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THE ASYMMETRIC VOLATILITY SPILLOVER AND DYNAMIC CORRELATION ACROSS EQUITY MARKETS IN CHINA AND THE UNITED STATES

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Abstract

This paper aims to study the volatility spillover effects as well as the dynamic conditional correlation between stock market returns in China and the U.S. Firstly, the analysis uses a vector autoregression with a bivariate BEKK-GARCH model to capture the asymmetric volatility transmissions between the two markets during the sample of 1996-2019. Then a VAR-DCC-GARCH model is employed to estimate the dynamic conditional correlation between these two market returns. Finally, linear regression and Granger Causality test are conducted to further explore the effect of the U.S policy rates on such correlation. In order to account for the U.S monetary stances during the unconventional period, a combination of Fed fund rates and Shadow rates developed by Wu and Xia (2016) is used as policy rates. The main empirical results suggest (1) evidence of unidirectional volatility spillover from the U.S. to China market; but no spillover from China to U.S; (2) the dynamics of the conditional correlations from the VAR-DCC-GARCH model exhibit increases in correlation between the stock returns of China and U.S after 2008 financial crisis and recent trade war; (3) a linear regression shows that there is negative relationship between U.S policy rates and the dynamic conditional correlation, with the correlation coefficient r=-0.62. Granger Causality test suggests that the U.S policy rates do cause the change of the conditional correlation but not the other way around.

Keywords

Dynamic, Autoregression, BEKK-GARCH Model, Stock Market, Correlation

I. Introduction

With the globalization and financial liberalization in recent decades, the financial markets around the world become more connected and intertwined than ever before. Among them, the connections between the stock markets in the U.S and China become increasingly important and dominated. As the most developed economy in the world, the stock market of the United States has a huge impact on global stock markets. The subprime mortgage crisis that broke out in the United States in 2007 triggered a global financial tsunami. The global financial crisis has not only caused violent turmoil in the US stock market directly but has also quickly spread to major world stock markets. The S&P 500 Index has fallen by 40% in less than a year. Meanwhile, as the world's second-largest stock market by value, without any domestic financial crisis, the Chinese stock market has also suffered an unprecedented crash. In just one year from October 2007 to October 2008, the Shanghai Stock Exchange Index plummeted from more than 6,100 points to less than 1700 points. On March 23, 2018, U.S. President Trump officially signed a trade memorandum with China, imposing tariffs on goods imported from various industries to China, setting off the first shot of the China-US trade war. The stock market responded quickly to the trade war with huge shocks. The Dow Jones Industrial Average fell nearly 3%, the Standard & Poor's index fell 2.52%, and the Nasdaq index fell 2.43%. It also caused the Shanghai Composite Index to fall by 3.39%. It's obvious that the connections between stock markets in China and the U.S become stronger in the recent decade. Therefore, it's important to understand the dynamic relationship and spillover effects between these two markets.

Specifically, this study focuses on the volatility spillover between stock market returns in China and the U.S, as well as the dynamic correlation between them. More importantly, the effect of the U.S monetary policy on the dynamic correlation has been investigated. The main methodologies employed in this study are the VAR-BEKK-GARCH model and the VAR-DCC-GARCH model. These two models are used for different proposes. The full rank BEKK-GARCH model is conducted to incorporate the asymmetric volatility spillover effect between the two market returns, while the DCC-GARCH model is applied to estimate the dynamic conditional correlation between them. In both models, instead of the normally distributed disturbances, the student-t distribution is assumed. After the estimation of the dynamic correlation, and linear regression and Granger Causality test are employed to explore the effect of the U.S monetary policy on such a time-varying correlation. The combination of the Fed fund rates and Shadow rates developed by Wu and Xia (2016) is used to represent the stances of the U.S monetary policy. It allows the unconventional monetary policy such as QE to be reflected in the rates. The combined rates are shown in figure 1.2.

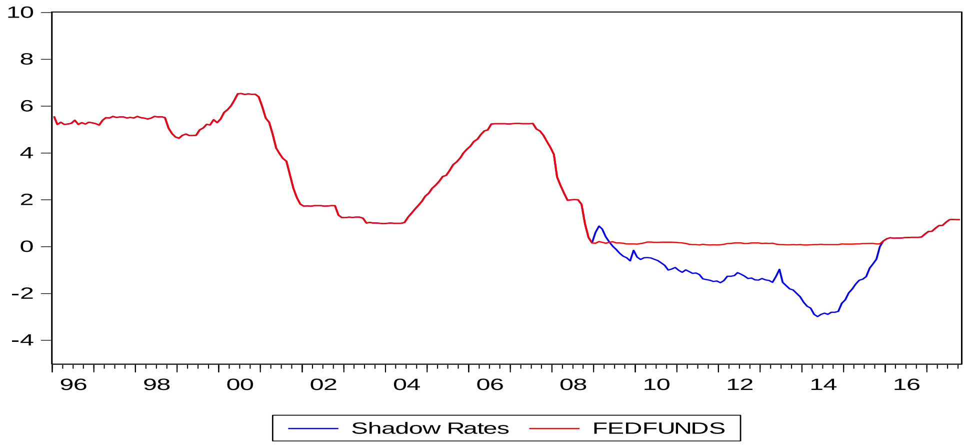


Figure 1.2

The structure of the paper organizes as follows: Section 2 reviews the literature on the studies of volatility spillover effect, the dynamic relationship between different stock market performances, as well as the multivariate GARCH model. Section 3 describes the data. Section 4 describes the multivariate GARCH methodologies used in the study. Section 5 explains the empirical results, and Section 6 concludes.

II. Literature review

Some early scholars focused on the relationship between financial markets in developed countries. For example, Hamao, Masulis, and Ng (1990) studied the spillover effect between the US stock market and the Japanese stock market based on the ARCH model and found that there was a one-way volatility spillover effect from New York to London and Tokyo, from London to Tokyo. Theodossiou and Lee (1993) used the GARCH-M model to study the volatility spillover effects among US, British, Canadian, German, and Japanese stock markets and found that the volatility spillover effect has spread from the US stock market to all four stock markets, from the British stock market to the Canadian stock market, From the German stock market to the Japanese stock market. Similarly, Koutmos (1995) used the asymmetric multivariate EGARCH model to analyze the volatility spillover effects between the three international financial centers in New York, London, and Tokyo. The analysis conclusions confirmed the asymmetry of risk transmission between the three major markets. In addition to the typical spillover effects between the three major financial centers, there is also a significant asymmetry. When a negative impact occurs, the volatility spillover effect is more significant than the positive impact. Karolyi (1995) used the binary GARCH model to study the time-varying characteristics of volatility spillover effects and correlations between two mature capital markets in the United States and Canada. Empirical results show that the characteristics of volatility spillovers as well as correlations are not static but change over time. In the early 1980s, there was a significant volatility spillover effect between the capital markets of the two countries, and in the late 1980s, the volatility spillover effect was no longer obvious between the capital markets of the two countries. Athanasios et al. (2009) used the GARCH-BEKK model to study the volatility and error spillover effects of the three major financial regions in Europe through cross-listed companies in the stock markets of various countries and identified the main volatility spillovers and main volatility exporters in each region. Angkinand, Barth, and Kim (2010) used the structural vector autoregressive framework to explore the spillover effects of the US financial crisis on many advanced economies. Their results show that when a crisis occurs, the interdependence of developed markets increases significantly. Huang (2011) also studied the volatility spillover effect between the US stock market and the Japanese stock market based on the wavelet and GARCH-BEKK model and found that the return rate and volatility spillover direction and size change with time. Ibrahim and Brzeszczynski (2014) studied the volatility spillover effect between international markets with the background of the financial crisis and found that the volatility spillover effect is mainly concentrated on the information transmission of the largest developed stock markets.

With the development of emerging markets, the role of emerging markets has become more and more important, and economists have begun to shift their focus from developed markets to emerging markets. Chordhury

(1994) selected daily return data of stock markets in the United States, Japan, and other emerging countries in Asia, and studied the correlation between volatility through impulse response and variance decomposition. It is found that the trend of the US stock market can lead to changes in other emerging stock markets in Asia such as Japan, South Korea, and other countries. Gualielmo, Nikitas, and Nicola (2006) studied the changes in the spillover effects of Asian, European, Japanese, and US stock markets before and after the Asian financial crisis in 1997 based on multivariate GARCH-BEKK, and found that the volatility relationship between countries was transmitted in two directions before the crisis, and After the crisis, there was a one-way spillover from the crisis country to other countries. Francies and Kamil (2009) used the VAR model to construct the spillover index, studied the volatility spillover effects among the stock markets of 19 countries in the United States, the United Kingdom, France, Germany, and Asia, and found that the spillover effects between stock markets in different countries were different in different periods. Also, Yilmaz (2010) investigated the extent of the spread of Southeast Asian stock markets and found that there is a direct volatility spillover relationship between their stock markets through the analysis of the variance of stock returns. Beirne, Caporale, Schulze, and Spagnolo (2013) explored the volatility spillover effects of 41 markets in Asia, Europe, Latin America, the Middle East, and North Africa by applying the three-variable VAR-GARCH model, and found that Europe is the main transmitter of volatility spillovers. And it has the largest impact in Asia, while Latin America and the Middle East have regional spillover effects. Abbas and Ali (2013) investigated the transmission of volatility between Asian regional stock markets (Pakistan, China, India, and Sri Lanka) and three regional and developed stock markets (US, UK, and Singapore). These scholars have found that countries with closer economic ties in different regions have more pronounced volatility spillover effects. Bekiros (2014) studied the volatility impact of the BRIC markets in the US financial crisis and the subsequent euro debt crisis and found that after these crises, almost four markets have become more international. Walid et al. (2016) investigated the spillover effects between the US market and the five most important emerging stock markets, namely the BRICS (Brazil, Russia, India, China, and South Africa) based on the DCC-GARCH model. The empirical results confirm dynamic Correlation and asymmetry of volatility spillover between Brick Country Stock Markets and U.S markets. Yin and Liu (2017) also used dynamic conditional multiple generalized autoregressive conditional heteroscedasticity (DCC-MVGARCH) to analyze the volatility spillover effects of 51 stock indexes in four regions of the Americas, Europe, Asia-Pacific, and Africa and found that the financial crisis has promoted and strengthened the conditional correlations in the short term, and the European stock market is the information dissemination hub of the global stock market. Most recently, Saqib Gulzar, Ghulam Mujtaba Kayani, Hui Xiaofeng, Usman Ayub & Amir Rafique (2019) use VECM-BEKK-GRACH model to examine the financial cointegration and spillover effect of the global financial crisis to emerging Asian financial markets (India, China, Pakistan, Malaysia, Russia, and Korea) and find that a shock in the U.S. financial market has a short-term impact on the returns of emerging financial markets while the past shocks and volatility have more effect on the selected stock markets.

The spillover effects of the Chinese stock market and other markets are mainly studied by Chinese scholars. Wang Yuanlin (2011) used the GARCH-BEKK model to conduct empirical research on the volatility spillover effect between China's stock market and major international stock markets. It is found that there is a one-way volatility spillover effect between the SSE Composite Index, the S & P 500 Index, and the Nikkei 225 Index, while a two-way volatility spillover effect exists between the SSE Composite Index and the Hong Kong Hang Seng Index. Mohammadi and Tan (2015) examined the dynamics of daily returns and volatility in stock markets of the USA, Hong Kong, and mainland China over January 2001 to February 2013 employing a multivariate GARCH-types model (DCC-GRACH and BEKK-GARCH). Their results confirmed that there existed the unidirectional spillover in returns and volatility from the US to the other three markets, while correlations between mainland China and other markets were relatively significant. The patterns of dynamic conditional correlation from the DCC model suggest a modest increase in conditional correlation between China and the other stock markets since the financial crisis. Rui and Ahmed (2017) conducted a study of Hong Kong and Shanghai stocks and markets and found that the volatility spillover effect from Shanghai to Hong Kong increased significantly after the Shanghai-Hong Kong Stock Connect. Emawtee, Robert, and Wei (2018) studied the size and transmission channels of volatility spillover effects between different industries in the United States, China, and Australia, and found that most industries have two-way volatility spillover effects. Spillover effects are becoming increasingly apparent. Li An, Chen Meilin and Qiao Haishu (2016) studied the impact of China's stock market reform on the United States, Britain, Germany, and France in developed markets, as well as on the BRICS stock markets by constructing the MGARCH-BEKK model in stages, and mainly explored its volatility Spillover and shock transmission effects have found that the impact of China's stock market on developed markets is still weak, while the volatility spillover effect on emerging markets is more significant. Liang Qi, Li Zheng, Hao Xiangchao (2015) Based on the perspective of multidimensional information spillovers, they studied the linkage of stock markets in 17 countries around the world and the international integration of Chinese stock markets and their risk transmission. They measured the direction of information spillovers in Chinese stock markets. The study found that no matter the overall spillover between the sample stock markets or the directional spillover of the Chinese stock market, there were significant differences in the dynamic characteristics of yield and volatility spillovers. Zheng Haoyang (2018) examined the mean spillover effect, impulse response, and volatility spillover effect between China, Japan, and South Korea stock markets from two perspectives: linear and nonlinear. It is found that the Korean stock market has a significant one-way mean spillover effect on the Chinese and Japanese stock markets but there is a two-way mean spillover effect between China and Japan. According to volatility, there is a one-way fluctuation spillover effect between the Korean stock market and the Chinese stock market while there is a significant two-way fluctuation spillover effect between China and Japan. Zhou Kaiguo and Yang Haisheng (2018) analyzed the stock markets in the Asia-Pacific region and found that in the past 20 years, with the continuous increase in financial cooperation in the Asia-Pacific region, the dynamic correlations among the stock market in the Asia-Pacific region has increased. By employing the VAR-BEKK-GARCH model, Ngo Thai Hung (2018) finds that that the volatility of the Chinese market has had a significant impact on the other markets in Southeast Asia (Vietnam, Thailand, Singapore, and Malaysia).

In terms of the causes and mechanism of such volatility spillovers and dynamic conditional correlations, some studies focus on the effect of macroeconomic variables. Robert and Wang (1998) find that the variation of the dynamic correlations among the U.S, U.K, and Japan could be explained by the relative monetary policy, inflations, GDPs and employment. Flavin (2002) uses the gravity model to study the effect of the countries' market caps and locations on their correlation and finds that the location (board sharing or not) is an important factor. Pretorius (2002) studies the effect of macroeconomic factors on the dynamic correlations among stock markets in developing countries and concludes that the closer the counties' GDP growth, exchange rate and interest rate, the higher the correlations. Shipeng Zhou (2015) employs the MGARCH type model to find that globalization has increased the volatility spillovers as well as dynamic correlations among stock markets in different countries.

III. Data

The empirical work in this study requires monthly data on stock prices for The Shanghai Stock Exchange Composite Index (SSE) and the S&P 500 index (SPY). The price data of both indexes are from the Yahoo Finance website. These are two widely used indexes to represent the overall stock market prices in China, and U.S. Federal Funds Rate and Shadow Rate proposed by Wu and Xia (2016) are used to represent the monetary policy stances of the U.S. Since Greenspan adjusted the real interest rate as the main tool for macroeconomic regulation and control in 1993, the federal funds rate has continued to be the main instrument of U.S monetary policy. However, during the period after 2007-2008 Global Financial Crisis, specifically from December 16, 2008, to December 15, 2015, the effective federal funds rate is below 25 basis points, and the Fed has implemented several unconventional monetary policies. To catch such effect, We use the shadow rate constructed by Wu and Xia (2016) as a replacement of the effective federal funds rate during the times when the unconventional monetary policy is implemented. Importantly, the Wu-Xia shadow rate allows the policy to drop below zero and whenever it is above 1/4 percent, it is exactly equal to the effective federal funds rate by construction.
Unit roots in each stock index are tested using the augmented Dickey-Fuller test. The results suggest that all log prices are non-stationary in level, but stationary in first-difference. Thus, we work with monthly returns, which are obtained as the first difference of the natural logarithm of the prices.

$$R_{i,t} = [\log(P_{i,t}) - \log(P_{i,t-1})]$$

Figure 3.1 shows the log return of both markets. (represented by SSE and SPY)

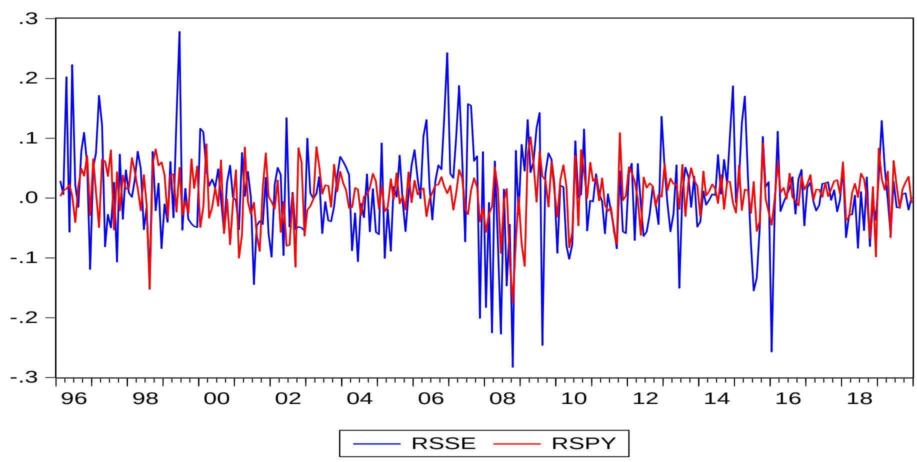


Figure 3.1

The summary statistics of both return series are shown below in Figure 3.2. The main results are: (1) Average monthly returns are positive with SSE at 0.58% and SPY at 0.71%. (2) SSE exhibits more volatility than the SPY, as reflected in standard deviations. (3) Both return series have negative skewness, which implies more negative change than the positive one. (4) Both return series exhibit the excess kurtosis.

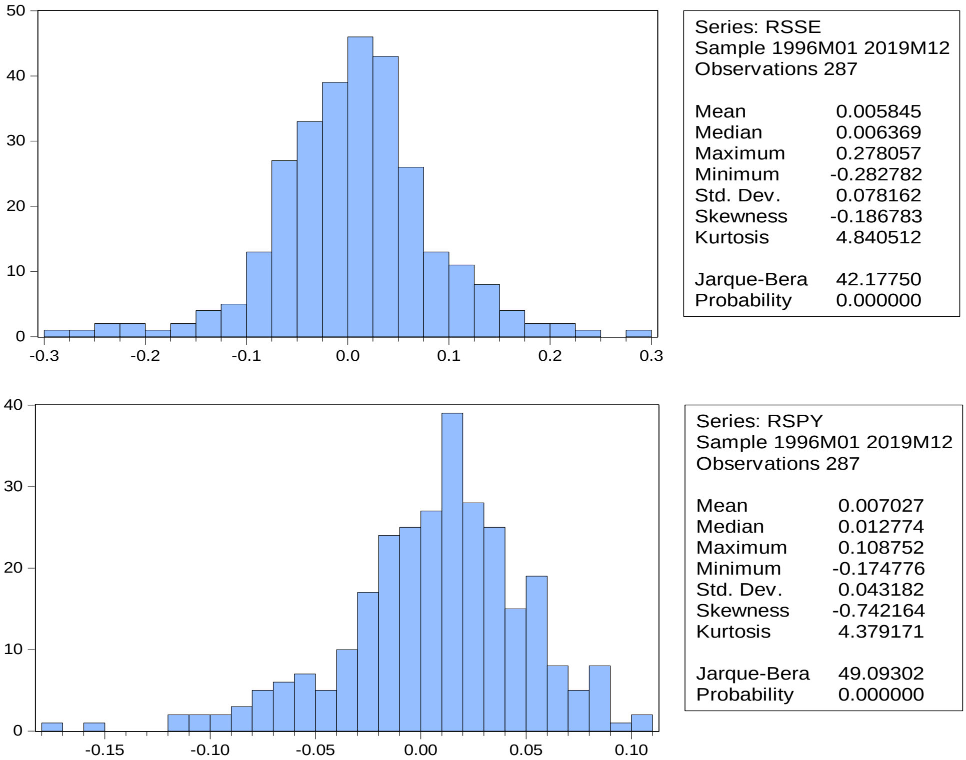


Figure 3.2

Various empirical distribution tests suggest that the normal distributions are rejected for both return series at 1% significant level. The test results are shown in the Appendix. The results also imply that the traditional assumption of normally distributed disturbances is not appropriated in the GARCH modeling of our study. The issue will be discussed and addressed in the methodology section.

IV. Methodology

Vector Autoregressive (VAR) Model

To account for the spillovers in returns between Chinese and U.S stock markets, a bivariate VAR model is used to estimate interrelationships between them:

$$R_t = \Phi_0 + \Phi_1 R_{t-1} + \ldots + \Phi_p R_{t-p} + \varepsilon_t$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t)$$

Where *Rt* is a two-variable vector of returns in both markets (RSSE and RSPY) at time *t*. *p* is the lag length and Φ is the coefficient matrices. ε_t is a vector of errors. The conditional variance-covariance matrix is *Ht* given the information set Ω_{t-1}. According to the above equation, the return of one market depends on *p* lags of itself as well as *p* lags of the other market return.

Multivariate GARCH Models

After taking into account for direct dependence between both returns by the VAR model, it allows us to study the volatility spillover effects as well as the dynamic conditional correlations between these two returns through the analysis of the temporal dependence of the conditional variance, *Ht*. It will be analyzed by two different multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models: The BEKK model of Engle and Kroner (1995), and the dynamic conditional correlation (DCC) model of Engle (2002). Note that these two models are employed for different purposes in this paper.

BEKK-GARCH

In the full rank BEKK model suggested by Engel and Kroner (1995), the interactions are allowed among the conditional variances and covariance. In other words, the model is capable of capturing the asymmetry of the volatility spillovers between these two returns. The standard bivariate BEKK-GARCH (1,1) model can be written as

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

Where

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}$$

A is a square matrix that illustrates how the conditional variances are related to the past squared errors, which capture the effect of shocks on conditional variance or volatility. B is also a square matrix that reflects how past conditional variance affects the present one. C is a lower triangular matrix. Then the previous equation can be rewritten as

$$\begin{aligned} h_{11,t+1} = {} & a_{11}^2\varepsilon_{1,t}^2 + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + 2a_{11}\varepsilon_{1,t}\varepsilon_{3,t} + a_{21}^2\varepsilon_{2,t}^2 + 2a_{21}\varepsilon_{2,t} + b_{11}^2h_{11,t} \\ & +2b_{11}b_{12}h_{12,t} + 2b_{11}h_{13,t} + b_{21}^2h_{22,t} + 2b_{21} \end{aligned}$$

$$\begin{aligned} h_{22,t+1} = {} & a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + 2a_{12}\varepsilon_{1,t} + a_{22}^2\varepsilon_{2,t}^2 + 2a_{22}\varepsilon_{2,t} + b_{12}^2h_{11,t} \\ & +2b_{12}b_{22}h_{12,t} + 2b_{12} + b_{22}^2h_{22,t} + 2b_{22} \end{aligned}$$

In the above equations, a11 and a22 reflect the traditional ARCH effect of the volatility where b11 and b22 reflect the GARCH effect of the volatility. a12; a21; b12; b21 estimate how shocks and volatility are transmitted across markets, namely the cross-market spillover effects.

DCC-GARCH

Engle (2002） has proposed the Dynamic Conditional Correlational Autoregressive Conditional Heteroscedasticity Model (DCC-GARCH) where the conditional correlation is allowed to vary over time. Since then, the DCC-GARCH model has been widely used to estimate the dynamic conditional correlation between two or more time series. In this study, the author adopted the DCC-GARCH model of Engel (2002)

$$H_t = D_t R_t D_t$$

Where

$$D_t = diag\left(h_{11t}^{1/2}, h_{22t}^{1/2} \dots h_{nnt}^{1/2}\right)$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$$

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

Where

$$\bar{Q} = T^{-1}\sum_{t=1}^{T}\varepsilon_t\varepsilon_t'$$

In the above equations, $\overline{Q}$ is the unconditional covariance matrix. α and β are non-negative scalar parameters with the restriction that $0<\alpha+\beta<1$. If the value of $\alpha+\beta$ is estimated to be close to one, it indicates a high persistence in the conditional variance.

<u>Estimation</u>

The estimation of the parameters for both GARCH models can be conducted by log-likelihood maximization. Traditional GARCH models always assume Gaussian distribution for innovations. However, in order to capture the excess of kurtosis in both return series, the author assumes that innovations follow a Student's *t* distribution with *v* degrees of freedom in this paper since the student's *t* distribution is more useful than normal distribution when working in the presence of skewness and kurtosis.

The joint density function of student's t distribution is

$$f(u_t|\Psi_{t-1}) = \frac{\Gamma(\frac{v+N}{2})}{(\sqrt{\pi})^N\Gamma(\frac{v}{2})}(\sqrt{v})^{-N}|H_t|^{-\frac{1}{2}}[1+\frac{u_t'H_t^{-1}u_t}{v}]^{-\frac{v+N}{2}}$$

Where *Ht* is the conditional variance-covariance matrix and ut is the vector of errors. Since the Likelihood function is

$$L = \prod_{i=1}^{t} f(u_i|\Psi_{i-1})$$

Log-likelihood function becomes

$$l_n = -\frac{1}{2}[p\log(2\pi) + \log|H_t| + u_t' H_t^{-1} u_t]$$

$$l_t = \log[\Gamma(\frac{v+N}{2})] - \frac{N}{2}\log(\pi) - \log[\Gamma(\frac{v}{2})] - \frac{N}{2}\log(v-2) - \frac{1}{2}\log|H_t| - \frac{v+N}{2}\log(1+\frac{u_t' H_t^{-1} u_t}{v-2})$$

Where v represents the degrees of freedom, Γ( ) is the gamma function and N represents the number of series.

V. Empirical Results

Volatility spillovers between returns of SPY and SSE

As mentioned above, the VAR-BEKK-GARCH model is employed to explore the volatility spillover effects between returns of SPY and SSE. The sample includes the monthly data between 1996 and 2019 and the innovations are assumed to follow student's *t* distribution. The estimated results are shown in Table 5.1 below

Bekk

MV-GARCH, BEKK - Estimation by BFGS

Convergence in 42 Iterations. Final criterion was 0.0000037 <= 0.0000100

Monthly Data From 1996:03 To 2019:12

Usable Observations		286			
Log-Likelihood		874.3428912			
	Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1.	RSSE{1}	0.070285713	0.055980741	1.255533818	0.209285039
2.	RSPY{1}	-0.101883819	0.081874174	-1.244395073	0.213354195
3.	Constant	0.006129625	0.003833943	1.598778097	0.109869917
4.	RSSE{1}	0.026624579	0.024500144	1.086711139	0.27716449
5.	RSPY{1}	-0.07573179	0.056787183	-1.333607098	0.182332656
6.	Constant	0.01222968	0.002055134	5.950795171	2.66843E-09
7.	C(1,1)	0.022768288	0.004250779	5.356261923	8.49613E-08
8.	C(2,1)	0.006726477	0.003322648	2.024432847	0.042925635
9.	C(2,2)	7.71986E-07	0.023015866	3.35415E-05	0.999973238
10.	A(1,1)	0.335173786	0.06657156	5.03478939	4.78374E-07
11.	A(1,2)	0.10707998	0.035102765	3.050471335	0.002284825
12.	A(2,1)	-0.135263902	0.121082402	-1.117122711	0.263941861
13.	A(2,2)	0.313057373	0.069974858	4.473855093	7.68218E-06
14.	B(1,1)	0.88399121	0.032635786	27.08656068	1.4178E-161
15.	B(1,2)	-0.063508379	0.021241509	-2.989824251	0.00279138
16.	B(2,1)	0.057371248	0.061711396	0.929670249	0.352541843
17.	B(2,2)	0.929919462	0.028912763	32.16294057	5.8233E-227
18.	Shape	7.473199129	1.81952188	4.107232352	4.00428E-05

Table 5.1

The above table consists of two main parts. The first 6 rows reflect the estimated results of the VAR(1) model. According to the results, there is no significant direct spillover effect among returns. This finding is consistent with the results of previous studies where the spillover effect between the U.S and Chinese stock market returns is either tiny or insignificant. In addition, the shape parameter reflects the degree of freedom in the student's t distribution.

The rest of the table mainly shows the estimated results of the BEKK-GARCH model. As described in the previous section, A(1,1) and A(2,2) (row 10 and row 13) reflect the ARCH effects, which implies how the volatility of the returns responses to its own lagged square innovations. Both estimated value of A(1,1) and (2,2) are highly significant, suggesting the existence of ARCH effect. Similarly, the significance of B(1,1) and B(2,2) (row 14 and row 17) reflects the existence of the GARCH effect. Overall the significant estimation of A(1,1), A(2,2), B(1,1) and B(2,2) suggests that the GARCH model is appropriated to use in such a situation.

One of the main advantages of the full rank BEKK-GARCH model is the capability to capture the cross-market volatility spillovers between two or more returns. Such spillover effects are reflected in the off-diagonal entries of matrix A and matrix B. According to the above table, both A(1,2) and B(1,2) are significant while both A(2,1) and B(2,1) are significant, suggesting the existence of the asymmetric volatility spillovers. More specifically, the significant estimation of A(1,2) instead of A(2,1) provides the evidence of a unidirectional ARCH effect from SPY to SSE, which implies that past shocks in the U.S. stock market do affect the variances of the

China market. Similarly, the significant estimation of B(1,2) instead of B(2,1) suggests the unidirectional GARCH effect from SPY to SSE, where the volatility of the Chinese market responds significantly to past volatility of U.S market, not vice versa. To further explore this relationship, a Wald test is employed below. The test results are shown in Table 5.2.

Wald Test

Null Hypothesis	Wald	P value
H0: A(1,2)=B(1,2)=0	10.798305	0.00452041
H0: A(2,1)=B(2,1)=0	1.264988	0.53126505

Table 5.2

The Wald test confirms that there are asymmetric shock and volatility spillover effects between the U.S and Chinese stock market returns since the null hypothesis of volatility spillover from SPY to SSE (A(1,2)=B(1,2)=0) is rejected at 1% significant level while the existence of spillover from SSE to SPY (A(2,1)=B(2,1)=0) can not be rejected at 5% (or 10%) significant level.

Dynamic Conditional Correlations

After the discovery of the asymmetric volatility spillover effects between the U.S and Chinese stock market returns, it's valuable to construct the time-varying conditional correlation between them and explore the factor affecting it. Firstly, A VAR-DCC-GARCH model is applied to estimate such correlations. The results are shown below in Table 5.3

Log-Likelihood		876.6794052			
	Variable	Coeff	Std Error	T-Stat	Signif
1.	RSSE{1}	0.060763134	0.066446454	0.914467667	0.36047116
2.	RSPY{1}	-0.055550467	0.090560757	-0.613405511	0.539608243
3.	Constant	0.002707249	0.00384855	0.703446686	0.481777421
4.	RSSE{1}	0.019770257	0.027569926	0.717095027	0.473315464
5.	RSPY{1}	-0.087041146	0.057103312	-1.524274914	0.127440051
6.	Constant	0.011598522	0.001997071	5.807766212	6.33118E-09
7.	C(1)	0.00041283	0.000214527	1.924367774	0.054308501
8.	C(2)	0.000110505	6.72489E-05	1.643222172	0.100336974
9.	A(1)	0.159377755	0.065925231	2.417553227	0.015625249
10.	A(2)	0.228877335	0.070339447	3.253897266	0.001138334
11.	B(1)	0.767731852	0.069765833	11.00441024	3.63889E-28
12.	B(2)	0.73935185	0.071203358	10.38366546	2.94256E-25
13.	DCC(1)	0.023375212	0.021013289	1.112401367	0.265965613
14.	DCC(2)	0.965534412	0.034517959	27.97194427	3.5663E-172
15.	Shape	8.452555616	2.626575079	3.218090236	0.001290472

Table 5.3

Note that in the above table, the α and β are represented by DCC(1) and DCC(2) in row 13 and row 14. The value of α+β is equal to 0.989, which is very close to 1. It indicates a high persistence in the conditional variance. The estimated dynamic conditional correlations are shown in figure 5.4.

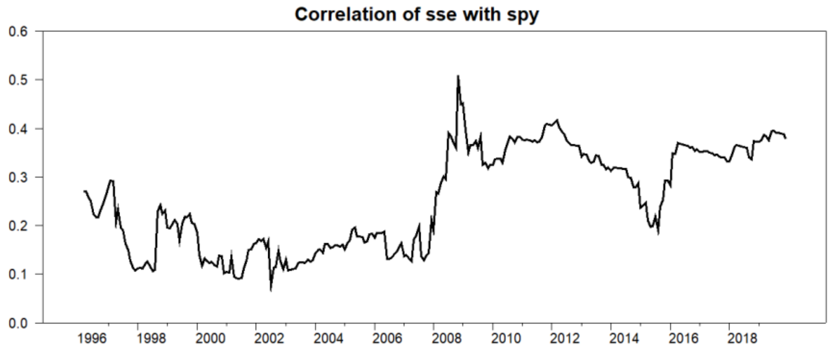
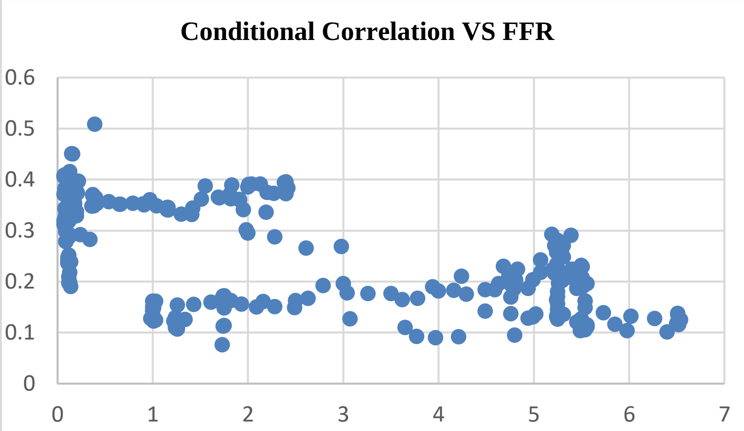


Figure 5.4

The pattern of the dynamic correlation in the above figure reveals the following: (1) There is a large increase in conditional correlation between the U.S and Chinese stock markets after the 2007 financial crisis when the U.S adopted unconventional monetary policy. The correlation peaked at 0.5 around 2009. (2) The conditional correlation decreased around 2015 when the U.S exited the unconventional monetary policy. (3) The correlation has increased again after 2016 when the Trump administration entered the White House. It increased even more after the Trump administration declared the trade war with China.

The Effect of The U.S Monetary Policy on Conditional Correlation

Given the asymmetry of the volatility spillovers, a linear regression and Granger Causality test will be employed to further explore the effect of the U.S monetary policy on the dynamic conditional correlation (DCCCORR) estimated above by DCC-GARCH model. However, before the application of the regression, both the effective Fed Fund rates (FFR) and the combined rates of FFR and shadow rates (FFR/Shadow) developed by Wu and Xia (2016) are plotted against conditional correlations. The graphs are shown below in figure 5.5.



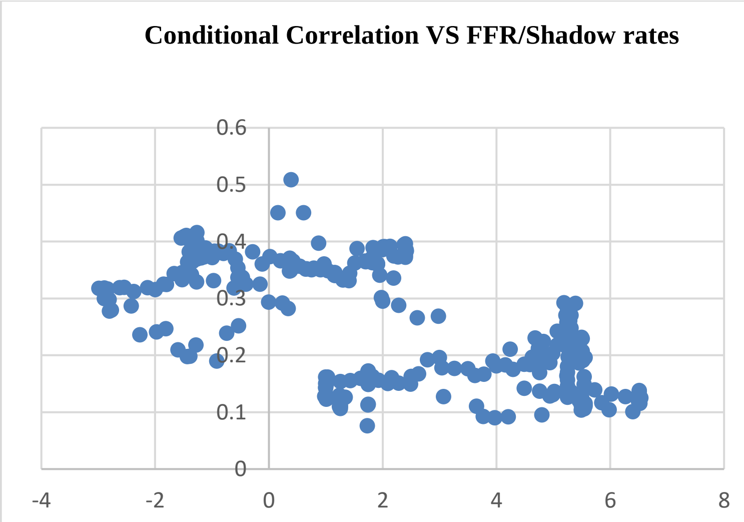


Figure 5.5

According to the above figures, the combined rates of FFR and shadow rates (FFR/shadow) seem to be a better measure of the U.S monetary policy stances since FFR stays around 0 under the unconventional policy period. Such a situation will create nonlinearity in the regression. A Ramsey RESET test confirmed the intuition. (see table 5.6)

Ramsey RESET Test

Specification: DCCCO... FFR
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	2.562636	282	0.0109
F-statistic	6.567103	(1, 282)	0.0109
Likelihood ratio	6.560866	1	0.0104

Specification: DCCCO... FFR/Shadow
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	1.615373	282	0.1073
F-statistic	2.609431	(1, 282)	0.1073
Likelihood ratio	2.625065	1	0.1052

Table 5.6

According to the above test results, the linearity of the regression between conditional correlation and FFR is rejected, while the linearity of the regression between conditional correlation and FFR/Shadow can not be rejected. It suggests that the combined rate is a better independent variable in the linear regression. The results of the linear regression are shown below in table 5.7.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FFR/Shadow	-0.024310	0.001811	-13.42093	0.0000
C	0.300905	0.005983	50.29663	0.0000

R-squared	0.388929	Mean dependent var	0.253581
Adjusted R-squared	0.386770	S.D. dependent var	0.104190
S.E. of regression	0.081590	Akaike info criterion	-2.167225
Sum squared resid	1.883916	Schwarz criterion	-2.141593
Log likelihood	310.8295	Hannan-Quinn criter.	-2.156950
F-statistic	180.1214	Durbin-Watson stat	0.076611
Prob(F-statistic)	0.000000		

Table 5.7

The result shows that the conditional correlation is negatively correlated with FFR/Shadow rates with R^2 equal to 0.39 (r=-0.62). To further identify the causal relationship between the combined rates and conditional correlation, the Granger Causality test is conducted. The result is shown below in table 5.8.

Null Hypothesis:	Obs	F-Statisti...	Prob.
FFR/Shadow does not Granger Cause DCC...	280	2.56479	0.0275
DCCCORR does not Granger Cause FFR/Shadow		1.01476	0.4093

Table 5.8

The test result is clear. The null hypothesis of FFR/Shadow not causing dynamic conditional correlation is rejected while the conditional correlation not causing FFR/Shadow can not be rejected. Therefore the combined rates (FFR/Shadow) will negatively affect the conditional correlation between the U.S and Chinese stock market returns, which implies that the U.S monetary expansion will increase the stock market comovement between U.S and China. By contrast, the U.S monetary contraction will make them more independent. Such a result is of great importance, especially in portfolio management and policymaking. For instance, during monetary expansion in the U.S, the traditional portfolio management strategies including diversifying part of the asset in China may not work very well due to the increased correlation between U.S and Chinese markets. Meanwhile, the central banks of both countries should take the effects of monetary policy on conditional correlation into account.

VI. Conclusion

This paper investigates the volatility spillover effect as well as the dynamic conditional correlation between the U.S and the Chinese stock market. Then the effect of U.S monetary policy on the conditional correlation is examed. The study reveals the following main result.

1. A bivariate VAR-BEKK-GARCH model has employed to exam the volatility spillovers between the U.S and Chinese stock market returns represented by SPY and SSE. The VAR result shows no evidence of return spillover effects, but the BEKK-GARCH result suggests significant ARCH and GARCH effects, indicating the volatility spillover effects between the two markets. In addition, the Wald test confirms the asymmetry of the volatility spillover: there is unidirectional volatility spillover from the U.S stock market to the Chinese stock market.

2. Given the existence of volatility spillovers, A DCC-GARCH model is then applied to estimate the dynamic conditional correlation between the U.S and the Chinese stock market. The estimated results suggest that the conditional correlation largely increased after the 2007 financial crisis and increased again around 2018 when the U.S-China trade war broke out.

3. Since the existence of unidirectional volatility spillover from the U.S stock market to China, the effect of U.S monetary policy on the dynamic conditional correlation is investigated by linear regression and Granger Causality test. The combination of Fed Fund rates and shadow rates developed by Wu and Xia (2016) is used to represent the U.S monetary policy rate. The results show that the U.S monetary policy rates do cause the change of the conditional correlation and the relationship is negative with R^2 equal to 0.39. It implies that the U.S monetary

policy plays an essential role in the volatility spillovers as well as comovement between the U.S and Chinese stock markets.

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Appendix

ADF test for unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.18510	0.0000
Test critical values:	1% level	-3.453072	
	5% level	-2.871438	
	10% level	-2.572116	

*MacKinnon (1996) one-sided p-values.

RSS

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.40170	0.0000
Test critical values:	1% level	-3.453072	
	5% level	-2.871438	
	10% level	-2.572116	

*MacKinnon (1996) one-sided p-values.

Empirical Distribution Test for RSPY
Hypothesis: Normal

Sample (adjusted): 1996M02 2019M12
Included observations: 287 after adjustments

Method	Value	Adj. Value	Probability
Lilliefors (D)	0.065196	NA	0.0050
Cramer-von Mises (W2...	0.326356	0.326925	0.0002
Watson (U2)	0.261760	0.262216	0.0004
Anderson-Darling (A2)	1.979748	1.984976	0.0000

Empirical Distribution Test for RSSE
Hypothesis: Normal

Sample (adjusted): 1996M02 2019M12
Included observations: 287 after adjustments

Method	Value	Adj. Value	Probability
Lilliefors (D)	0.071597	NA	0.0012
Cramer-von Mises (W2...	0.307936	0.308472	0.0003
Watson (U2)	0.307015	0.307550	0.0001
Anderson-Darling (A2)	2.055722	2.061150	0.0000