Information Spillover Effect Changes of Major Financial Markets: Evidence from the 2015 Chinese Stock Market Crash

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ABSTRACT

This study investigates how the 2015 stock market crash in China affects the characteristics of information spillover among China, Hong Kong, and the United States. The VAR-BEKK-GARCH and DCC-MGARCH models are employed to confirm the changes. Results show that the 2015 crash strengthens both mean and volatility spillover transmitted from the Chinese stock market to others. The dynamic conditional correlations between stock markets rise significantly after the crash. These findings provide reference for financial authorities to well prevent domestic financial markets from being affected by international risk spillovers, and help investors to adopt profitable strategies

Keywords: *Information spillover, stock market crash, VAR-BEKK-GARCH, DCC-MGARCH*

1. INTRODUCTION

With the progress of economic integration and information technology, international financial markets are closely connected to each other. However, when systematic risk events happen in one country, they would be transmitted to other economies with the "contagion" effect, resulting in market turbulence and even the crash of the financial system.

In the mid of June 2015, the Chinese stock market experienced a historic plummet.Few studies examine the spillover effect change after the 2015 stock market crash. Does the 2015 crash lead to contagion effect on global economies? Does the crash alter the direction of risk transmission? How does the information spillover work across countries after the crash? The address of the questions above would contribute to the prevention of financial turbulence as well as the establishment of a healthy and open market.

2. LITERATURE REVIEW

Early research on information spillover focuses on the linkage relationship between stock markets in developed countries. Many studies have reached a consistent conclusion on the dominance of the US stock market in the global financial market. The movement of one single foreign stock market cannot significantly explain the changes in the US stock market (Eun and Shim, 1989; Soydemir, 2000)[1]. The research of Tsai (2014) shows that the spillover effect of the US stock market on other markets presents asymmetry and is significantly related to market fear sentiment.[2] Later, as emerging markets become the new focus of investment, many researchers are concerned about the contagious effects of systemic risks and the spillover effects of extreme risk events (Zhou et al., 2018). Soydemir (2000) verifies that the comprehensive impact of emerging markets on the US stock market is statistically significant, and that the transmission speed of information spillover in emerging markets is related to their economic structures. Lean and Teng (2013) adopt the DCC-MGARCH model to analyze the impact of the United States, Japan, China, and India on the Malaysian stock market.[3] They find that the process of financial integration between the Chinese and Malaysian markets could be traced back to April 2004, and that the volatility spillover effect of the US on the Malaysian market tends to disappear.

Regarding the empirical research on global stock market information spillover, the methods adopted in the existing literature mainly include the following: (1) Granger causality test. The traditional Granger causality test method is based on the time-invariant model and cannot capture the dynamic behaviour of the time series. Hong et al. (2009) proposed a generalized causality test method based on the cross-correlation coefficient CCF, which reflects the cumulative effect of financial market linkage and the long memory effect by assigning corresponding weights to the information of the lag period in the financial market.[4] Billio et al. (2012) propose the Dynamic Causality Index (DCI) based on the Granger Causality Network to analyze risk dynamics more effectively[5]. (2) GARCH family model. The heteroscedasticity modelling method adopted by the GARCH family models introduces the concept of time-varying conditional volatility when describing the clustering phenomenon of security volatility. The standard empirical methods mainly include DCC-MGARCH(Engle,2002) and AR-BEKK-GARCH (Engle and Kroner, 1995). Forbes and Rigobon (2002) point out that using conditional correlation coefficient to estimate the contagion effect between stock markets will cause coefficient bias, because correlation coefficients are conditional on market volatility. [6]Almeida et al. (2018) verify the effectiveness of the DCC-MGARCH model in low-volatility samples.[7] (3) Copula model. Embrechts et al. (2002) prove the mixed Copula theory can capture the nonlinear and asymmetric relationship between sample indices. [8]

3. METHODOLOGY

3.1. Vector Autoregressive Model

We use the vector autoregressive (VAR) model to capture the possible occurrence of the mean spillover effect of each market index. The Granger causality test is chosen to determine the causality connection among the return rate of three market indexes. The mean equation is more useful for identifying and characterizing the correlation between market returns, which is shown as follows.

$$R_{n,t} = \beta_{i,0} + \sum_{j=1}^{k} \beta_{1,n,j} * R_{1,t-j} + \sum_{j=1}^{k} \beta_{2,n,j} * R_{2,t-j} + \sum_{j=1}^{k} \beta_{3,n,j} * R_{3,t-j} + \varepsilon_{n,t} \quad (n = 1,2,3)$$

$$\varepsilon_t = \left(\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}\right) \quad \varepsilon_t | I_{t-1} \sim N(0, H_t)$$

$R_{1,t}$, $R_{2,t}$ and $R_{3,t}$ each represents the return rate of HK index, CSI300 index and S&P500. The standardized residual term ε_t of the mean equation satisfies the N(0, H_t) distribution under the information set I_{t-1}. H_t is the 3×3 order conditional variance-covariance matrix of ε_t. We choose the optimal lag order (k) based on multiple standards, such as AIC, BIC, and LR, while $\beta_{m,n,j}$ is chosen based on the result of the Granger causality test. The criterion for assessing the mean spillover effect is to evaluate whether $\beta_{m,n,j}(m \neq n, j = 1,2,\ldots,k)$ equals 0. Supposed that all $\beta_{1,2,j}$ are insignificant statistically 0, it shows that the mainland stock market has no mean spillover effect on the HK stock market.

3.2. BEKK-GARCH Model

We adopt the BEKK-GARCH model of Engle and Kroner (1995) to obtain in-depth information on the volatility spillover effect of various market indexes.[9] The quantitative nature of the model avoids the problem of the non-positive definiteness of the covariance matrix in optimization. Another advantage of the model is that it allows the conditional variance and covariance of the return to affect each other and no need to estimate too many parameters.

More importantly, the BEKK model provides a variance equation based on the residual matrix, as shown in the following equation:

$$H_t = C'C + \sum_{i=1}^{k} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{i=1}^{k} G_i' H_{t-i} G_i$$

C is a 3×3 order upper triangular matrix, A_i and G_i are both 3×3 order parameter matrices. The diagonal elements in A_i and G_i, denoted by $a_{m,n}$ and $g_{m,n}$, reflect the impact of the lagging residual squares and lagging volatility of each market itself on the current volatility. If the diagonal elements are not statistically significant, there are no ARCH and GARCH effects in themselves. The variance equation of the three-variable GARCH-BEKK (1,1,1) model is as follows.

$$H_t = \begin{bmatrix} H_{11,t} & H_{12,t} & H_{13,t} \\ H_{21,t} & H_{22,t} & H_{23,t} \\ H_{31,t} & H_{32,t} & H_{33,t} \end{bmatrix}$$

$$= \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix}$$

$$+ \begin{bmatrix} a_{11,t} & a_{12,t} & a_{13,t} \\ a_{21,t} & a_{22,t} & a_{23,t} \\ a_{31,t} & a_{32,t} & a_{33,t} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} & \varepsilon_{2,t-1} & \varepsilon_{3,t-1} \end{bmatrix} \begin{bmatrix} a_{11,t} & a_{12,t} & a_{13,t} \\ a_{21,t} & a_{22,t} & a_{23,t} \\ a_{31,t} & a_{32,t} & a_{33,t} \end{bmatrix}$$

$$+ \begin{bmatrix} g_{11,t} & g_{12,t} & g_{13,t} \\ g_{21,t} & g_{22,t} & g_{23,t} \\ g_{31,t} & g_{32,t} & g_{33,t} \end{bmatrix}' \begin{bmatrix} H_{11,t-1} & H_{12,t-1} & H_{13,t-1} \\ H_{21,t-1} & H_{22,t-1} & H_{23,t-1} \\ H_{31,t-1} & H_{32,t-1} & H_{33,t-1} \end{bmatrix} \begin{bmatrix} g_{11,t} & g_{12,t} & g_{13,t} \\ g_{21,t} & g_{22,t} & g_{23,t} \\ g_{31,t} & g_{32,t} & g_{33,t} \end{bmatrix}$$

The non-diagonal elements of A_i, which are denoted by $a_{m,n}$ (m≠n), assess whether and how the volatility of market m influences market n. The elements of G_i, which are denoted by $g_{m,n}$ (m≠n), capture the persistence of volatility transmission between market m and market n. If the results show $a_{m,n}$=0 and $g_{m,n}$=0, the conditional variance of market n is only affected by its residual and the conditional variance of the previous period, so there is no volatility spillover effect of market m. If $a_{m,n} \neq 0$ or $g_{m,n} \neq 0$, it indicates that market m has a volatility spillover effect on market n.

3.3. DCC-MGARCH Model

The traditional CCC-MGARCH model assumes that the correlation coefficient between two different random components is a constant, which has significant limitations in practice. This paper adopts the DCC-MGARCH model proposed by Engle (2002), which constructs a time-varying conditional correlation coefficient matrix and is widely utilized in quantitative analysis.[10]

The DCC-MGARCH model decomposes the covariance matrix H_t into a diagonal matrix D_t with the conditional variance of the univariate GARCH process as the diagonal element and a time-varying conditional correlation matrix R_t.

$$H_t = D_t R_t D_t$$

$$D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \sqrt{h_{33,t}}\right)$$

$$h_{ii,t} = \tau_i + \sum_j^k \theta_i \varepsilon_{i,t-j}^2 + \sum_j^k \varphi_i h_{i,t-j}$$

R_t is decomposed into a 3×3 symmetric positive definite matrix Q_t and a diagonal matrix with $\sqrt{q_{ii,t}}$ as the diagonal element.

$$R_t = diag\left(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, \sqrt{q_{33,t}}\right) Q_t diag\left(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, \sqrt{q_{33,t}}\right)$$

Q_t is the conditional covariance matrix of the error terms, whereas $\bar{Q}$ is the unconditional covariance matrix of the standardized errors matrix. ε_t is the standardized residual terms.

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta Q_{t-1}$$

The parameter α indicates the impact of a lagging period of the standardized residual on the dynamic correlation coefficient matrix, while β reflects the persistence characteristics of the correlation. The equation satisfies the constraint conditions of α+β<1, α>0 and β>0.

$$L_t(\theta|I_{t-1}) = -\frac{1}{2}\left(-nln(2\pi) + ln|D_t R_t D_t| + \varepsilon_t' D_t^{-1} R_t^{-1} D_t^{-1} \varepsilon_t\right)$$

$$u_t = D_t^{-1}\varepsilon_t$$

In the process of solving unknown parameters by maximizing the log-likelihood value $L(\theta)$, we decompose the log-likelihood function value into the fluctuation part $L_v(\theta)$ and the correlation part $L_c(\theta)$.

$$L(\theta) = \sum_t L_t(\theta|I_{t-1}) = L_v(\theta) + L_c(\theta)$$

$$L_v(\theta) = -\frac{1}{2}\sum_t \left(nln(2\pi) + ln|D_t|^2 + u_t' u_t\right)$$

$$L_c(\theta) = -\frac{1}{2}\sum_t \left(ln|R_t| + u_t' R_t^{-1} u_t - u_t' u_t\right)$$

We firstly estimate the univariate GARCH model of the return rate of the single market stock index and further estimate the dynamic conditional correlation coefficient matrix based on the standardized residual ε_{t-1} estimated in the previous step.

4. EMPIRICAL RESULTS

4.1. Data description

This article utilizes the daily Shanghai Shenzhen CSI 300 Index (CSI300), Hang Seng Index (HSI) and Standard & Poor 500 Index (SP500) as the representatives of Chinese, Hong Kong and the US stock market, respectively. The sample period is from January 4, 2013 to December 28, 2018, where June 12, 2015 is adopted as a demarcation to divide the sample into two subsamples (before and after the stock market crash). Such division enables us to investigate whether the interaction relationship changes during the crash and whether the crash has a contagion effect on international markets. Stock return is calculated through the log difference of ending prices (Return = 100*ln(P_t/P_{t-1})). The sample sizes before and after the crash are 558 and 821, respectively. Considering that Chinese and Hong Kong markets basically trade at the same time, and they have a time difference of 12-13 hours from the US, we correspond the overnight US stock return to the next-day Chinese and Hong Kong stock return.

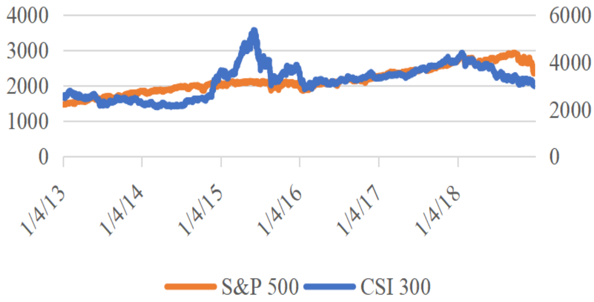

Figure 1 Chinese CSI 300 and US S&P 500 indices (Jan 4, 2013 - Dec 28, 2018)

Table 1 Descriptive statistics

	Mean	Std. dev.	Skewness	Kurtosis	JB stat.	ADF stat.
Panel A: Before crash (2013/1/7 - 2015/6/12)						
CSI 300	0.134	1.500	-0.114	6.171	229.926	-23.433
HSI	0.028	0.973	0.052	4.063	32.902	-22.080
S&P500	0.064	0.717	-0.397	3.857	34.030	-24.360
Panel B: After crash (2015/6/16 - 2015/12/28)						
CSI 300	-0.067	1.196	-0.419	6.998	1519.027	-27.765
HSI	-0.006	1.194	-0.311	6.980	421.149	-28.422
S&P500	0.021	0.905	-0.271	8.351	664.000	-29.028

Figure 1 shows the graphical representations of the Chinese CSI 300 and US S&P 500 indices. During the period, stock markets tend to move in the same direction, especially after August 2015. Table 1 illustrates the descriptive statistics of index returns. China has the highest standard deviation before and after the 2015 crash, reflecting its immaturity as an emerging market. The negative skewness indicates a higher weight on the left tail, and the high kurtosis implies fat-tailed distributions. The Jarque-Bera statistic significantly rejects the null hypothesis of Gaussian distribution. Thus, the DCC-MGARCH and BEKK-GARCH modelling are built with the student T distribution. The augmented Dickey-Fuller statistic rejects the existence of unit root, demonstrating the data series as stationary.

4.2. Results of the BEKK-GARCH model

The VAR model is constructed with the index return, and it shows that one lag is optimal. Table 2 presents the Granger causality test both before and after the stock market crash. We find an increase in the chi statistics, which indicates that stock markets influence each other more dramatically after the 2015 crash. To clarify the pattern of information spillover, we further develop the VAR(1)-GARCH(1,1)-BEKK(1) model with mean and variance equations shown in Table 3 and Table 4, respectively.

Table 2 Granger causality test before and after the 2015 stock crash

Equation	Excluded	Before crash		After crash	
		chi2	P value	chi2	P value
CHN	HK	1.003	0.606	5.403	0.067
	US	2.420	0.298	37.471	0.000
HK	CHN	2.183	0.336	4.437	0.109
	US	46.533	0.000	144.440	0.000
US	CHN	0.790	0.674	2.409	0.300
	HK	0.102	0.950	7.162	0.280

According to the conditional mean equation, China does not receive mean spillover from Hong Kong or the US before the 2015 stock market crash. After the crash, it is significantly affected by the US market changes. Mean spillover from China and the US to Hong Kong is strengthened after the crash with a significant increase in the T-test statistics. In addition, the return of US market is only associated with its past mean performance even after the occurrence of market turbulence, but the coefficients of Hong Kong and China, though still insignificant, deliver a rise in T-test statistics.

Table 3 Conditional Mean Equations of China, Hong Kong and US market

	Before crash			After crash		
	Coefficient	T-Stat.	Prob.	Coefficient	T-Stat.	Prob.
Panel A: Conditional Mean Equation of China						
Constant	9.07E-05	2.548	0.011	5.13E-04	1.356	0.175
CHN_{-1}	0.014	0.275	0.784	-0.010	-0.261	0.794
HK_{-1}	-0.029	-0.459	0.646	-0.027	-0.706	0.480
US_{-1}	0.054	0.710	0.477	0.257	6.255	0.000
Panel B: Conditional Mean Equation of Hong Kong						
Constant	0.000	0.249	0.803	0.001	1.704	0.089
CHN_{-1}	-0.052	-1.789	0.074	-0.050	-2.017	0.044
HK_{-1}	0.060	1.273	0.203	-0.086	-2.726	0.006
US_{-1}	0.375	7.352	0.000	0.500	14.400	0.000
Panel C: Conditional Mean Equation of the United States						
Constant	0.001	2.669	0.008	0.001	3.728	0.000
CHN_{-1}	-0.017	-0.895	0.371	-0.023	-1.443	0.149
HK_{-1}	0.013	0.395	0.693	0.012	0.483	0.629
US_{-1}	-0.036	-0.845	0.398	-0.084	-2.300	0.021

As shown by conditional variance equation, Hong Kong and the US already present significant volatility spillover on China before the crash. If the indices of the US or Hong Kong encounter a negative information shock, Chinese index would suffer a similar fall as well. This trend is more prominent after the occurrence of the 2015 market turbulence, illustrated by the enlarged T-test statistics. Such change also happens in Hong Kong, which is only influenced by its own past volatility before 2015. After the crash, the Hang Seng Index receives spillover from both China and US at the significance level of 1%. Different from the independence of mean performance, the US market is affected by the volatility change in Hong Kong and China both before and after the crash. The dramatic rise of the test statistics reflects the impact of the 2015 turbulence.

Table 4 Conditional Variance Equations of China, Hong Kong and US market

	Before crash			After crash		
	Coefficient	T-Stat.	Prob.	Coefficient	T-Stat.	Prob.
Panel A: Conditional Variance Equation of China						
Constant	1.72E-07	0.227	0.820	4.11E-07	1.307	0.191
CHN_{-1}	7.70E-06	2.424	0.015	2.58E-06	3.653	0.000
HK_{-1}	0.192	4.686	0.000	0.120	6.985	0.000
US_{-1}	0.261	7.563	0.000	0.182	9.438	0.000
Panel B: Conditional Variance Equation of Hong Kong						
Constant	4.02E-06	1.779	0.075	9.04E-07	2.146	0.032
CHN_{-1}	9.65E-07	1.444	0.149	1.17E-06	3.077	0.002
HK_{-1}	1.75E-06	1.834	0.067	6.54E-07	3.098	0.002
US_{-1}	2.67E-06	1.460	0.144	1.39E-06	3.646	0.000
Panel C: Conditional Variance Equation of the United States						
Constant	0.366	5.953	0.000	0.382	10.905	0.000
CHN_{-1}	0.961	90.399	0.000	0.976	271.253	0.000
HK_{-1}	0.848	16.499	0.000	0.909	58.625	0.000
US_{-1}	0.958	50.593	0.000	0.989	300.963	0.000

In summary, as is shown by the result of VAR(1)-GARCH(1,1)-BEKK(1) model, before the 2015 stock market crash, volatility spillover plays the main character in the cross-market interactions. China receives the one-way mean spillover and two-way volatility spillover from the US. Hong Kong accepts unilateral mean spillover from China and the US, and it is only affected by its own past volatility changes. The US market is only affected by its own mean performance, but it has bilateral volatility spillover with China and unilateral effect from Hong Kong. As Chinese stock price falls off the cliff in June 2015, systematic risk is transmitted to international markets, and the spillover effect is strengthened significantly. All three markets present significant two-way volatility spillover among each other, indicating that they are mutually associated in a much closer way and sensitive to global information shock.

4.3. Results of the DCC-multivariate GARCH model

In order to further explore the interaction relationship among the three markets, we build up the DCC-multivariate GARCH(1,1) model with the full sample period in order for the dynamic conditional correlation series. The estimation results are shown in Table 5.

Table 5. DCC-MGARCH coefficient estimation results			
	Coefficient	T-Statistic	P-Value
Panel A: Estimation for China			
α	0.065	5.49	0.000
β	0.928	79.99	0.000
Constant	0.016	2.88	0.004
Panel B: Estimation for Hong Kong			
α	0.040	3.3	0.001
β	0.940	46.23	0.000
Constant	0.023	1.97	0.049
Panel C: Estimation for the US			
α	0.189	5.89	0.000
β	0.781	23.8	0.000
Constant	0.033	3.76	0.000
Panel D: Joint DCC coefficient estimates			
□	0.012	2.43	0.015
□	0.964	53.93	0.000

The Q statistic test is performed on the standardized residual of the model, and results show that there is no autocorrelation and no ARCH effect. α is the coefficient of the lagged standardized residual, reporting the impact of external market change. β is the coefficient of the lagged conditional variance, showing how markets are affected by their past shocks. The sum of the two coefficients reflects the persistence of changes. According to the model estimation, the openness of the US is much higher than the other two markets (α=0.189), while China and Hong Kong are less sensitive to external changes. Furthermore, α is smaller than β in all markets, meaning that the three markets have a strong memory feature on their own past performance. With the sum of coefficients being close to 1, the GARCH model presents solid stationarity (0<α+β<1), and the impact of volatility change would last for a long period. As for the DCC parameters, both $\square_1$ and $\square_2$ are significant at the level of 95%, thereby confirming the time-varying nature of conditional correlation in the three markets.

Figure 2 shows the dynamic conditional correlation among the three markets. During the full sample period, China and Hong Kong have an extremely high correlation of over 0.5, which continues to rise steadily. As the special administrative region of China, Hong Kong acts as a bridge connecting the onshore and offshore financial markets. With the opening of Shanghai Connect in 2014 and Shenzhen Connect in 2016, stock interactions between Mainland China and Hong Kong markets turn to be of much higher frequency and efficiency. With the deep association in politics and economy, the performance of Hong Kong stock market is bound with Mainland China. According to Hong Kong Exchange[11], by the end of 2018, mainland enterprises (including H shares and red chips) have accounted for 60% of total market capitalization. On the other hand, the dynamic conditional correlation between the Hong Kong and the US is much more volatile, basically ranging from 0.15 to 0.5. During the 2015 stock market crash, the correlation rises dramatically and later falls back to the initial level. In June 2016, the correlation reaches the highest level of 0.46. This may be due to the announcement of the United Kingdom's withdrawal from the European Union. The UK is closely associated with both markets, since Hong Kong is its past colony and the US is its traditional ally. The correlation between China and US also experiences a rapid rise with the breakout of the stock market crash and reaches its zenith in September 2015. Even though the two markets have two-way volatility spillover effect after the crash, their correlation is not as strong as the other two pairs and ranges from 0.01 to 0.25. This finding is consistent with Sheu and Cheng (2011) that the Chinese market is relatively more independent from external impact.[12]

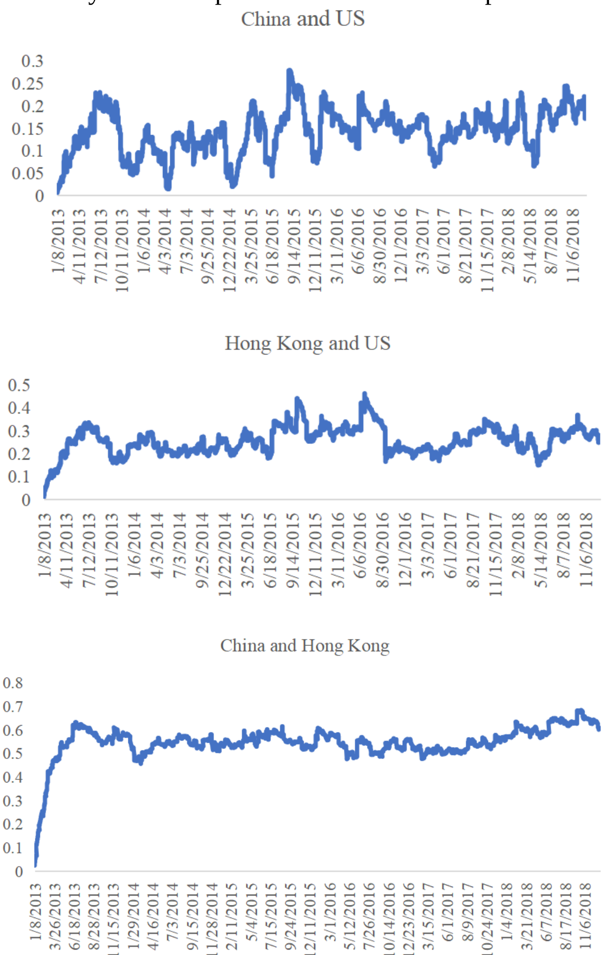

Figure 2 Dynamic conditional correlation among China, Hong Kong and US stock markets

5. CONCLUSION

The most obvious finding that emerged from this study is that China is changing its role on global market from a passive receiver of risk information to an active disseminator. Furthermore, we discuss the dynamic conditional correlation among the three stock markets. As a systematic risk event happens in a country, the downside risk transmitted to international financial markets results in a rapid increase in the correlation between economies. Meanwhile, the changes in volatility spillover caused by the 2015 crash do not finish with the ending of the crisis but continue to influence subsequent market performance.

Taken together, these findings have significant implications for the understanding of how systematic risk events change the information spillover pattern in global financial markets. The insights gained from this study may be of assistance to the financial authorities and transnational investors. Financial authorities can attach more attention to the spillover risk of the macroeconomic policy adjustments of major economies in the world, and avoid the rapid accumulation of potential downside risks. Transnational investors can use the pattern of cross-market risk spillovers to diversify investment portfolio risks or realize risk-free arbitrage.

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