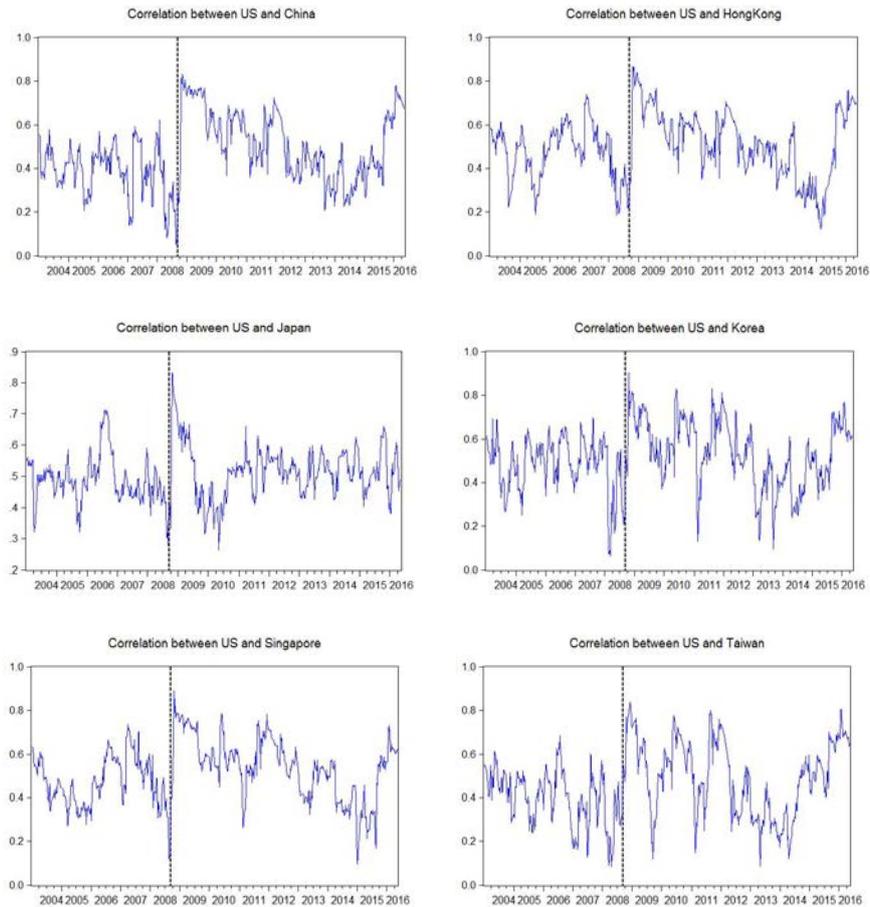
In contrast to the other countries, there is no volatility spillover effect between the US and China, pair-wise, indicated by the insignificance of all off-diagonal coefficients $(a_{12}, a_{21}, g_{12}, g_{21})$. In fact, China is relatively less liberalized than other markets and less co move with the US market. So the Chinese stock market is an alternative portfolio investment with other markets. These findings indicate that conditional variances are transmitted with differing degrees of volatility spill overs, consistent with the “meteor shower” process of Engle *et al.* (1990).

The estimated degrees of freedom coefficients (*d.f.*) are all significant at the 1% level, indicating that the Student’s *t*-distribution fitted the estimated residuals well.⁶⁾ We also report ρ_i , the eigenvalues of the estimate of

⁵⁾ Note that the variable $i = 1$ represents the US market while the variable $i = 2$ is one of six Asian stock markets.

⁶⁾ Note that a Student’s *t*-distribution tends to normality when its degree of freedom (*d.f.*) increases or equals to 30. The value of *d.f.* closes to 2 indicates a very leptokurtic distribution for the residuals (Le Pen and Sévi, 2010, p. 763). The value of *d.f.* in this study is more than 2 but less than 30, so that the assumption of Student’s *t*-distribution captures

Figure 2 Conditional Correlations between the US and Asian Stock Markets



$(A \otimes A + G \otimes G)$. The largest eigenvalues were less than one, but close to it, suggesting that covariances were stationary but with a high level of persistence in volatility transmission across the US and Asian stock markets.

Figure 2 shows the estimated conditional correlation dynamics obtained from the BEKK model with a Student's t -distribution. All correlations show sudden spikes on the date of the Lehman Brothers bankruptcy, indicating that

higher peak and fatter tail characteristics in the residuals.

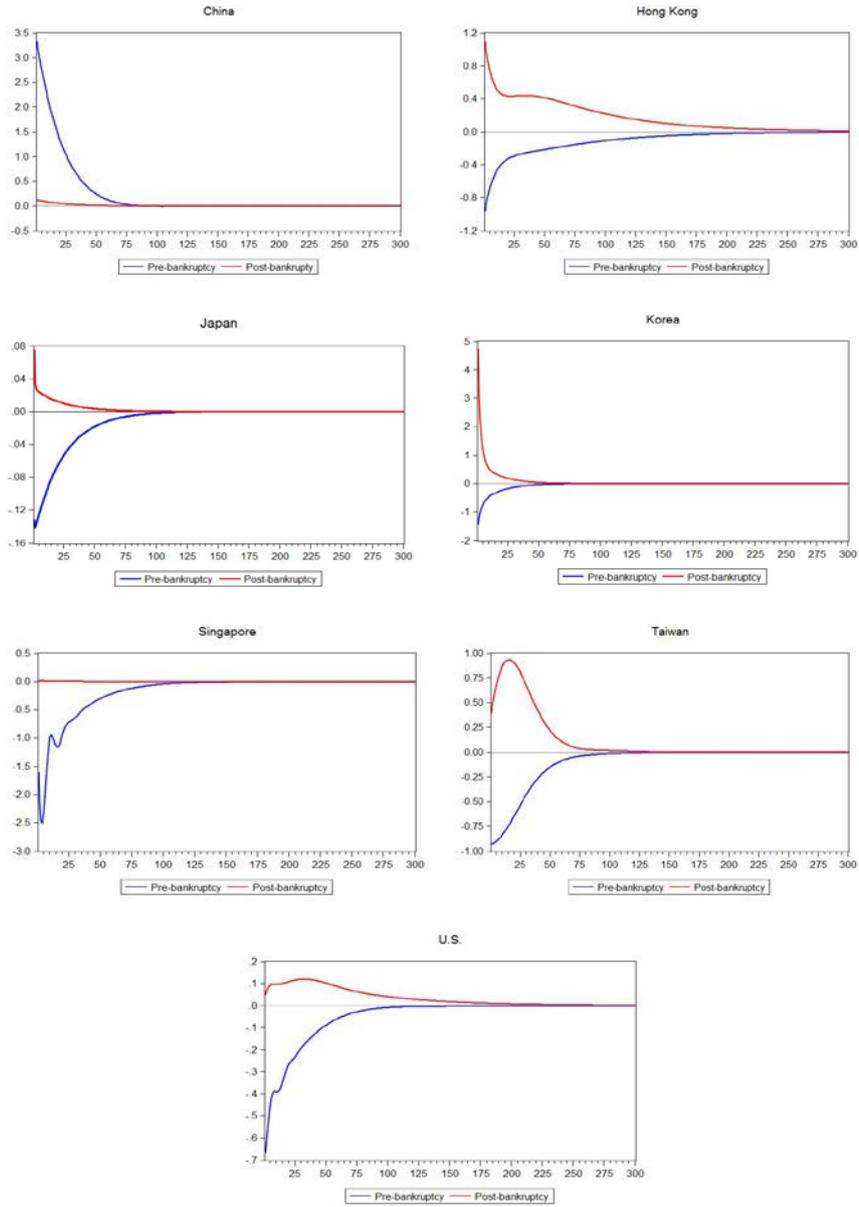
the 2008 GFC intensified correlations between the US and Asian stock markets. This finding supports the null hypothesis of a contagion effect.

4.2. VIRF for the 2008 GFC

In this section, we examine the persistence of volatility shocks in the stock markets using the VIRF of Hafner and Herwartz (2006). We investigate one observed historical shock, the 2008 GFC that fell within our data set. The 2008 GFC was triggered by a liquidity shortfall in the US banking system, caused by the subprime mortgage crisis. The crisis deepened with the Lehman Brothers bankruptcy. Thus, the news of the bankruptcy of Lehman Brothers on September 12, 2008, signalled the unravelling of a series of events that came to be known as the 2008 global financial crisis. For this reason, we consider that date as the base point for our analysis.

Figure 3 shows the time profile of the impulse response of volatilities pre-bankruptcy (blue line) and post-bankruptcy (red line). In the pre-bankruptcy (September 12, 2008) period, the volatility impulse responses contributed to a negative impact on expected conditional variance, except for China. This means that the expected conditional variance following shocks tended to decrease, rather than increase, in the stock markets. Indeed, it seems that risk-averse investors are reluctant to react to market shocks before the bankruptcy of Lehman Brothers. However, all volatility impulse responses in post-bankruptcy (September 19, 2008) demonstrate a positive impact on expected variance over the time window except for Singapore. Within this context, Korea shows the highest responsive pass-through from the shocks to the one-step ahead expected conditional variances. Moreover, the impulse responses started from a high positive level, abruptly declining in a short period but disappearing slowly over a longer period. For the Hong Kong stock market, the impulse responses began at 1.2 and then slowly declined to zero up to the 250 time window. The smallest positive impact in the post-bankruptcy period is observed for Singapore. It seems that the Singapore stock market is more liberalized and efficient than other Asian markets because it quickly reverts to

Figure 3 VIRF for the 2008 GFC Around the Bankruptcy of Lehman Brothers



zero in the post-period of Lehman Brothers bankruptcy. Furthermore, Japan has a very similar pattern of impulse response functions with other markets.

Overall, these results indicate that the impact of shocks on expected conditional variance in the post-bankruptcy period differed substantially from that pre-bankruptcy. In fact, it seems that only large shocks, such as the bankruptcy of Lehman Brothers, result in an increase in expected conditional variances. Furthermore, there is significant differentiation in terms of the magnitude and the persistence of the volatility impulse responses across the Asian stock markets examined due to different investor reactions to shocks in each.

5. CONCLUSIONS

In this study, we investigated volatility transmission effects between the US and six Asian markets — China, Hong Kong, Japan, Korea, Singapore, and Taiwan — using a bivariate GARCH-BEKK model. We also showed the impact of shocks on stock market volatility using the volatility impulse response function (VIRF).

Our empirical findings extend unique contributions to the literature. First, these empirical results show that the US and Asian stock markets are interrelated by their volatilities. The relationships provide explanations for the changes in volatility in these Asian stock markets. Second, we find that the 2008 global financial crisis intensified volatility transmission across the US and Asian stock markets. The intensity of volatility indicates that one large shock increased the correlation not only in its own assets or market but also in other assets or markets. Third, with respect to the size and persistence of volatility transmission among stock markets, we find that one large shock, the bankruptcy of Lehman Brothers, resulted in an increase in expected conditional volatilities post-bankruptcy. Moreover, the magnitude and the persistence of the volatility impulse responses differs across the Asian stock markets examined due to differing investor reactions to shocks in each market. Overall,

these findings have important implications, with regard to volatility transmission and building market stabilisation methods during turbulent market periods, for policy makers, regulators, and market investors.

Although our study is important to shed a light on the volatility shock transmission between US and Asian stock markets, its shock transmission is complicated and different factors may be affecting these markets. The recent discussion suggests that the financial factors such as exchange rates, interest rates, speculation, and derivative markets may play role on the dynamics of stock volatility. Thus, it is necessary to investigate the impacts of various factors on volatility of stock markets. In this context, future studies can extend the literature at least in two ways. First, we consider the quantile regression to identify the impact factors of volatility in bullish and bearish stock markets. The recent ongoing financial crises provide a unique opportunity to investigate the dynamics of volatility in the different regimes. Secondly, we also develop the co-movement of stock markets using the multivariate volatility models with exogenous variables such as above financial factors. The multivariate volatility model provides a flexibility to examine the spillover including the exogenous variables.

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