International Journal of Economics, Finance and Management Sciences
2015; 3(3): 213-230
Published online April 30, 2015 (http://www.sciencepublishinggroup.com/j/ijefm)
doi: 10.11648/j.ijefm.20150303.18
ISSN: 2326-9553 (Print); ISSN: 2326-9561 (Online)

Stock Markets Linkages Before, During and After Subprimes Crisis: Bivariate BEKK GARCH (1, 1) and DCC Models

Samar Zlitni Abdelkefi[1], Walid Khoufi[2]

[1]Faculty of Economics and Management of Sfax, Sfax, Tunisia
[2]School of High Business Studies of Sfax, Sfax, Tunisia

Email address:
samarzlitniabdelkefi@yahoo.fr (S. Z. Abdelkefi), Walid.khoufi@yahoo.fr (W. Khoufi)

To cite this article:
Samar Zlitni Abdelkefi, Walid Khoufi. Stock Markets Linkages Before, During and After Subprimes Crisis: Bivariate BEKK GARCH (1, 1) and DCC Models. *International Journal of Economics, Finance and Management Sciences*. Vol. 3, No. 3, 2015, pp. 213-230. doi: 10.11648/j.ijefm.20150303.18

Abstract: The purpose of this paper is to apply the Bivariate BEKK- GARCH (1, 1) and DCC- GARCH models in evaluating volatility spillovers and dynamic conditional correlation between stock indices. In this paper, the causal relation between stock markets (Nasdaq and each of these indices: Cac 40, Dax 30, Ftse 100, Global Dow Hangseng, Nikkei 225, Russell 2000, Shanghai, S&P 500 and Stoxx 600) is examined through applying Granger Causality test. The sample period started from January, 5th 2001 to September, 17th 2014. The whole sample period was divided into three sub-periods: Pre-crisis, global financial crisis and Post-crisis. Overall results proved unilateral and bilateral relationship between the variables. DCC model's coefficients prove significant interdependence for all indices except Hangseng, Shanghai and S&P500.

Keywords: Stock Markets, USA, Asia, Europe, Volatility Spillovers, Granger Causality Test, Impulse Responses, Bivariate BEKK GARCH (1, 1), DCC Models

1. Introduction

A central issue in asset allocation and risk management is whether financial markets become more interdependent mainly during financial crises. This issue acquired dramatic importance during the five major crises of the 1990's. Common to all these episodes was the fact that the financial turbulence that originated in one market widespread to other markets and countries in a way that was hard to explain on the basis of changes in fundamentals. The word "transmission volatility" became popular in the academic literature. Recent financial crises provide us with an opportune backdrop to analyze the transmission volatility effects among stock markets. Research on market linkages has gained great attention in the academic literature because of the following reasons, [1]. Firstly, the results from such research have important implications on international diversification benefit. Close co-movements among international stock markets increase local investors' exposure to foreign shocks and therefore restrict the diversification benefit. Secondly, research on market linkages also shed important light on international market integration. Stock markets can be considered integrated if their prices have a tendency to move successively. In this research, we attempt to assess the impact of terrorist attempt of 09/11/2001, Subprime financial crisis and Sovereign debt crisis in Europe on stock markets. The US market is included in the current analysis because previous studies have found that the US is the main driving force behind the Asian and European markets[2,3]. We use the Granger causality test to examine the potential causal relationships at bivariate level, impulse response functions and variance decomposition analysis. For this purpose, we analyze the behavior of eleven stock markets from America, Europe and Asia from 01/05/2001 until 09/17/2014. In this paper, we employ Bivariate BEKK and DCC GARCH (1, 1) framework to delve into the process and the magnitude of Nasdaq's impacts on different stock markets.

Our results on the transmission phenomenon proof a significant effect of US shocks on most markets. DCC analysis proves significant interdependence for all indices except Hangseng, Shanghai and S&P500.This paper is organized as follows: first, we present a literature review and models (Bivariate BEKK and DCCGARCH (1, 1)). Then, some statistical tests will be discussed (Unit Root, Correlation Matrices, Lag Length Selection, Granger Causality and

Impulse Response: Eviews 8 Software). Thereafter, empirical results of BEKK and DCC models will be presented (Win Rats 6.1 Software). The last section concludes.

2. Literature Review

Many studies have attempted to provide better understanding of the changes in market linkages after an adverse financial event, such as the 1987 stock market crash and the 1997 Asian financial crisis. Reference [4] analyzes the causal relationships between stock prices and exchange rates in Asia. Reference [5] provides another analysis on market co-movements in BRIC Equity markets. Factor analysis is used to examine whether the common factors affecting market returns vary in the pre- and post-crash periods. The result indicates a stronger presence of international interdependence. Moreover, authors find that the increased co-movements among the markets persist for a long period of time. Reference [6] studies correlation and volatility transmission across international stock markets using a bivariate GARCH Analysis. Error-correction analysis suggests that the US has substantial influence on the European market, but the reverse is not true. Reference [7] provides another piece of evidence on the increased market co-movements. Results from their principal component analysis show fewer significant principal components, indicating that the co-movements between the US and twelve European stock markets become more harmonious. Contrarily, reference [8] shows that there is only interdependence not contagion. Reference [9] investigates investors' reactions to the 1997 Asian financial crisis for six Asian closed-end country funds. The result implies that international investors react and turn pessimistic before local investors. Reference [10] studies the effect of the Asian financial crisis on 13 international stock markets. Their investigation shows a dramatic increase in feedback relationships between the stock markets after the financial crisis. Additionally, using the factor analysis, they find a significant reduction in the number of common factors affecting the market returns. Reference[11] and [12] concluded that the co-movements among international stock markets are more harmonized after the crisis. From a review of recent studies on market linkages, we observe that most research,[13,14, 15],find stronger co-movements among the global markets after a financial turbulence with the majority of the studies focus on the 1987stock market crash. Relatively, the research studying the effect of 1997 Asian financial crisis on market linkages seems to be inadequate.

3. BEKK and DCC Models

3.1. Bivariate BEKK GARCH (1, 1)

In this paper, we employ the BEKK [16] parameterization of the bivariate GARCH model, which does not impose restriction of constant correlation among variables over time. The model addresses the difficulty with VECH of ensuring that the H matrix is always positive definite by incorporating quadratic forms.

BEKK parameterization for the bivariate GARCH (1, 1) model is represented by:

$$\text{Ht} = \text{CC}' + \text{A}\varepsilon\text{t-1}\varepsilon'\text{t-1A}' + \text{B Ht-1B}' \quad (1)$$

Where the individual elements for C, A and B matrices are given as:

$$A = \begin{bmatrix} \beta 0 & \beta s 0 \\ & \beta 0 s \beta s \end{bmatrix} \; B = \begin{bmatrix} \delta 0 & \delta s 0 \\ & \delta 0 s \delta s \end{bmatrix} C = \begin{bmatrix} \alpha 0 & \alpha s 0 \\ & \alpha 0 s \alpha s \end{bmatrix} \quad (2)$$

Where H_t is the conditional variance matrix, C is an upper triangular matrix of parameters, B is a 2 x 2matrix of parameters which depicts the extent to which current levels of conditional variances are related to past conditional variances, and A is a 2 x 2 matrix of parameters that measures the extent to which conditional variances are correlated with past squared errors. Expanding the conditional variance for each equation in the bivariate BEKK-GARCH (1,1) model gives:

$$h^2{}_0 = \alpha_0 + \beta^2{}_0\varepsilon^2{}_{0\text{-}1} + 2\ \beta_0\beta_{s0}\varepsilon_{s\text{-}1}\ \varepsilon_{0\text{-}1} + \beta^2{}_s 0\varepsilon^2{}_{s\text{-}1} + \delta^2{}_0 h^2{}_{0\text{-}1} + 2\ \delta_0\delta_{s0} hs_{0\text{-}1} + \delta^2{}_{s0} h^2{}_{s\text{-}1} \quad (3)$$

$$h_{s0} = \alpha_{s0} + \beta_s\beta_0\varepsilon^2{}_{s\text{-}1} + (\beta_s\beta_{s0} + \beta_s\beta_0)\ \varepsilon_{s\text{-}1}\ \varepsilon_{0\text{-}1} + \beta_{0s}\beta_0\varepsilon^2{}_{0\text{-}1} + \delta_s\delta_0 h^2{}_{s\text{-}1} + (\delta_{0s}\delta_{s0})\ hs_{0\text{-}1} + \delta_{0s}\delta_0 h^2{}_{0\text{-}1} \quad (4)$$

$$h^2{}_s = \alpha_s + \beta^2{}_s\varepsilon^2{}_{s\text{-}1} + 2\ \beta_s\beta_{0s}\varepsilon_{s\text{-}1}\ \varepsilon_{0\text{-}1} + \beta^2{}_{0s}\varepsilon^2{}_{0\text{-}1} + \delta^2{}_s h^2{}_{s\text{-}1} + 2\delta_s\delta_{0s} h^2{}_{s0\text{-}1} + \delta^2{}_{0s} h^2{}_{0\text{-}1} \quad (5)$$

This feature permits the direct transmission of volatility and shocks from one market to another. Overall, this model allows us to capture both return and volatility spillover effects between Nasdaq and each index. Under the assumption of conditional normality, the parameters of a multivariate GARCH model can be estimated by maximizing the log-likelihood function.

$$\text{Max log } L_T(\theta) = \sum_{t=1}^{T} \quad l_t(\theta) \quad (6)$$

$$l_t = \frac{TN}{2}\log(2\,\Pi) - \frac{1}{2}\sum_{t=1}^{T} \quad (\log H_t) + \varepsilon'_t H_t \varepsilon_t \quad (7)$$

Where θ denotes all the unknown parameters to be estimated, N is the number of series and T is the number of observations.

3.2. Dynamic Conditional Correlation Model

DCC model has the following form: $H_t = D_t R_t D_t$ (8)

Where

$$D_t = \text{diag}\ (h^{½}{}_{11t} \ldots h^{1/2}{}_{NNt}). \quad (9)$$

Note that each h_{iit} is a univariate GARCH model.

$$R_t = \text{diag}\ \ (q^{1/2}{}_{11t} \ldots q^{1/2}{}_{NNt})\ Q_t\ \text{diag}\ (q^{1/2}{}_{11t} \ldots q^{1/2}{}_{NNt}) \quad (10)$$

The matrix $Q_t = (q_{ijt})$ is the N×N symmetric positive definite matrix updated by the following:

$$Q_t = (1- \alpha - \beta)\,\bar{Q} + \alpha\, u_{t-1} u'_{t-1} + \beta\, Q_{t-1} \tag{11}$$

Where

$$u_{it} = \varepsilon_{it}\sqrt{hiit} \tag{12}$$

The major advantage of using DCC GARCH model is the detection of possible changes in conditional correlations varying in time which allowed us to detect the dynamic behavior of investors in response to new information. In addition, measured dynamic conditional correlations prove the existence of a contagion effect due to herd behavior that appears in the financial markets during the crisis, [17, 18, 19]. Dynamic Conditional Correlation (DCC) has no bias on volatility. DCC offers a great measure of correlation, [20].

4. Data and Statistical Tests

4.1. Data

Our database consists of daily returns relative to CAC 40, DAX 30, FTSE 100, Global Dow Hanseng, Nasdaq, Nikkei 225, Russell 2000, Shanghai, S&P 500 and STOXX 600. The formula is written as follows:

$$R_t = \ln (P_t / P_{t-1}) \times 100 \tag{13}$$

Where R_t is the return of the index, P_t and P_{t-1} are respectively closing price at time t and (t-1).

The period lasts between 01/05/2001 and 17/09/2014. It is divided into three sub- periods: the first includes the terrorist attack of 09/11/2001 (from 01/05/2001 until 06/29/2007), the second considers the Subprime crisis (07/02/2007-12/29/2009) and the last includes sovereign debt crisis in Europe (01/02/2010-09/17/2014).

4.2. Unit Root Test (Table 1)

Before investigating the linkages among different stock indices, the Augmented Dickey-Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests are applied to examine the stationary properties of series. The null hypothesis of ADF test is that the series has a unit root, whereas stationary is the null hypothesis in the KPSS test. Thus we perform KPSS test as confirmatory test of the results of ADF. But if two approaches are contradicted, KPSS is preferred. The results of these tests are summarized in the following table (we consider three sub-periods). All series are stationary during the whole period.

Table 1. *Unit Root Tests.*

Panel a 01/05/2001-06/29/2007					Panel b 07/02/2007-12/29/2009			
Indices	**Kpss constant**	**Adf constant**	**Kpss constant and trend**	**Adf constant and trend**	**Kpss constant**	**Adf constant**	**Kpss constant and trend**	**Adf constant and trend**
Cac	0,699*	-38,811***	0,064***	-38,923***	0,330***	-27,530***	0,102***	-27,587***
Dax	0,661*	-39,312***	0,048***	-39,449***	0,251***	-25,473***	0,091***	-25,510***
Ftse	0,526*	-40,788***	0,052***	-40,880***	0,278***	-27,240***	0,098***	-27,278***
Global dow	0,479*	-32,162***	0,063***	-32,249***	0,227***	-23,097***	0,174*	-23,096***
Hangs	0,727*	-37,941***	0,066***	-38,124***	0,144***	-24,620***	0,109***	-24,606***
Nasdaq	0,310***	-38,440***	0,079***	-38,477***	0,278***	-27,020***	0,125**	-27,059***
Nikkei	0,396**	-40,017***	0,052***	-40,093***	0,259***	-25,330***	0,075***	-25,372***
Russell	0,132***	-38,689***	0,052***	-38,691***	0,205***	-27,082***	0,086***	-27,110***
Shanghai	0,677*	-39,519***	0,179*	-39,942***	0,395*	-23,591***	0,120**	-23,651***
Sp 500	0,343***	-39,456***	0,053***	-39,517***	0,274**	-20,179***	0,128**	-20,232***
Stoxx	0,712*	-38,686***	0,060***	-38,816***	0,369**	-26,204***	0,122**	-26,268***

Table 1. *Continue.*

Panel c 01/02/2010-09/17/2014			
Kpss constant	**Adf constant**	**Kpss constant and trend**	**Adf constant and trend**
0,144***	-13,800***	0,036***	-32,616***
0,059***	-6,543***	0,036***	-30,378***
0,029***	-16,242***	0,022***	-31,251***
0,124***	-8,495***	0,035***	-29,972***
0,043***	-31,978***	0,037***	-31,965***
0,065***	-16,280***	0,023***	-34,566***
0,286***	-34,286***	0,054***	-34,334***
0,037***	-8,518***	0,036***	-21,443***
0,142***	-33,292***	0,032***	-33,317***
0,087***	-8,502***	0,023***	-35,627***
0,089***	-17,199***	0,033***	-31,268***

*, ** and ***denotes coefficients are significant at 1%, 5% and 10% level respectively

4.3. Correlation Matrices(Table 2)

Table 2. *Correlation Matrices.*

PANEL A											
	Cac	**Dax**	**Ftse**	**Gdow**	**Hang**	**Nasd**	**Nikkei**	**Russ**	**Shang**	**Sp500**	**Stoxx**
Cac	1,000										
Dax	0,868	1,000									
Ftse	0,863	0,762	1,000								
Gdow	0,784	0,786	0,720	1,000							
Hangseng	-0,046	-0,030	-0,048	-0,018	1,000						
Nasdaq	0,475	0,581	0,408	0,689	0,012	1,000					
Nikkei	0,313	0,264	0,287	0,487	0,014	0,190	1,000				
Russell	0,498	0,586	0,437	0,713	-0,015	0,849	0,184	1,000			
Shanghai	-0,013	0,003	-0,016	0,024	0,042	0,020	0,059	0,016	1,000		
Sp500	-0,009	-0,010	-0,016	-0,044	0,007	-0,020	-0,033	-0,021	-0,001	1,000	
Stoxx	0,949	0,881	0,911	0,794	-0,042	0,486	0,320	0,513	-0,009	-0,014	1,000
Panel b											
	Cac	Dax	Ftse	Gdow	Hang	Nasd	Nikkei	Russ	Shang	Sp500	Stoxx
Cac	1,000										
Dax	0,920	1,000									
Ftse	0,936	0,871	1,000								
Gdow	0,843	0,823	0,827	1,000							
Hangseng	-0,004	0,001	-0,038	0,010	1,000						
Nasdaq	0,588	0,628	0,569	0,754	0,045	1,000					
Nikkei	0,489	0,467	0,481	0,563	-0,037	0,181	1,000				
Russell	0,537	0,566	0,507	0,703	0,048	0,951	0,127	1,000			
Shanghai	-0,007	-0,011	-0,029	-0,032	0,048	-0,036	-0,025	-0,036	1,000		
Sp500	-0,155	-0,107	-0,134	-0,130	-0,024	-0,116	-0,096	-0,089	-0,012	1,000	
Stoxx	0,978	0,925	0,952	0,856	-0,003	0,608	0,512	0,552	-0,012	-0,145	1,000
Panel c											
	Cac	Dax	Ftse	Gdow	Hang	Nasd	Nikkei	Russ	Shang	Sp500	Stoxx
Cac	1,000										
Dax	0,927	1,000									
Ftse	0,855	0,827	1,000								
Gdow	0,863	0,837	0,810	1,000							
Hangseng	0,087	0,089	0,068	0,077	1,000						
Nasdaq	0,627	0,618	0,650	0,810	0,061	1,000					
Nikkei	0,210	0,222	0,249	0,287	0,035	0,159	1,000				
Russell	0,620	0,614	0,603	0,804	0,074	0,891	0,121	1,000			
Shanghai	-0,013	-0,016	-0,019	-0,007	0,065	-0,001	-0,024	0,006	1,000		
Sp500	-0,049	-0,038	-0,021	-0,059	-0,026	-0,063	0,013	-0,074	-0,007	1,000	
Stoxx	0,954	0,932	0,888	0,858	0,092	0,643	0,252	0,623	-0,010	-0,041	1,000

Correlation analysis reveals a highly significant correlation between European markets: Stoxx-Cac (0.949), Stoxx-Ftse (0.911), Stoxx-Dax (0.881), Cac-Dax (0.868) Cac-Ftse (0.863) during stable period followed by Nasdaq-russell (0.849) Stoxx-Global Dow (0.794). By against, a very weak correlation was recorded between Hangseng and Shanghai and other stock indices. During Subprime crisis, the correlation between Nasdaq and other indices are slightly increased except S&P500, Shanghai and Nikkei. The strongest correlation was recorded between Stoxx and Cac (0.978). European markets are highly correlated in turbulent times. The post-crisis period is characterized by a slight decrease in correlation between markets. The correlation between the European markets is quite large, Cac-Stoxx (0.954), Cac-Dax (0.925), Ftse-Stoxx (0.888), Cac-Ftse (0.855) and Dax-Ftse (0.827), [21].

4.4. Lag Length Selection (Table 3)

Before running Granger causality test, Impulse responses functions and Variance decomposition, the selection of lag length should be done first. The choice of lag length mainly depends on the information criteria since there are so many restrictions on Likelihood ratio test. If two criteria show contradictable results, SBIC is more reliable.

Table 3. *Lag Length Selection.*

Panel a: 01/05/2001-06/29/2007							
Indices	P	LogL	LR	FPE	AIC	SC	HQ
Nasd-cac	2	-2747.129	30.57945	0.143732	3.735946	3.771835*	3.749327*
Nasd-dax	1	-2874.541	76.58309	0.169894	3.903172	3.924705*	3.911201
Nasd-ftse	1	-2466.008	141.5369	0.097671	3.349604	3.371137*	3.357632
Nasd-gdow	1	-2466.008	141.5369	0.097671	3.349604	3.371137*	3.357632
Nasd-hang	3	-2699.882	17.05271	0.135551	3.677346	3.727590*	3.696079
Nasd-nikkei	1	-2843.466	231.9189*	0.162889*	3.861065*	3.882598*	3.869093*
Nasd-russ	2	-1885.535	13.63150*	0.044723	2.568476	2.604364*	2.581857
Nasd-shang	1	-3193.591	4.010110	0.260361*	4.330070*	4.337247*	4.332746*
Nasd-sp 500	2	-1828.578	80.04160	0.041401	2.491299	2.527187*	2.504679*
Nasd-stoxx	1	-2470.650	155.3747	0.098287	3.355895	3.377427*	3.363923
Panel b: 07/02/2007-12/29/2009							
Indices	P	LogL	LR	FPE	AIC	SC	HQ
Nasd-cac	1	-1298.707	219.4387	0.365040	4.668005	4.714440*	4.686138
Nasd-dax	1	-1287.977	144.5614	0.351291	4.629614	4.676049*	4.647747
Nasd-ftse	1	-1285.540	179.3731	0.348241	4.620894	4.667329*	4.639027
Nasd-gdow	1	-1159.948	198.5926	0.222194	4.171550	4.217985*	4.189683
Nasd-hang	1	-1610.828	10.59705	1.115119*	5.784715*	5.831149*	5.802848
Nasd-nikkei	2	-1410.498	26.61327	0.552408	5.082284	5.159675*	5.112506
Nasd-russ	2	-948.1012	15.22190	0.105627*	3.427911*	3.505302*	3.458133*
Nasd-shang	1	-1571.027	10.59829*	0.967115*	5.642316*	5.688750*	5.660449
Nasd-sp 500	2	-961.9194	74.09975	0.110980	3.477350	3.554741*	3.507572*
Nasd-stoxx	1	-1244.785	208.1000	0.300991	4.475081	4.521515*	4.493214
Panel c: 01/02/2010-09/17/2014							
Indices	P	LogL	LR	FPE	AIC	SC	HQ
Nasd-cac	1	-1508.149	103.7943	0.057948	2.827542	2.855420*	2.838102
Nasd-dax	1	-1418.675	122.2108	0.049031	2.660457	2.688336*	2.671017
Nasd-ftse	1	-1111.207	141.5892	0.027613	2.086287	2.114166*	2.096847
Nasd-gdow	1	-890.6668	107.8637	0.018292	1.674448	1.702327*	1.685008*
Nasd-hang	7	-1618.452	10.80885*	0.074466	3.078342	3.217736*	3.131145
Nasd-nikkei	1	-1721.006	171.1210	0.086231	3.225034	3.252913*	3.235595
Nasd-russ	1	-954.8125	169.0350	0.020619	1.794234	1.822113*	1.804795*
Nasd-shang	3	-1657.391	12.53619*	0.077725	3.121179	3.186230*	3.145820
Nasd-sp 500	4	-659.7670	43.34218*	0.012154*	1.265671*	1.349307*	1.297353*
Nasd-stoxx	1	-1185.074	147.6604	0.031697	2.224228	2.252106*	2.234788

4.5. Granger Causality Test (Table 4)

It tests the dynamic relationship between variables. It's stated in terms of improving the predictability of a variable. Reference [22] argues that at Granger temporal succession is central and can not discuss the causality without considering time.

In the first sub-period, a unidirectional causality is detected from Nasdaq to European and Japanese markets. Nasdaq's previous values of the realized volatility have significant explanatory power for predicting the realized volatility of European markets (Cac, Dax, Ftse and Stoxx) and the Japanese one (Nikkei 225). No causal relationship recorded between Nasdaq-Hangseng and Nasdaq-Shanghai: US market has no influence on these stock market indices. Unilateral causality from the S&P500 and Russell towards Nasdaq. During Subprime crisis (PANEL B), the unidirectional relationship from Nasdaq to Dax, Ftse, Global Dow and Nikkei persists. French market has an impact on the US (Nasdaq). The third sub-period, characterized as Post-Subprime crisis highlights significant bidirectional causality (at 5% level) between Nasdaq and European markets (Cac, Dax, Ftse and Stoxx).

Note that, according to the two previous periods, no Granger causality is recorded between American (Nasdaq) and Chinese markets while the former has an impact on Hong Kong and Japan. After Subprime crisis, Russell influenced Nasdaq.

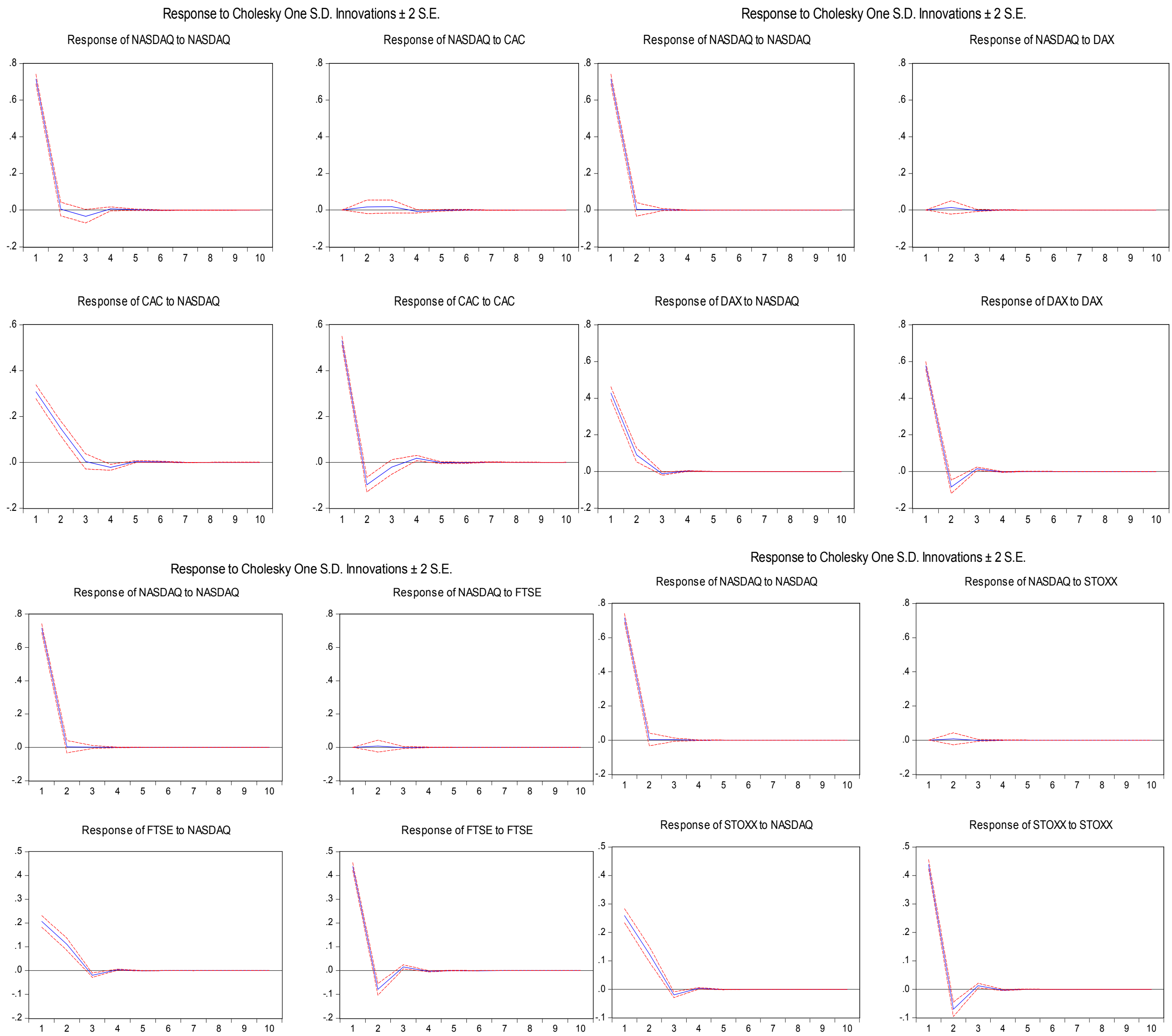
Table 4. Granger Causality Test.

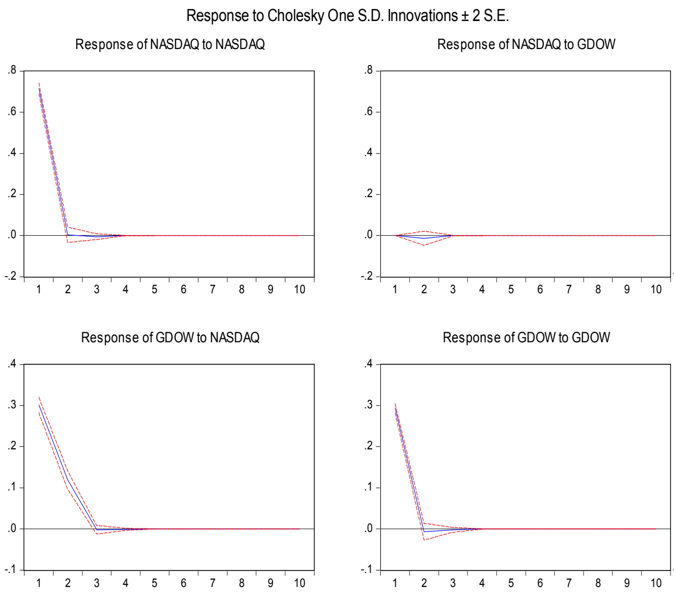
Null hypothesis	Panel A		Panel B		Panel C	
	Obs	CONCLUSION	Obs	CONCLUSION	Obs	CONCLUSION
CAC does not Granger Cause NASD NASD does not Granger Cause CAC	1478	NASD→CAC	566	NASD↔CAC	1078	NASD↔CAC
DAX does not Granger Cause NASD NASD does not Granger Cause DAX	1479	NASD→DAX	566	NASD→DAX	1078	NASD↔DAX
FTSE does not Granger Cause NASD NASD does not Granger Cause FTSE	1479	NASD→FTSE	566	NASD→FTSE	1078	NASD↔FTSE
GDOW does not Granger Cause NASD NASD does not Granger Cause GDOW	1479	NASD→GDOW	566	NASD→GDOW	1078	NASD↔GDOW
HANG does not Granger Cause NASD NASD does not Granger Cause HANG	1478	No causality sense	566	No causality sense	1072	NASD→HANG
NIKKEI does not Granger Cause NASD NASD does not Granger Cause NIKKEI	1479	NASD→NIKKEI	565	NASD→NIKKEI	1078	NASD→NIKKEI
RUSS does not Granger Cause NASD NASD does not Granger Cause RUSS	1478	RUSS→NASD	565	No causality sense	1078	RUSS→NASD
SHANG does not Granger Cause NASD NASD does not Granger Cause SHANG	1479	No causality sense	566	No causality sense	1076	No causality sense
SP500 does not Granger Cause NASD NASD does not Granger Cause SP500	1478	SP500→NASD	565	SP500→NASD	1075	NASD↔SP500
STOXX does not Granger Cause NASD NASD does not Granger Cause STOXX	1479	NASD→STOXX	566	NASD→STOXX	1078	NASD↔STOXX

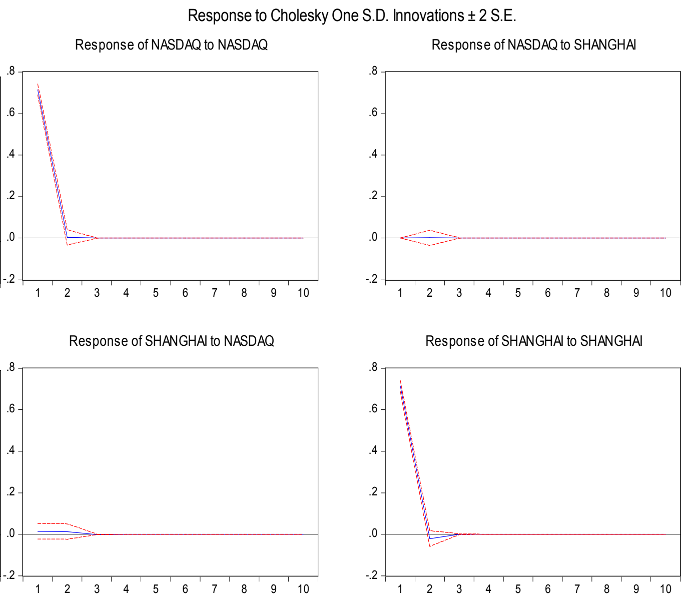
4.6. Impulse Response Functions (Figure 1)

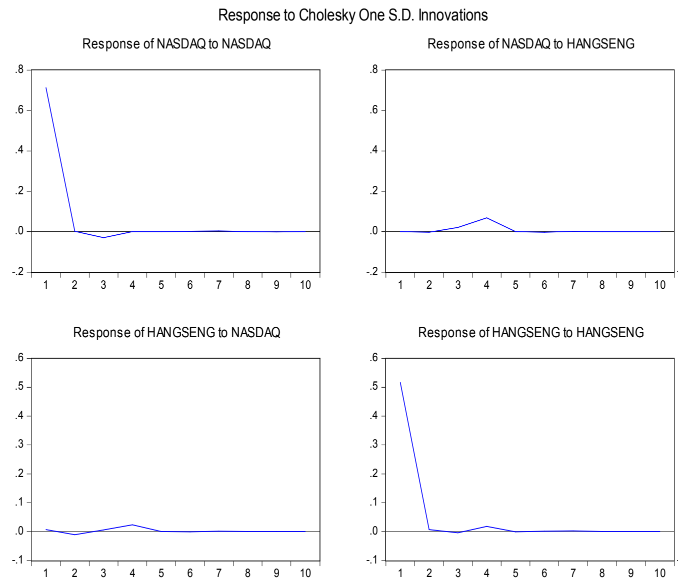
Granger causality tests show causal links between stock markets. Results suggest the probable existence of a dynamic interaction between stock markets to the point that each market might react to a shock on another. The knowledge of the magnitude of the responses to shocks and identification of the time taken by the market to dampen the effect of a random shock are determined through impulse response functions, [23]. Impulse responses explain the sources of propagation of shocks. Impulse response function shows that Nasdaq reacts positively to its own shock; effects wear off after four periods. French market has reacted positively and negatively, shock effects dissipated after five periods. During Subprimes crisis, Nasdaq's magnitude reaction to its shock increases during the first two periods positively and negatively, the shock disappears from the sixth day. The amplitude of Cac's reaction increases positively and negatively, from the fifth period the shock's impact fades. During post-crisis period, the shock's effects on the Nasdaq dissipated after three periods. Cac's response is positive and its effect wears off after four days: shock spreads. Impulse response functions of Nasdaq and Dax show that the first responds positively to its own shock, the effect wears off quickly. German index reacts positively; the shock influence's disappeared after three periods. During financial turbulence, Nasdaq's response amplitudes increase for the two last ones. Dax's reaction is positive for the first two periods and negative for the third day. During European Debt crisis, indices' amplitudes highlight a slight decrease. Considering Nasdaq and FTSE 100, we find that Nasdaq's response to its own impact is positive and the effect of the shock wears off in the third period. For UK, the response is also positive but with lower amplitude. During the second sub-period Nasdaq responds to its own impact positively and negatively.UK reacts positively and negatively too. The shock's effect on the UK dissipated after seven times. During the European Debt Crisis, response amplitudes of the two indices are reduced compared to the previous period and the shock disappears from the fifth period. For Nasdaq- Stoxx 600, we note that during calm period, US market responds positively to its own shock for four periods. The financial turbulence increases the amplitude of the Nasdaq's response to its own impact; the effect persists six days like during European debt crisis. Stoxx's impulse responses reveal positive reaction to a shock on Nasdaq whose effect is dissipated after four periods. The magnitude of the response increased during the financial turbulence and the shock lasts seven days. Then, it decreases during the European Debt crisis and the shock wears off after six times. At regional level, in the first sub-period, Nasdaq and Global Dow reacted positively. Shock effect's ends the fourth day. During Subprimes crisis, the amplitudes' shock increase and it has five days to soften. Sovereign Debt crisis is characterized by a slight decrease in the Nasdaq and Global Dow's amplitude; from the fourth day the shock fades. Nasdaq and Russell 2000 react similarly: during the stable period react positively and the shock is still four times. Turbulent period shows an increase in the amplitude of the reaction; the shock disappears after seven days. We note a reduction of this magnitude during sovereign debt crisis in Europe. Shock's duration is reduced to five times. Concerning impulse responses of Nasdaq and S&P500, results show that Nasdaq's response to its own impact is positive whose effect disappears five days after. During Subprimes crisis, the reaction's amplitude decreases and the shock persists six days. While following a shock on the S&P500, Nasdaq responds positively. Impulse response functions of Nasdaq and indices belonging to Asia reveal different aspects: for Nasdaq – Hangseng. In calm period, Nasdaq responds positively to its own shock and the effect is dissipated the fourth day. During Subprimes crisis, the reaction's amplitude increases showing the power of the shock, the effect disappears four times after. During European debt crisis, it took ten periods to fade. Hong Kong does not react to a shock on Nasdaq. Concerning Nasdaq-Nikkei, the first one responds positively to its own impact, the shock remains four times to end. During the second sub-period, the response's magnitude increase sand its effect disappears the seventh day while during the European debt crisis, a slight decrease was recorded at the magnitude of the US index to its own shock, the effect lasted four times. Nikkei 225 reveals that Japanese market reacts positively to a shock on the US market during four periods after which the shock disappears. During subprimes Crisis, Nikkei responds positively with higher amplitude compared to the quiet period for three days and negatively to the fifth period. The shock's effect ends the sixth day. During European Debt crisis, the Japanese's and five days are sufficient so that the shock dissipates. For Nasdaq-Shanghai, the analysis reveals that the first one responds positively to its own shock for three days during calm period. An increase in the Nasdaq's amplitude is shown during the second sub-period; shock's effect is dissipated from the fourth day. A decrease is highlighted during European Debt crisis and the shock disappears eight periods after. The Chinese market seems independent since no reaction is recorded following the shock on Nasdaq during three sub-periods.

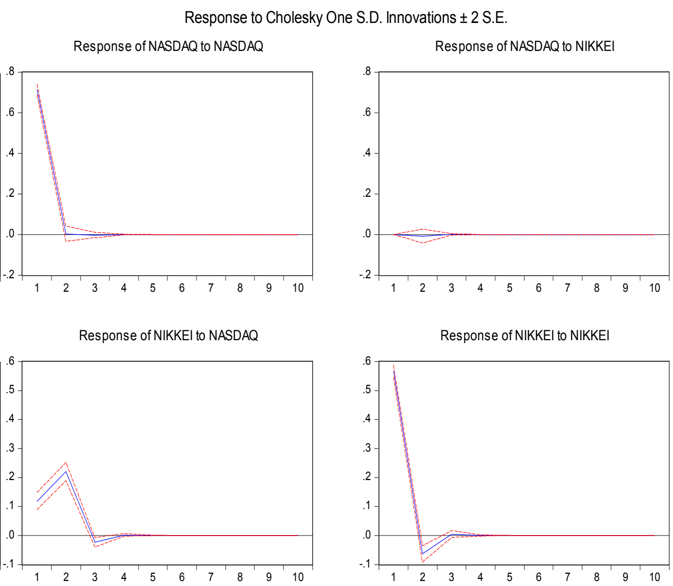
Panel A

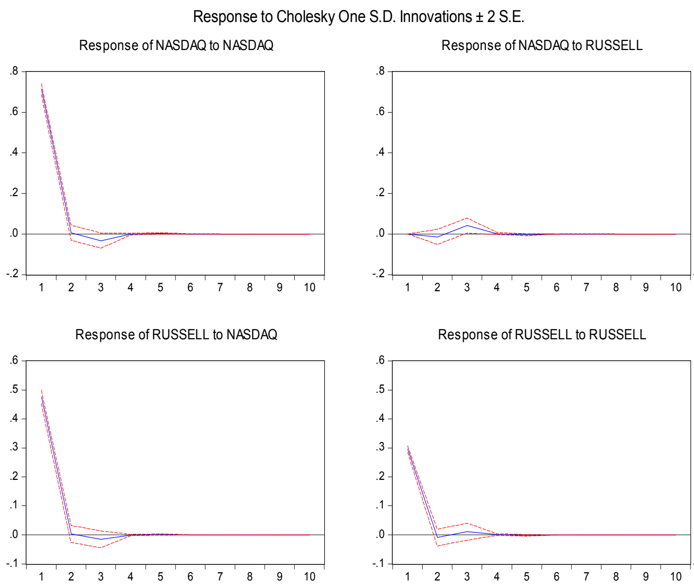


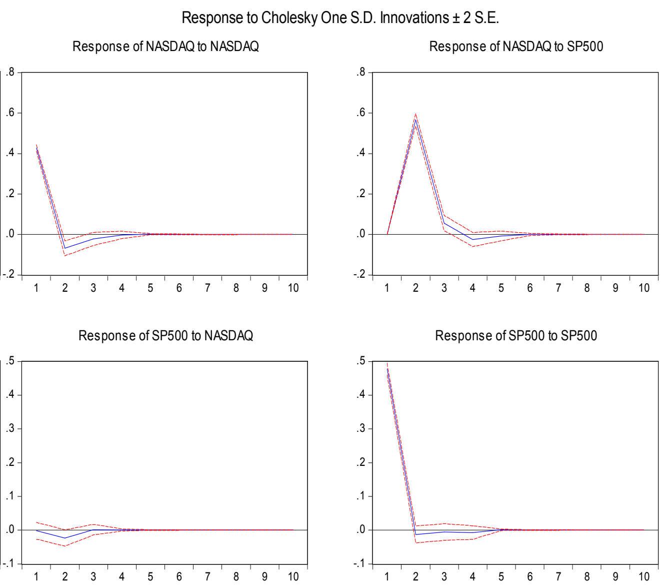

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to GDOW
Response of GDOW to NASDAQ
Response of GDOW to GDOW


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to SHANGHAI
Response of SHANGHAI to NASDAQ
Response of SHANGHAI to SHANGHAI

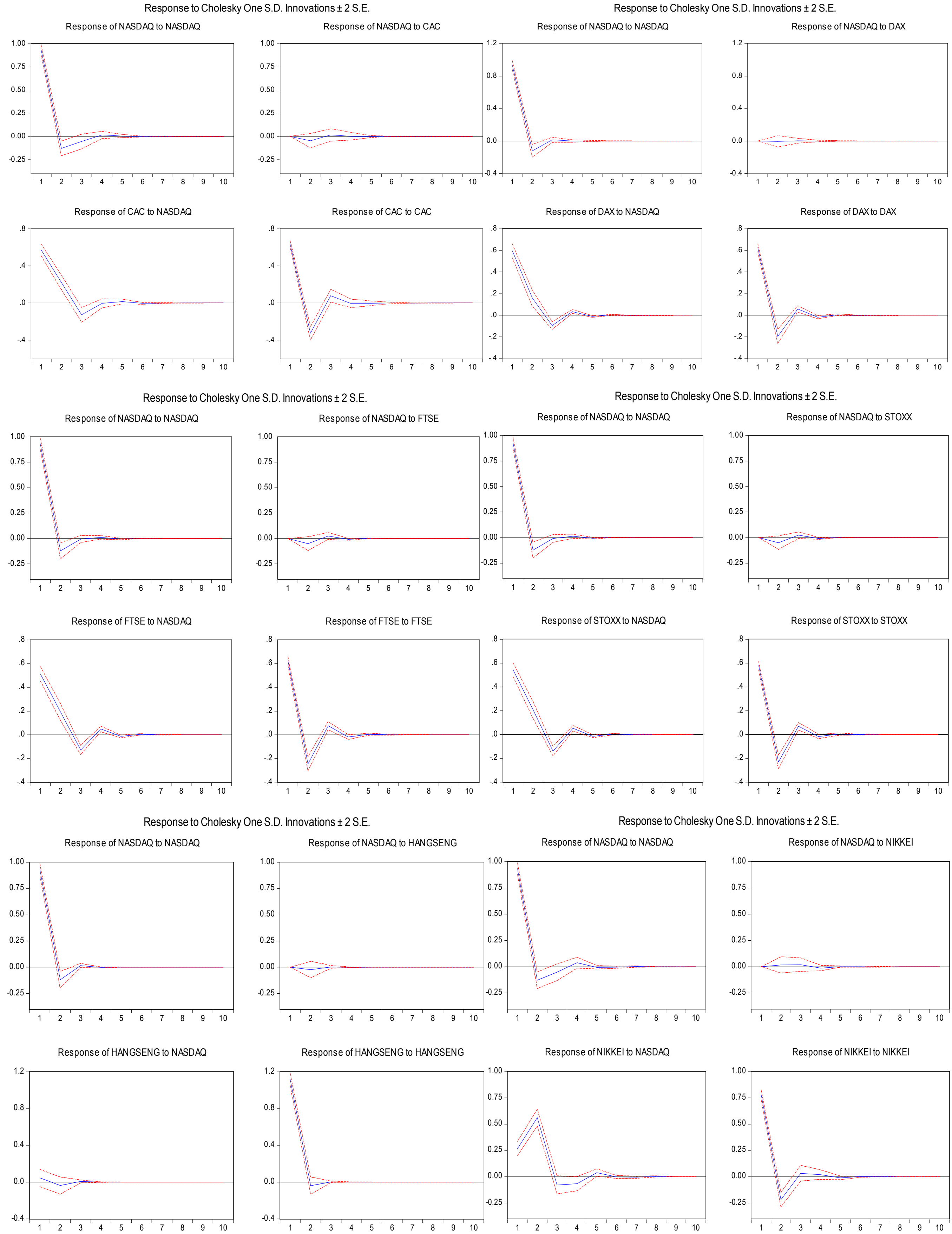

Response to Cholesky One S.D. Innovations
Response of NASDAQ to NASDAQ
Response of NASDAQ to HANGSENG
Response of HANGSENG to NASDAQ
Response of HANGSENG to HANGSENG

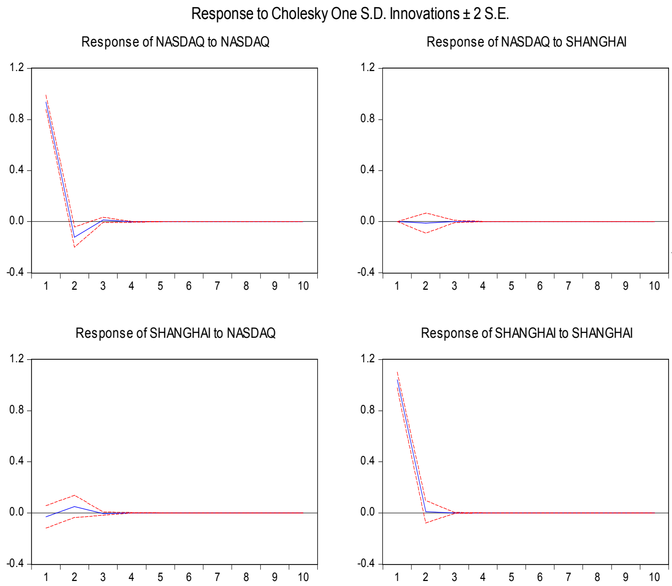

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to NIKKEI
Response of NIKKEI to NASDAQ
Response of NIKKEI to NIKKEI

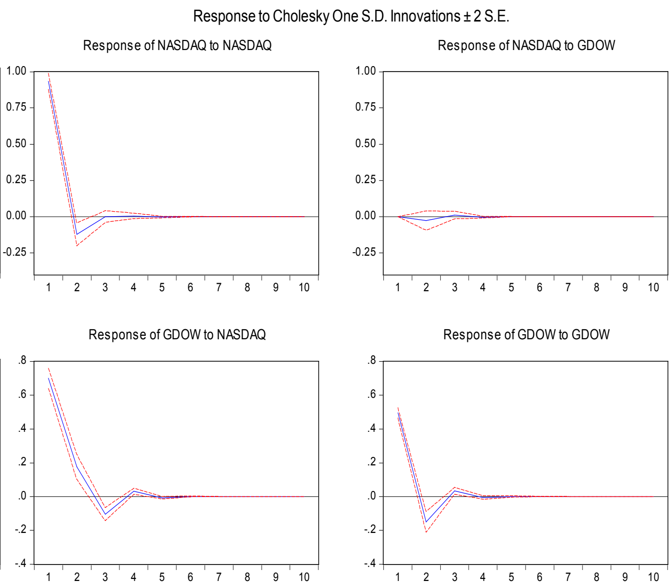

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to RUSSELL
Response of RUSSELL to NASDAQ
Response of RUSSELL to RUSSELL

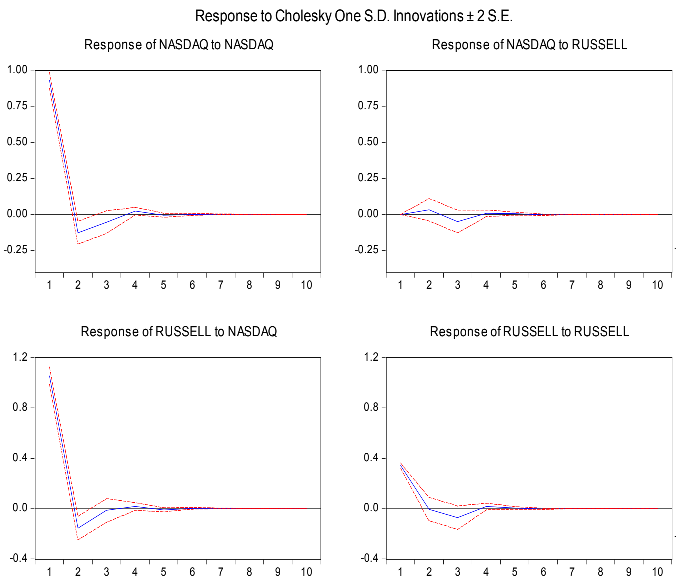

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to SP500
Response of SP500 to NASDAQ
Response of SP500 to SP500

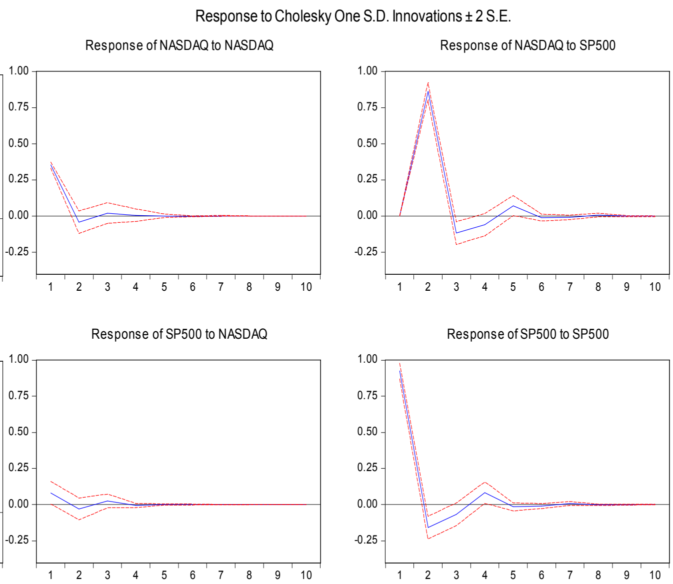
Panel B


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to CAC
Response of CAC to NASDAQ
Response of CAC to CAC
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to DAX
Response of DAX to NASDAQ
Response of DAX to DAX
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to FTSE
Response of FTSE to NASDAQ
Response of FTSE to FTSE
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to STOXX
Response of STOXX to NASDAQ
Response of STOXX to STOXX
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to HANGSENG
Response of HANGSENG to NASDAQ
Response of HANGSENG to HANGSENG
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to NIKKEI
Response of NIKKEI to NASDAQ
Response of NIKKEI to NIKKEI

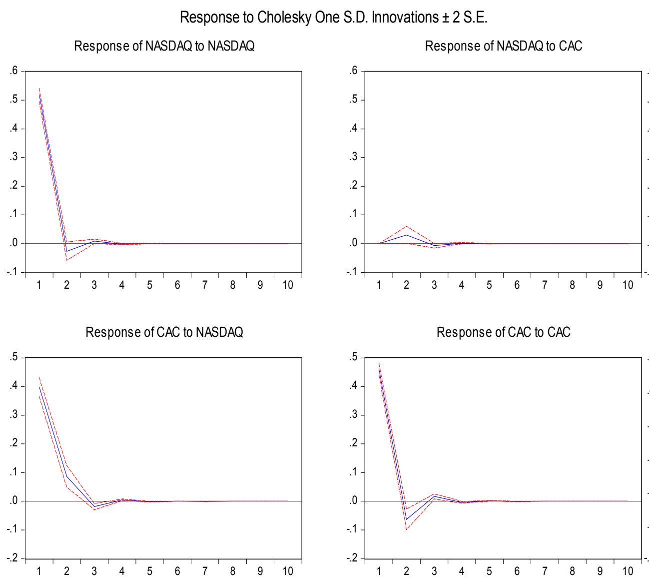

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to SHANGHAI
Response of SHANGHAI to NASDAQ
Response of SHANGHAI to SHANGHAI

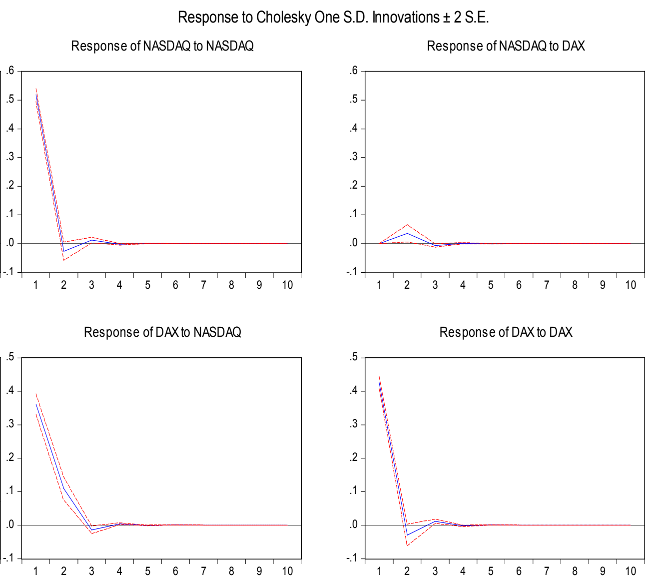

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to GDOW
Response of GDOW to NASDAQ
Response of GDOW to GDOW

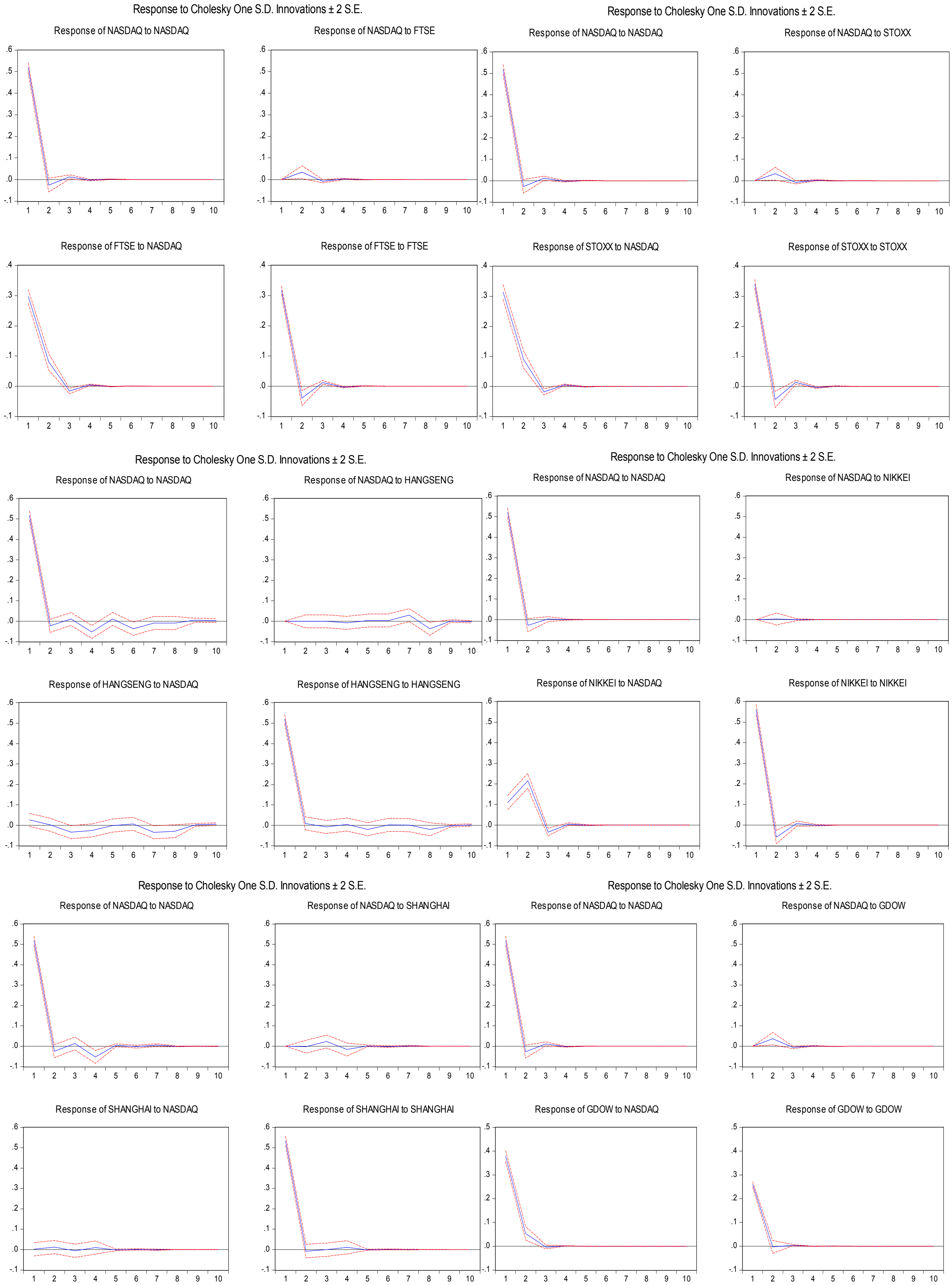

Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to RUSSELL
Response of RUSSELL to NASDAQ
Response of RUSSELL to RUSSELL


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to SP500
Response of SP500 to NASDAQ
Response of SP500 to SP500

Panel C


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to CAC
Response of CAC to NASDAQ
Response of CAC to CAC


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to DAX
Response of DAX to NASDAQ
Response of DAX to DAX


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to FTSE
Response of FTSE to NASDAQ
Response of FTSE to FTSE
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to STOXX
Response of STOXX to NASDAQ
Response of STOXX to STOXX
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to HANGSENG
Response of HANGSENG to NASDAQ
Response of HANGSENG to HANGSENG
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to NIKKEI
Response of NIKKEI to NASDAQ
Response of NIKKEI to NIKKEI
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to SHANGHAI
Response of SHANGHAI to NASDAQ
Response of SHANGHAI to SHANGHAI
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of NASDAQ to NASDAQ
Response of NASDAQ to GDOW
Response of GDOW to NASDAQ
Response of GDOW to GDOW

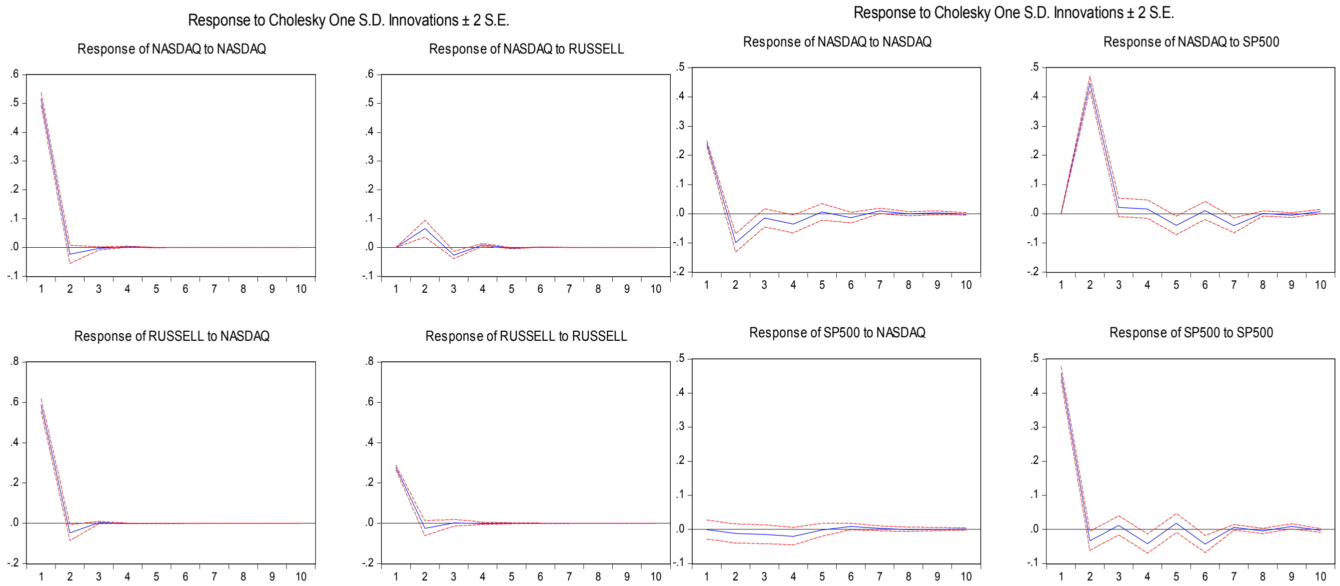


***Figure 1.** Impulse Responses.*

5. Results and Discussions

5.1. Bivariate BEKK- GARCH (1, 1) Estimation (Table 6)

This paper applies bivariate GARCH-BEKK model to effectively capture the own and cross volatility spillovers between stock markets. Results reveal the asymmetric nature of the US market transmissions to other markets. The own-volatility spillover effects of Nasdaq A (1, 1) increases during Subprimes crisis. That of French market is reduced from one period to another, it is becoming more mature. This result shows that after having suffered from terrorist attack, French market begins to reform its financial system to defend foreign shocks. During the first sub-period, we are seeing a one-way transmission average and variance of volatility generated by the US market to the French. During the global financial crisis, a bidirectional transmission is recorded. Cross coefficients variance's analysis shows that B (1, 2) and B (2,1) range from(-0.2018, -0.0026) and (0.4244, 0.1203)respectively. This reveals that US volatilities' impact have a greater effect on French market's current volatility. Post-subprimes crisis is characterized by a unidirectional average transmission from US market without feedback effect, but there is a two-way transmission in variance. Volatility effects show a slight growth from one period to another for Nasdaq, that of the German market decreases during the Subprimes crisis and is doubled during Sovereign debt crisis. Transmission coefficients in specific variance index are close to unity for Nasdaq proving that volatility shocks do not disappear quickly over time in this market as confirmed by [24].The pre-crisis period is characterized by two-way transmission in average and variance. Variance transmission persists during the global financial crisis but there is one-way transmission (in average) from Nasdaq. The third sub-period records unidirectional transmission in average and variance from German market only .UK stock market is becoming more mature as the coefficient A (2.2) decreases from one period to another. A bidirectional variance (at the 10% level) is detected during the pre-crisis period. Financial crisis highlights a two-way transmission on average and a significant transmission (at the 5% level) from Nasdaq to United Kingdom (8.52%). During the Sovereign debt crisis, we are seeing a bidirectional transmission on average (at 1% level) and variance. The own volatility-effect B (1, 1) and B (2.2) are high highlighting the persistence of the shock in both markets. For Global Dow, no transmission is detected during the pre-crisis but during Subprimes crisis, there is a significant transmission from Nasdaq (-39.43%) and bidirectional in variance. Post-financial crisis reveals bidirectional transmission as well on average as variance. The own-volatility spillover effects of Hangseng drops from one period to the other showing that open economies have significantly low volatility. According to investigations of [25], we confirm that Hong Kong as an international financial center has a sophisticated trading system and a transparent accounting information which reduces the information asymmetry's problems for foreign investors. Hong Kong's stock market transmits the volatility slightly. During financial turbulence, there is a bidirectional transmission in average (91.47% for Nasdaq and -9.82% for Hong Kong) and in variance (-13.49% for the former and 14.68 % for the second). It persists during European crisis. The transmission's direction between Japanese and American market highlights that coefficients are relatively low and are not significant during the financial crisis. Note that for Nasdaq, own variance transmission coefficients are close to unity: US market is more influential than the Japanese. Cross-volatility coefficients' analysis reveals that during quiet period, there is a bi-directional transmission on average but low one-way variance (6.95%) from US market to the Japanese. Financial crisis involves a bidirectional communication between the US and Japanese markets in contrast to the post-financial crisis period that characterized by absence of volatility transmission. There's no transmission between New York and Chicago during the three sub-periods. Coefficients B (1, 1) and B (2.2) are close to unity which shows that shocks caused by terrorist attacks and financial crisis persist over time. Own coefficient-volatility suggests that China is able to reform its financial system after Subprimes crisis. With financial globalization, the Chinese market is becoming more mature. Unidirectional transmission in average (7.34%) was detected between US and Chinese markets during period of stability. In times of crisis, we are seeing a bidirectional transmission in average (-83.72% from Nasdaq and 6.57% Shanghai). We note a negative transmission in variance (-11.48%) from the Chinese stock market. A unilateral transmission from China to United States was detected without feedback effect during the European debt crisis. S&P500'sanalysis shows a bidirectional transmission (in average and variance) during pre-crisis period while financial crisis is characterized bya one-way transmission variance from Nasdaq to S&P 500. Absence of volatility's transmission characterizes the post-crisis period. Stoxx 600's own volatility is greater than that of Nasdaq. It highlights that past volatility effects are greater in Europe than in the USA. It is consistent with the research of [26] who admit that open economies have significantly lower volatilities. The own variance transmission's coefficient relative to Nasdaq is close to one during the two first sub-periods. A similar result was recorded at the Stoxx 600. Cross-volatility's coefficients show a meaningful transmission (for the two first sub-periods). European debt crisis is marked by a bilateral transmission in variance and a unidirectional one (in average) from Nasdaq.

Table 6. *Estimated coefficients for variances- covariances matrix of bivariate BEKK GARCH (1, 1) model.*

Panel A (pre-crisis period)

	NA NI 1		NA H 1		NA SHA 1		NA SP 1		NA RU 1	
Variable	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif
1. SI{1}	0,026	0,373	0,025	0,260	0,004	0,894	0,023	0,059	-0,020	0,326
2. II{1}	-0,074	0,001	0,049	0,010	0,014	0,359	1,267	0,000	-0,008	0,728
3. Const	0,044	0,002	-0,050	0,000	0,019	0,192	-0,006	0,307	0,032	0,006
4. SI{1}	0,414	0,000	0,052	0,105	0,074	0,001	-0,060	0,001	0,002	0,892
5. II{1}	-0,096	0,001	-0,227	0,000	0,165	0,000	-0,007	0,793	-0,026	0,270
6. Const	0,037	0,019	0,118	0,000	0,022	0,208	0,017	0,075	0,036	0,003
7. C(1,1)	0,000	0,990	0,009	0,429	-0,030	0,001	-0,033	0,000	0,074	0,000
8. C (2,1)	-0,026	0,419	-0,395	0,000	0,204	0,108	0,038	0,000	0,117	0,000
9. C (2,2)	0,331	0,000	0,000	1,000	0,228	0,030	-0,002	0,895	0,000	1,000
10. A (1,1)	0,072*	0,000	0,115*	0,000	0,157*	0,000	-0,343*	0,000	0,275*	0,000
11. A (1,2)	0,507*	0,000	-0,939*	0,000	0,073**	0,012	-0,059**	0,019	0,017	0,658
12. A (2,1)	-0,056*	0,000	0,050*	0,006	-0,004	0,791	-0,019***	0,091	-0,070	0,112
13. A (2,2)	0,344*	0,000	0,924*	0,000	0,675*	0,000	0,174*	0,000	0,214*	0,000
14. B (1,1)	0,995*	0,000	0,980*	0,000	0,985*	0,000	0,934*	0,000	0,968*	0,000
15. B (1,2)	0,069*	0,000	0,036	0,290	0,000	0,962	-0,050*	0,001	0,014	0,267
16. B (2,1)	0,002	0,780	-0,071*	0,002	0,003	0,626	0,027*	0,000	-0,003	0,829
17. B (2,2)	0,552*	0,000	0,003	0,945	0,756*	0,000	0,978*	0,000	0,934*	0,000

Panel A (pre-crisis period) (continue)

	NA G1		NA F 1		NA C 1		NA D 1		NA STX 1	
Variable	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif
1. SI{1}	-0,026	0,455	-0,018	0,537	-0,024	0,368	-0,030	0,285	0,000	0,987
2. II{1}	-0,039	0,455	0,000	1,000	0,025	0,174	0,006	0,834	0,014	0,719
3. Const	0,026	0,044	0,019	0,149	0,016	0,236	0,019	0,157	0,012	0,354
4. SI{1}	0,147	0,000	0,164	0,000	0,208	0,000	0,209	0,000	0,227	0,000
5. II{1}	-0,015	0,650	-0,185	0,000	-0,260	0,000	-0,172	0,000	-0,185	0,000
6. Const	0,047	0,000	0,020	0,053	0,050	0,000	0,038	0,003	0,022	0,023
7. C(1,1)	0,056	0,000	0,034	0,000	-0,033	0,000	0,029	0,005	0,016	0,701
8. C (2,1)	0,077	0,000	0,056	0,001	-0,021	0,584	0,036	0,096	0,054	0,000
9. C (2,2)	0,021	0,269	0,063	0,000	0,057	0,005	0,054	0,000	0,000	1,000
10. A (1,1)	0,228*	0,000	0,141*	0,000	0,155*	0,000	0,118*	0,000	-0,009	0,782
11. A (1,2)	0,030	0,281	-0,032	0,269	-0,256*	0,000	-0,085*	0,001	-0,206*	0,000
12. A (2,1)	-0,042	0,458	0,047	0,171	0,012	0,573	0,064**	0,034	0,354*	0,000
13. A (2,2)	0,261*	0,000	0,329*	0,000	0,589*	0,000	0,334*	0,000	0,329*	0,000
14. B (1,1)	0,979*	0,000	0,990*	0,000	0,986	0,000	0,995*	0,000	0,991*	0,000
15. B (1,2)	0,008	0,345	0,012**	0,050	0,057*	0,000	0,022*	0,000	0,258*	0,000
16. B (2,1)	-0,013	0,573	-0,019***	0,098	-0,003	0,640	-0,018**	0,033	-0,537*	0,000
17. B (2,2)	0,925*	0,000	0,921*	0,000	0,871*	0,000	0,937*	0,000	0,706*	0,000

Panel B (Subprimes Crisis)

	NA NI 2		NA H 2		NA SHA 2		NA SP 2		NA RU 2	
Variable	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif
1. SI {1}	-0,152	0,000	-0,161	0,000	-0,126	0,003	0,013	0,304	-0,199	0,090
2. II {1}	-0,016	0,697	-0,057	0,036	0,034	0,068	1,003	0,000	0,057	0,555
3. Cons	0,054	0,065	0,052	0,058	-0,029	0,389	0,032	0,001	0,038	0,163
4. SI {1}	0,589	0,000	-0,107	0,171	0,153	0,014	-0,080	0,052	-0,162	0,245
5. II {1}	-0,152	0,000	-0,111	0,009	-0,048	0,407	-0,160	0,000	-0,012	0,917
6. Cons	-0,026	0,371	0,011	0,819	0,113	0,033	0,030	0,280	0,023	0,479
7. C(1,1)	-0,003	0,986	0,004	0,928	0,096	0,260	0,199	0,000	0,078	0,006
8. C (2,1)	0,090	0,310	-0,400	0,000	0,401	0,413	0,005	0,861	0,117	0,009
9. C (2,2)	0,149	0,000	0,302	0,000	-0,786	0,003	0,000	1,000	0,075	0,000
10.A (1,1)	0,073	0,276	0,012	0,760	0,162*	0,000	-0,705*	0,000	0,384**	0,011
11.A (1,2)	-0,295*	0,000	0,914*	0,000	-0,837*	0,000	-0,253*	0,010	0,070	0,702
12.A (2,1)	0,168*	0,000	-0,098*	0,000	0,065*	0,005	-0,200*	0,000	-0,119	0,422
13.A (2,2)	0,028	0,608	0,233*	0,000	0,932*	0,000	0,168*	0,000	0,220	0,186
14.B (1,1)	0,915*	0,000	0,940*	0,000	0,947*	0,000	0,106	0,536	0,989*	0,000
15.B (1,2)	0,620*	0,000	-0,134*	0,008	-0,148	0,175	-0,507*	0,000	0,096	0,204
16.B (2,1)	-0,781*	0,000	0,146*	0,000	-0,114*	0,001	0,027	0,161	-0,023	0,661
17.B (2,2)	0,433*	0,000	0,659*	0,000	-0,192*	0,009	0,961*	0,000	0,874*	0,000

Panel B (Subprimes Crisis) (continue)

	NA G2		NA F 2		NA C2		NA D 2		NA STX 2	
Variable	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif
1. SI {1}	-0,103	0,071	-0,071	0,114	-0,086	0,073	-0,112	0,027	-0,064	0,155
2. II {1}	0,011	0,841	-0,050	0,326	-0,023	0,630	0,010	0,839	-0,043	0,380
3. Cons	0,069	0,011	0,050	0,093	0,044	0,077	0,049	0,076	0,046	0,094
4. SI {1}	0,306	0,000	0,345	0,000	0,399	0,000	0,312	0,000	0,378	0,000
5. II {1}	-0,151	0,006	-0,325	0,000	-0,342	0,000	-0,257	0,000	-0,322	0,000
6. Cons	0,040	0,151	0,023	0,424	-0,001	0,977	0,013	0,664	-0,002	0,932
7. C(1,1)	-0,126	0,034	0,075	0,027	0,195	0,000	0,183	0,000	0,130	0,153
8. C (2,1)	-0,022	0,768	-0,045	0,473	0,229	0,000	0,181	0,000	0,210	0,085
9. C (2,2)	0,000	1,000	0,135	0,002	0,000	1,000	0,000	1,000	0,007	0,998
10.A (1,1)	0,025	0,696	0,039	0,486	0,021	0,766	0,177**	0,011	-0,037	0,599
11.A (1,2)	-0,394*	0,000	-0,343*	0,000	-0,389*	0,000	-0,262*	0,000	-0,381*	0,000
12.A (2,1)	0,028	0,523	0,264*	0,000	0,139***	0,051	-0,063	0,471	0,236*	0,002
13.A (2,2)	0,169*	0,000	0,292*	0,000	0,271*	0,000	0,159**	0,018	0,309*	0,000
14.B (1,1)	0,997*	0,000	0,946*	0,000	0,995*	0,000	0,999*	0,000	0,995*	0,000
15.B (1,2)	0,536*	0,000	0,085**	0,032	0,424*	0,000	0,412*	0,000	0,402*	0,000
16.B (2,1)	-0,521*	0,000	0,025	0,673	-0,475*	0,000	-0,435*	0,000	-0,513*	0,000
17.B (2,2)	0,404*	0,000	0,868*	0,000	0,533*	0,000	0,580*	0,000	0,516*	0,000

Panel C (Post- Crisis Period)

	NA NI 3		NA H 3		NA SHA 3		NA SP 3		NA RU 3	
Variable	Coeff.	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif
1. SI {1}	-0,045	0,189	-0,065	0,049	-0,033	0,294	0,031	0,001	-0,253	0,000
2. II {1}	0,002	0,917	0,044	0,149	0,002	0,944	1,057	0,000	0,237	0,000
3. Cons	0,048	0,001	0,048	0,001	0,048	0,000	0,005	0,273	0,056	0,000
4. SI {1}	0,423	0,000	0,028	0,395	0,022	0,473	-0,056	0,057	-0,221	0,000
5. II {1}	-0,084	0,008	0,024	0,455	-0,014	0,635	-0,056	0,134	0,190	0,000
6. Cons	0,014	0,424	0,025	0,081	-0,004	0,832	0,039	0,002	0,055	0,000
7. C (1,1)	0,090	0,000	0,057	0,001	0,044	0,119	0,059	0,000	0,097	0,000
8. C (2,1)	0,054	0,028	0,072	0,000	0,432	0,000	0,003	0,825	0,093	0,000
9. C (2,2)	0,128	0,000	0,000	1,000	0,000	1,000	0,075	0,000	0,040	0,002
10. A (1,1)	0,292*	0,000	0,197*	0,000	0,3050*	0,000	-0,461*	0,000	0,352*	0,000
11. A (1,2)	0,023	0,601	-0,082*	0,005	-0,084	0,103	0,005	0,923	0,074	0,315
12. A (2,1)	-0,035	0,119	-0,175*	0,000	0,129*	0,000	-0,015	0,382	0,000	0,999
13. A (2,2)	0,276*	0,000	-0,219*	0,000	0,050	0,331	0,285*	0,000	0,276*	0,000
14. B (1,1)	0,938*	0,000	0,955*	0,000	0,929*	0,000	0,842*	0,000	0,923*	0,000
15. B (1,2)	-0,016	0,425	0,083*	0,000	0,024	0,491	0,007	0,793	-0,006	0,840
16. B (2,1)	0,011	0,263	-0,110*	0,000	-0,122*	0,006	0,004	0,684	-0,005	0,718
17. B (2,2)	0,930*	0,000	0,955*	0,000	0,574***	0,067	0,944*	0,000	0,935*	0,000

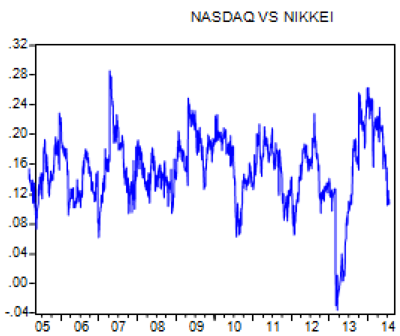
Panel C (Post- Crisis Period) (continue)

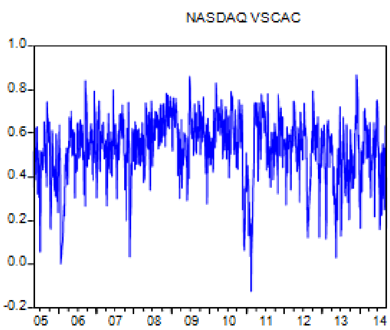
	NA G3		NA F 3		NA C 3		NA D 3		NA STX 3	
Variable	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif	Coeff	Signif
1. SI {1}	-0,103	0,031	-0,076	0,015	-0,040	0,263	-0,100	0,002	-0,071	0,076
2. II {1}	0,077	0,144	0,062	0,111	0,026	0,382	0,055	0,052	0,067	0,113
3. Cons	0,058	0,000	0,058	0,000	0,059	0,000	0,053	0,000	0,060	0,000
4. SI {1}	0,087	0,032	0,238	0,000	0,278	0,000	0,197	0,000	0,251	0,000
5. II {1}	-0,003	0,951	-0,154	0,000	-0,165	0,000	-0,084	0,010	-0,136	0,000
6. Cons	0,032	0,005	0,024	0,029	0,023	0,140	0,040	0,004	0,028	0,020
7. C (1,1)	0,097	0,000	0,093	0,000	0,108	0,000	0,098	0,000	0,101	0,000
8. C (2,1)	0,062	0,000	0,040	0,038	0,044	0,188	0,048	0,006	0,012	0,733
9. C (2,2)	0,018	0,001	0,039	0,101	0,067	0,000	0,062	0,000	0,034	0,510
10. A (1,1)	0,305*	0,000	0,247*	0,000	0,307*	0,000	0,249*	0,000	0,273*	0,000
11. A (1,2)	0,073*	0,004	0,134*	0,000	0,263*	0,000	-0,061	0,305	0,202*	0,000
12. A (2,1)	0,049	0,089	0,111*	0,009	-0,022	0,521	0,116*	0,007	-0,013	0,783
13. A (2,2)	0,217*	0,000	0,248*	0,000	0,189*	0,000	0,301*	0,000	0,172*	0,000
14. B (1,1)	0,938*	0,000	0,904*	0,000	0,834*	0,000	0,945*	0,000	0,818*	0,000
15. B (1,2)	-0,015***	0,090	-0,0837*	0,000	-0,201*	0,000	0,034	0,202	-0,166*	0,000
16. B (2,1)	-0,023***	0,057	0,048**	0,047	0,120*	0,000	-0,035***	0,075	0,194*	0,000
17. B (2,2)	0,962*	0,000	0,987*	0,000	0,993*	0,000	0,932*	0,000	0,997*	0,000

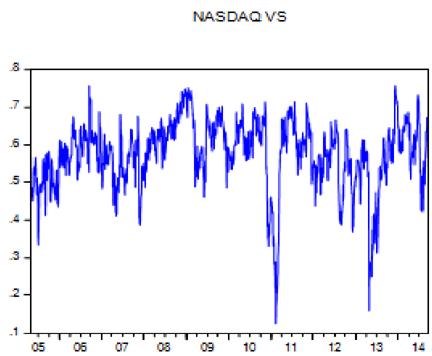
*, ** and *** denote coefficients are significant respectively at 1%, 5% and 10%.

5.2. DCC Results: Graphical Interpretation (Figure 2)

At regional level, we find that Nasdaq and Global Dow are highly correlated during the entire period except towards December 2010 when there was fall of the dynamic correlation reaching the value of -0.20. A very apparent independence characterizes the US indices (Nasdaq-S&P500). January 2009 and July 2013 are characterized by a negative correlation. Chicago demonstrated a strong interdependence with Nasdaq leading to the high correlation between them detected except October-December2010. For Asia, we note that except Japan, neither Hong Kong nor China seems to be interdependent with the US market (a result that is consistent with that found in the previous section bivariate GARCH coefficients BEKK, impulse response functions, variance decomposition and Granger causality test). Dynamic conditional correlations between United States and Japan fluctuated during the studied period without exceeding 0.30. A peak was recorded to the second half of 2007, marking the spread of the Subprimes crisis in Japan. Note that during post-crisis period, these markets are weakly correlated. From July 2013 until September 2014, it appears that this interdependence begins to recover. A separate study of some European indices reveals that American and German indices are strongly correlated to December 2006. They keep this high level until December 2010 to highlight the spread of the Subprimes crisis on Germany. The first quarter of 2011 is characterized by a drop in the correlation (0.12) then there has been an increase from April 2011 until March 2013 highlighting the spread of debt crisis in Europe to the US market. This correlation has dropped in the second quarter of 2013 and stabilized thereafter at 0.75 level. Dynamic conditional correlations between US and Stoxx seems particularly important from July 2006 until December 2007.Nasdaq and Stoxx are highly interdependent until December 2010 to support the spread of the crisis to European markets. Also, from July 2011 December 2012, this correlation was important involving the US market sensitivity to sovereign debt crisis in Europe. American and French markets prove interdependent in that dynamic conditional correlation is very important during Subprimes crisis and that of Europe. From January 2006 until September 2007, a strong dynamic correlation between Nasdaq and UK was marked. It declined towards December 2007 to rise sharply until December 2011 showing the interdependence that characterizes the two markets during the Subprime crisis. We note that the FTSE 100 stock index seems successfully transmit the European crisis to the American market.







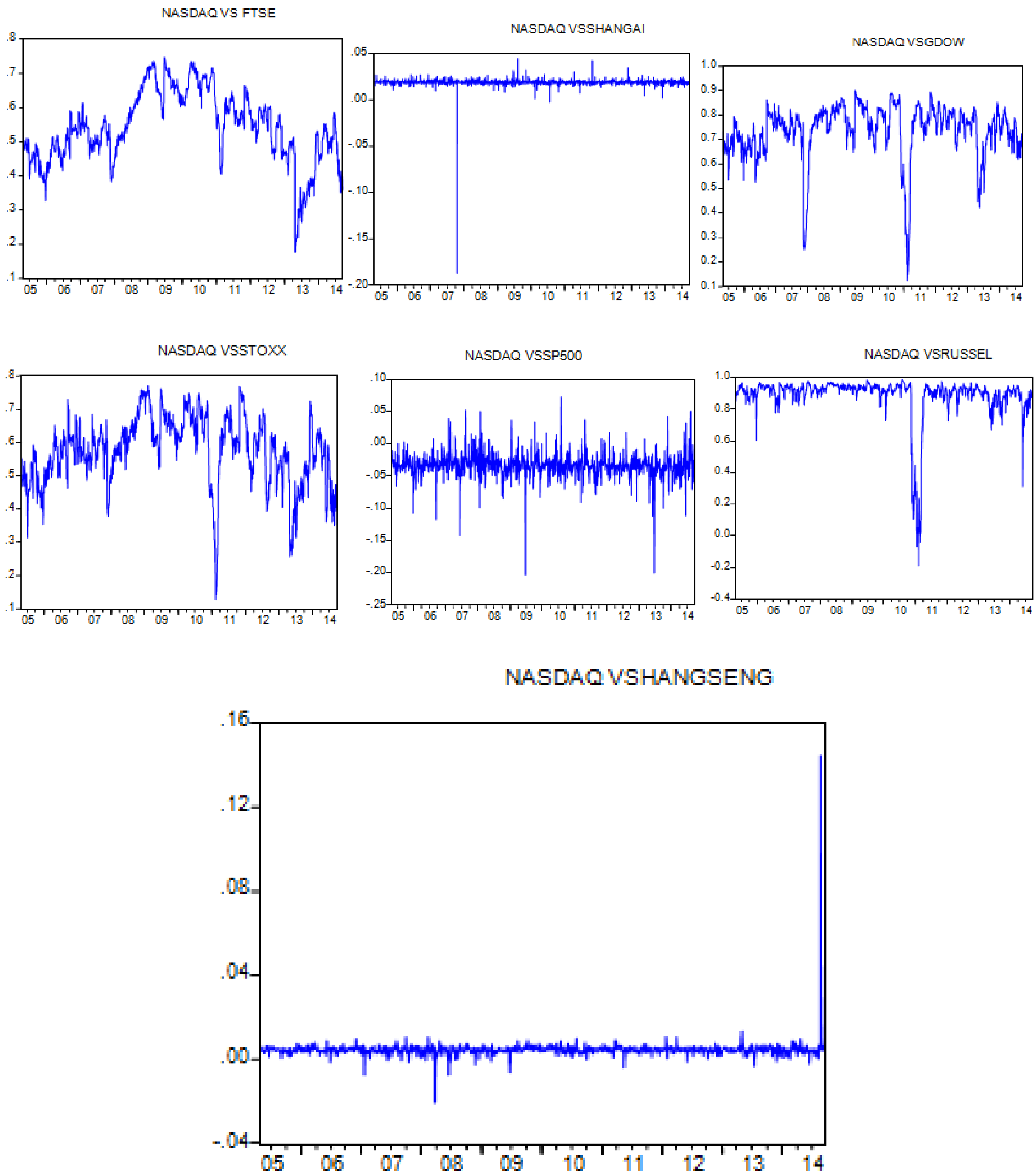


Figure 2. *Dynamic Conditional Correlations' Graphics.*

6. Conclusion

The literature highlights that recent decades have been marked by the phenomenon of financial sectors' deregulation in some countries. Financial system's repressions characterizing recent years have been responsible for placing this new liberalization process which aims to achieve a better financial development. Marked by a succession of financial crises and shocks, this new direction has left doubts about its efficiency and ability to achieve the stated objectives. Financial integration involves the creation of free trade areas, common markets become a reality for the majority of developed countries, emerging and developing. The application of ever increasing integration movement was essentially so as to stimulating investment and strengthening macroeconomic and financial stability. Our investigation involves that during the three sub-periods, no sense of causality is detected between US and Chinese markets. Results show unilateral causality from Nasdaq to European and Japanese markets without feedback effect in quiet period. During the subprimes crisis, a two-way causal direction is detected between Nasdaq and French stock market, and unilateral to UK, Germany, Global Dow and Japan. No sense of causality between Nasdaq and Russell and Hangseng. Post-crisis period is characterized by bidirectional causality between Nasdaq and European markets, Global Dow and S&P500. During this period, Nasdaq managed to cause Hong Kong and Japan. In the pre-crisis period, Nasdaq showed volatility's transmission to European markets, Japan, Hong Kong and China. During global financial crisis, this stock index evidenced bidirectional transmission with Hong Kong, Japan, France and Stoxx 600 indexes. No transmission was detected between New York and Chicago.

During post-crisis period, Nasdaq revealed the stability in the relationship with European stock markets. There is also transmission to China, Hong Kong and Global Dow. Our study has captured interdependencies between the US market and other countries that reinforce particular in times of crisis (there is an increase in Dynamic Conditional Correlations coefficients) justified by the results of Granger causality test, Impulse Responses and Bivariate BEKK GARCH (1, 1) model.

DCC GARCH model has captured the dates of the terrorist attack, the global financial crisis and the European sovereign debt. With applying BEKK GARCH (1, 1) specification, our investigation is consistent with the literature supporting the idea that the US market is responsible for the transmission of volatility. The next article will discuss the multivariate case to highlight the interdependencies between international stock markets belonging to the United States, Europe and Asia. Markov Switching model is of great importance to study the phenomenon of contagion between international stock markets.

References

[1] O. Ratanapakorn and C. Sharma Subhash, "Interrelationships among regional stock indices", Review of Financial Economics (2), pp. 91-108, 2002.

[2] H.Al-Zeaud and S. O. Alshbiel, "Multivariate Volatility and Spillover Effects in Financial Markets Case Study USA and Major European Stock Markets". Interdisciplinary Journal of Contemporary Research Business, 4(6), 901 – 911, 2012.

[3] L. Baele, "Volatility Spillover Effects in European Equity Markets," Journal of Financial and Quantitative Analysis 40, 373-401, 2005.

[4] W.J. Granger, B.N. Huang and C.W. Yang, "Stock prices and Exchange Rates: Evidence from Recent Asia Flu". Department of Economics, UCSD, 1998.

[5] R. Bhar and B. Nikolova. "Return, Volatility Spillovers and Dynamic Correlation in the BRIC Equity Markets: An Analysis Using a Bivariate EGARCH Framework". Global Finance Journal, 9(3), 203 – 218, 2009.

[6] N. Bodkhe, B. Kamaiah andP. Sakthivel, "Correlation and Volatility Transmission across International Stock Markets: A Bivariate GARCH Analysis". International Journal of Economics & Finance, 4(3), 253 – 264, 2012.

[7] C. Chang, M. McAleer and R. Tansuchat, "Conditional Correlations And Volatility Spillovers Between Crude Oil And Stock Index Returns." North American Journal of Economics and Finance, 2012.

[8] KJ. Forbes, and R. Rigobon, "No contagion, only interdependence: Measuring stock market comovements". Journal of Finance, 57, 2223–2261, 2002.

[9] M. Pan, K. Chan and D. Wright, "Divergent expectations and Asian financial crisis of 1997",Journal of Financial Research, Vol 24, pp. 219–238, 2001.

[10] S. A. Tuluca, and B. Zwick, "The effects of the Asian crisis on global equitymarkets",The Financial Review, Vol 36, pp. 125–141, 2001.

[11] B.Gebka, and D. Serwa, "Intraand inter-regional spillovers between emerging capital markets around the world". Research in International Business and Finance, 21(2), 203–221, 2007.

[12] J. Chen, C. Huang and al, "Information Effects During the U.S. Subprime Crisis: Evidence from the Asia-Pacific Region", Journal of Emerging Markets Finance & Trade, Vol 1, pp. 75-87, 2010.

[13] A. Ng, "Volatility spillover effects from Japan and the US to the Pacific-Basin". Journal of International Money and Finance, Vol 2, pp. 207-233, 2000.

[14] A. Worthington and H. Higgs, "Transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis". International Journal of Finance & Economics, Vol 1, pp. 71-80, 2004.

[15] H. Li, "International linkages of the Chinese stock exchanges: a multivariate GARCH analysis", Applied Financial Economics (4-6), 2007.

[16] Y. Baba, R.F Engle, D. Kraft and K. Kroner, "Multivariate simultaneous generalized ARCH", University of California, San Diego, 1990.

[17] G. Corsetti, M. Pericoli and M. Sbracia, "Some Contagion, Some Interdependence: MorePitfalls in Tests of Financial Contagion", Journal of International Money and Finance, Vol 24, pp.1177-1199, 2005.

[18] T.C. Chiang, B.N. Jeon and H.Li, "Dynamic correlation analysis of financial contagion: Evidence from Asian markets", Journal of International Money and Finance, pp. 1206-1228, 2007.

[19] M.N. Syllignakis and G.P. Kouretas, "Dynamic Correlation Analysis of Financial Contagion: Evidence from the Central and Eastern European Markets", International Review of Economics & Finance, pp. 717–732, 2011.

[20] J.HCho and A.M Parhizgari,"East Asian Financial Contagion Under DCC GARCH", The International Journal of Banking and Finance, Vol.6, pp. 17-30, 2008.

[21] A. C. Johansson andC. Ljungwall, "Spillover effects among the greater China stock markets". World Development, 37(4), 839-851, 2009.

[22] K. Mukherjee and R. K. Mishra, "Stock Market Integration and Volatility Spillover: India and its Major Asian Counterparts". Research in International Business and Finance, 24(2), 235-251, 2010.

[23] P.Singh, B. Kumarand A. Pandey, "Price and volatility spillover across North American, European and Asian stock markets". International Review of Financial Analysis, 19, 55-64, 2010.

[24] A. Fernandez-Izquierdo and A. Lafuente Juan, "International transmission of stock exchange volatility: Empirical evidence from the Asian Crisis", Global Finance Journal, pp. 125-137, 2004.

[25] X. Zhang, F. Zhao and al, "Spillover effect between Shanghai, Shenzhen and Hong Kong stock market: A comparative analysis based on through train of Hong Kong stock", 2009 International Conference on Management Science and Engineering.

[26] G.M. Caporale, N.Pittis, and N. Spagnolo, "Volatility transmission and financial crises". Journal of Economics and Finance 30 (3), 376-390, 2006.