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Review

Correlations and volatility spillovers between China and Southeast Asian stock markets

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ABSTRACT

In this paper, we use multivariate GARCH models to illustrate dynamic conditional correlations and the volatility spillovers between Chinese and five Southeast Asian stock markets comprising of Singapore, Thailand, Indonesia, Malaysia and Philippines. Four multivariate GARCH models including BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation are compared and contrasted. It is found that the DCC-GARCH model fits the data best and this model is subsequently used to construct hedge ratios and optimal portfolio weights. The empirical results reveal that the dynamic conditional correlation between China and five Southeast Asian stock markets is positive on the whole, and get to its peak during the Asian financial crisis, U.S. subprime crisis and stock market crash in 2015. In addition, we can estimate dynamic hedge ratios by using conditional volatilities from the DCC model. A $1 long position in Shanghai composite index (SHPI) can be hedged for 27.32 cents with a short position in the FTSE Straits Times Index (SSPI) futures markets. Finally, we construct optimal two stock asset portfolios by using conditional variances and co-variances from the DCC model. Investors could construct stock portfolios of China and Southeast Asian countries to hedge stock investments, which can effectively reduce investment risks.

Contents

1. Introduction

With the deepening financial integration around the world, the correlation and interdependence of the world financial market is also increasing (Singh et al., 2015). Due to the interdependence of the financial markets, the asset price fluctuation of one country's financial market often has a lag effect on the volatility of other countries' financial markets, hence, the spillover effect of volatility will occur. Volatility spillovers are a common feature across several financial markets. The increasing global financial integration reinforces the existence of this effect and underscores the importance of studying the volatility spillover effect in different financial

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markets. The stock market acts as a barometer of the national economy which fully reflects the economic fluctuations of a country or region. Therefore, a study of the risk spillover effect of China's stock market and foreign stock markets is significantly important in monitoring and preventing the risk transmission across financial markets, maintaining the safe operation of financial systems and promoting economic development.

As an important part of China's surrounding environment, Southeast Asian market is located in the south of China and sits at the crossroads of Asia, the Pacific Ocean and the Indian Ocean. Its geographical location is of great importance to the Chinese economy. As a result, China has always regarded Southeast Asia as an important support for economic and financial cooperation when interacting with its neighboring countries. It is also a priority direction and important partner for China to promote the construction of "One Belt and One Road" initiative. As early as January 2010, China-ASEAN Free Trade Area (CAFTA) was officially launched. In September and October 2013, Chinese President Xi Jinping proposed a cooperative initiative to build the N̈ew Silk Road Economic Beltänd the 2̈1st Century Maritime Silk Road" respectively. The Southeast Asian countries agreed to this initiative and have actively aligned their development strategies to the initiative. The launch of CAFTA and the implementation of "one belt and one road" initiative have accelerated the economic, trade and financial links between China and Southeast Asian countries. As a result, trade and economic relations between China and Southeast Asian countries have become stronger. For instance, the trade volume between China and ASEAN was up to US$587.87 billion in 2018 and China has been the largest trading partner of ASEAN for the last 10 consecutive years. In the same vein, ASEAN has been the third largest trading partner of China after the EU and the USA for 8 consecutive years.

The launch of CAFTA and the in-depth implementation of the "One Belt and One Road" initiative has greatly promoted the development of economic and trade partnership between China and Southeast Asian countries. On the other hand, the degree of integration between China and ASEAN stock markets will be further deepened. In this context, is there any change in the correlation and volatility spillover between Chinese and Southeast Asian stock markets? Once the Southeast Asia stock markets produce extreme risk, is there a possibility that China will suffer an increased crisis contagion? A study of the correlation and volatility spillover effects can help to reveal the changing trend of volatility spillover between China and ASEAN stock markets. This provides effective monitoring and early warning for risk transmission across different financial markets. In addition, this provides important reference for promoting the steady development of China's economic cooperation with Southeast Asian countries and also promotes the development of the "one belt and one road" initiative.

The heart of modern finance is to Model and forecast volatility in which financial derivatives can be priced, the optimal portfolio can be constructed and risk management and hedging can be carried out through accurate estimation of correlation and volatility (Sadorsky, 2012). To date, however, a limited number of research studies have examined the relationships between Chinese and Southeast Asian stock markets (Chien, Lee, Hu, & Hu, 2015). Local and international literature sources on volatility spillovers between Chinese and Southeast Asian stock markets are relatively rare, and a few scholars have constructed hedging ratio and optimal portfolio weights by using conditional volatility. To address the gap in the literature, this paper uses multivariate GARCH models to model dynamic correlations and the volatility spillovers between Chinese and five Southeast Asian stock markets. Four multivariate GARCH models (BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation) are compared and contrasted. It is found that the DCC-GARCH model fits the data best and this model is then used to construct hedge ratios and optimal portfolio weights.

Several important findings in this paper are based on the analysis of DCC and optimal portfolio weights. In conclusion, our study indicates that the dynamic conditional correlation between China and five Southeast Asian stock markets is positive in total. Previously, the dynamic conditional correlation between China and five Southeast Asian stock markets reached a peak value during the Asian financial crisis, U.S. subprime crisis and stock market crash in 2015. It is worth noting that there is a relatively obvious co-movement between China and Southeast Asian stock markets and this co-movement which is more obvious after CAFTA was fully activated. In addition, we can estimate dynamic hedge ratios by using conditional volatilities from the DCC model. On average, a $1 long position in Shanghai composite index (SHPI) can be hedged for 27.32 cents with a short position in the FTSE Straits Times Index (SSPI). Similarly, a $1 long position in Shanghai composite index (SHPI) can be hedged for 13.71 cents with a short position in the Thailand SET Index (TSPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 17.6 cents with a short position in the Jakarta Composite Index (ISPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 17.66 cents with a short position in the FTSE Bursa Malaysia Composite Index (MSPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 13.75 cents with a short position in the Manila Composite Index (PSPI).

The remainder of the paper is organized as follows: in the second part, we review the literature on volatility spillover effect in financial markets; in the third part and the fourth part, we describe the empirical methods and data in this paper; In the fifth part, we demonstrate the empirical results of dynamic conditional correlation (DCC), hedge ratios and optimal portfolio weights; and finally, the sixth section summarizes the paper and puts forward countermeasures and suggestions.

2. Literature review

Generally, scholars from home and abroad mainly study the volatility spillover effect of stock market through two modeling methods. The first modeling method is cointegration and vector autoregression (VAR) model. Most studies mainly use empirical tools such as VAR, cointegration and variance analysis to analyze the volatility spillover effect between the stock markets of various countries. Eun and Shim (1989) used the VAR model to analyze 9 major world stock markets, and the conclusion drawn was that the USA stock market has a unidirectional price spillover effect on other stock markets. Jeon and Von Furstenberg (1990) used the VAR model to study the correlation between the stock prices of the world's major stock exchanges and they found that the degree of interdependence of the international stock index had significantly increased since the stock market crash at that time. Mathur and Subrahmanyam (1990) used the VAR model to study the correlation between the four Nordic countries and the USA stock market indexes and found that the USA stock market only affected the Danish stock market, not the Norwegian, Finnish or Swedish stock market. Liu (2016) explored the spillover effects between these markets by using the VAR model based on the stock market returns of the United States, Britain, Hong Kong and Japan. They found that the past performance of the United States market alwaysaffected the market returns of the United Kingdom, Britain, Hong Kong and Japan. Panda et al. (2019) explored the short-term and long-term interdependence between the stock markets in Africa and the Middle East and tried to analyze the rules of the volatility spillover of regional stock markets. They identified that there was a significant spillover effect in the regional stock market, but the response amplitude and duration of volatility spillover effect were very small. However, cointegration and vector autoregression (VAR) models assume that the conditional variance is time-invariant, so they cannot comprehensively depict the interaction between different stock market volatility. However, volatility spillover has obvious time-varying characteristics (Schwert, 1989), so cointegration and vector autoregression (VAR) models cannot provide a good description of the trend of volatility spillover effect.

The second modeling method involves the use of ARCH and GARCH family of models. The GARCH model makes the conditional variance obey a normal distribution ARMA process and gradually develops into the mainstream method to depict the volatility spillover effect in different stock markets. Miyakoshi (2003) used the binary EGARCH model to study the transmission effect of the return and volatility in the USA, Japanese stock markets and the other 7 stock markets in Asia. The study concluded that the USA stock market has a unidirectional transmission effect on the Asian stock market, while the Japanese stock market has a weak transmission effect, and the Asian stock market has an inverse volatility effect on the Japanese stock market. Miyakoshi (2003) used EGARCH model to examine the extent of the return and volatility spillovers from Japan and USA to seven Asian equity markets. They found that the volatility of Asian markets was influenced more by the Japanese stock market than the USA stock market. Hahm (2004) used the GARCH model and established that South Korea has a significant log volatility spillover effect on the United States, while there is no supporting evidence on the contrary. Cheng and Glascock (2005) used the GARCH and ARIMA models to study the stock market between the two sides of the Taiwan Straits and Hong Kong. The results showed that the level of integration between the three stock markets was weak. Moon and Yu (2010) used the GARCH model to analyze the short-term mean and volatility spillover effects between the S&P 500 index and the Shanghai stock exchange index. They found that there was evidence of symmetrical and asymmetric volatility spillover effects in Chinese and US stock markets after the suspension. Nishimura and Men (2010) used the EGARCH model to study the daily volatility and overnight volatility spillover effects of stock prices in China and G5 countries. They found strong evidence of short-term unidirectional volatility spillover effects in the United States, the United Kingdom, Germany and France. Kundu and Sarkar (2016) used the TGARCH-M model to analyze the behaviour of return and volatility spillover under two different stock market conditions (that is, rising and falling markets). The results show that the returns and fluctuations of one market have a significant asymmetric effect on the rise and fall of the other market, but the signs of this effect vary in countries and markets. Jebran, Chen, Ullah, and Mirza (2017) used the extended EGARCH model to explore asymmetric volatility spillovers in Asia emerging markets stock markets (China, Pakistan, Hong Kong, Sri Lanka and India) before and after the 2007 financial crisis. It was found that there were some significant bi-directional volatility spillover effects in Indian and Sri Lankan stock markets in these two sub-periods. However, volatility spillover in Hong Kong and India is also bi-directional.

It is worth noting that the univariate variable ARCH and GARCH model families cannot describe the cross effect and feedback effect among variables, so they can not accurately estimate the volatility spillover effect in different stock markets. Some scholars began to use the multivariate GARCH model to analyze the volatility spillover effect among stock markets. Multivariate GARCH model cannot only explain the source, direction and transmission intensity of shocks between different variables, but also obtain the effects of cross-variable shocks and volatility transmission from other variables. At the same time, it can capture the conditional volatility of current innovation and the influence of lag volatility (Wei, 2016). Early studies used the multivariate GARCH model to analyze volatility spillover effects among stock markets focusing on developed markets. The most studied developed markets include the United States, the United Kingdom, Japan, Germany and France. Foreign scholars generally believe that there is a significant volatility spillover effect among developed stock markets, and American stock markets often play the role of spillover transmitter (Dajčman & Festić, 2012; Jain & Sehgal, 2019; Karunanayake & Valadkhani, 2011; Tastan, 2005; Savva, 2009; Xiao & Dhesi, 2010). However, the academic research on the volatility spillover effect in emerging markets started relatively late and focused mostly on the volatility spillover effect between the developed markets and emerging markets (Abounoori & Tour, 2019; Alfreedi, 2019; Bala & Takimoto, 2017; Cardona et al., 2017; El Ghini & Saidi, 2017; Lee & Goh, 2016; Obadiaru, Oloyede, Omankhanlen, & Asaleye, 2018; Özdemir, 2020; Qarni & Gulzar, 2018; Qian & Diaz, 2017; Sarwar, Khalfaoui, Waheed, & Dastgerdi, 2019; Uludag & Khurshid, 2019; Yousaf et al., 2020; Zhang et al., 2020). These studies have confirmed that developed markets have significant volatility spillovers to emerging stock markets and also experience volatility spillovers from other emerging markets.

El Hedi Arouri et al. (2010), Güloğlu et al.(2016) and Hwang(2014) focus their research on the volatility spillover among Latin American stock market. Furthermore, Joshi (2011), Gulzar, Mujtaba Kayani, Xiaofen, Rafique, & Ayub, 2019, Hung (2019), Umer et al. (2018) and Vo and Tran (2020) centralize their study on the volatility spillover among Asia Pacific stock market. Bekiros(2014), Singh and Singh (2017) and Syriopoulos et al.(2015) focus their research on the volatility spillover among BRICS stock market. They analyze the spillover effects of volatility between emerging and developing markets. These studies have always been a field of interest for scholars at home and abroad. It appears that there is a dearth of literature at both national and international level on the volatility spillover effect between China and Southeast Asian stock markets. Only Majdoub and Sassi (2017) used the conditional volatility to construct the optimal hedging ratio and portfolio weight between China and emerging Asian Islamic stock markets. This paper seeks to address this gap between Chinese and Southeast Asian stock markets in order to construct the hedging ratio and optimal portfolio weight.

3. The empirical model

Generally, it is assumed that the movement of stock price or stock price index is a random walk; however, its rate of return or volatility series is a stationary series and the trend of stock price shows the phenomenon of peak and coarse tail. The volatility of return rate is clustered as well as the volatility spillover effect among stock markets. The standard GARCH model can be expressed as follows.

$$r_t = \mu + \varphi r_{t-1} + \varepsilon_t, \quad t = 1, 2, 3, \cdots, T \tag{1}$$

$$\sigma_t = w + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

Where Eq. (1) is the mean equation and Eq. (2) is the conditional variance equation, ε_{t-1}^2 is ARCH process and σ_{t-1}^2 is GARCH process.

The multivariate GARCH model is developed on the basis of the standard GARCH model, but compared with the standard GARCH model, it can only describe the vertical transmission of risk of a single financial asset. In this paper, four multivariate GARCH models (BEKK-GARCH, Diag-GARCH, CCC-GARCH and DCC-GARCH) are used to model the volatility spillover between the stock markets of China and five ASEAN countries.

The BEKK-GARCH (1.1) model can be expressed as follows.

$$H_t = C'C + A'H_{t-1} + B'\eta_{t-1}\eta_t B \tag{3}$$

Where $C'C$, $B'B$, $A'A$ and C are all 3×3 imensional matrices to make the positive definite matrix. The estimation of BEKK model is carried out by the maximum likelihood (QML) method, and the conditional distribution of error term is based on the joint Gaussian logarithmic likelihood function of a T observation sample.

$$\log L = -1/2\sum_{t=1}^{T}[k\log(2\pi) + \ln\left|H_t\right| + \eta_{t-1}H_t^{-1}\eta_t] \tag{4}$$

In this paper, the BEKK model is used as a standard model, and the other three models (Diag-GARCH、CCC-GARCH and DCC-GARCH model) are simply calculated and can be estimated by the following two steps. In the first step, a single-variable GARCH model is used to estimate the variance. The second step involves modelling the correlation based on the normalized residual obtained in the first step.

Finally, the dynamic conditional correlation model (DCC) proposed by Engle (2002) analyzes the conditional correlation among all variables. The DCC-GARCH model can usually be estimated using the following two steps. The first step is to estimate the GARCH process of the variable and the second step involves constructing a conditional correlation matrix with the standard residuals in the results. We define the DCC-GARCH model as follows:

$$r_{it} = \phi_{i0} + \sum_{i=1}^{6}\phi_{ij}r_{jt-1} + \varepsilon_{it} \tag{5}$$

$$\varepsilon_{it} = \upsilon_{it}h_{it}^{1/2}, \quad \upsilon_{it} \sim N(0, 1) \tag{6}$$

$$h_{it} = c_{ii} + \sum_{j=1}^{6}\alpha_{ij}\varepsilon_{j,t-1}^2 + \sum_{j=1}^{6}b_{ij}h_{j,t-1} \tag{7}$$

$$H_t = D_t^{1/2}R_tD_t^{1/2} \tag{8}$$

In Eqs. (5)–(8), r_{it} represents the return of series i, ε_{it} is random error term with conditional variance h_{it}. H_t is a 6×6 dimensional conditional covariance matrix, R_t is the conditional correlation matrix of h_{it}, and D_t is the time-varying standard deviation diagonal matrix on the diagonal, ε_t is random error vector that obeys the mean is 0 and the variance is 1.

$$D_t = \begin{bmatrix} h_{11t}^{1/2} & 0 & 0 & 0 & 0 & 0 \\ 0 & h_{22t}^{1/2} & 0 & 0 & 0 & 0 \\ 0 & 0 & h_{33t}^{1/2} & 0 & 0 & 0 \\ 0 & 0 & 0 & h_{44t}^{1/2} & 0 & 0 \\ 0 & 0 & 0 & 0 & h_{55t}^{1/2} & 0 \\ 0 & 0 & 0 & 0 & 0 & h_{66t}^{1/2} \end{bmatrix} \tag{9}$$

$$R_t = diag(q_{11t}^{-1/2}, \cdots, q_{66t}^{-1/2})Q_t diag(q_{11t}^{-1/2}, \cdots, q_{66t}^{-1/2})$$

Q_t is a symmetric positive definite matrix, and $Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1\varepsilon_{t-1}\varepsilon'_{t-1} + \theta_2 Q_{t-1}$. $\overline{Q}$ is a 6×6 unconditional correlation matrix of standard residual ε_t. The parameters θ_1 and θ_2 both are non-negative integers, and satisfy $0 \le \theta_1 + \theta_2 < 1$. The related estimator is $\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}$.

For constant conditional correlation model (DCC), $R_t = R$ and $R_{ij} = \rho_{ij}$. In the MGARCH model, we get $\rho_{ij} = 0$, for all i and j. There are many limitations to the MGARCH model because it assumes that the dynamic conditional correlation among the variables (DCC) are all 0 (we obtain $h_{ij} = 0$, For all i not equal to j). The t -statistic can be calculated by using the robust estimation of the covariance matrix.

4. Data description

The study involved analysis of the five major stock market indexes in Southeast Asia which include FTSE Straits Times Index (SSPI), Thailand SET Index (TSPI), Jakarta Composite Index (ISPI), FTSE Bursa Malaysia Composite Index (MSPI) and Manila Composite Index (PSPI). We considered the Shanghai composite index (SHPI) as the proxy variable of the Chinese stock market. All the time series data were obtained from Wind database and used daily closing prices. The sample period for the data set covers 1 January 1994 to 30 August 2019. Given the different trading time of stock markets in different countries, non-common trading days are excluded. A plot of the raw data shows that SSPI, TSPI, ISPI, MSPI and PSPI tend to move together as shown in Fig. 1. We found that stock indexes in Southeast Asia suffered a huge drop during the Asian financial crisis, U.S. dot bubble, U.S. subprime crisis and China's stock market crash in 2015.

For each stock price series, continuously compounded daily stock market returns are calculated as $100 \times \log(p_t/p_{t-1})$ where p_t is the daily closing price. The descriptive statistics for the daily returns can be seen in Table 1. We found that mean and standard deviation of daily returns in Indonesia and China are the largest. These results indicate that Indonesia and China have the highest level of daily returns in the sample period and are more volatile than the other countries. The daily returns in Singapore are the least, and the standard deviation is the smallest. Each time series presents a smaller skewness and a larger kurtosis, and the results of the Jarque-Bera test show that the variables disobey normal distribution. ADF test results show that all variables are stationary variables, and each variable presents a significant serial correlation based on the Ljung–Box Q test.

Table 2 shows Pearson correlation matrix of daily returns among sample countries. Pearson correlations show that there is a positive correlation among all sample countries (Table 2).We found that the highest pairwise correlation is between Singapore and Malaysia; while the pairwise correlation between Malaysia and China is the lowest. There are significant differences in pairwise correlation in different countries. However, pairwise correlation of daily returns between China and Southeast Asia is relatively low, reflecting that there are still some obstacles to financial integration between China and Southeast Asian countries.

Fig. 2 shows the time series graphs of the squared daily stock returns on the stock markets of all sample countries. We found that Chinese and Southeast Asian stock markets showed obvious volatility clustering during the Asian financial crisis and U.S. subprime mortgage crisis. This result shows that Asian financial crisis and U.S. subprime mortgage crisis have a very obvious spillover impact on the stock markets in China and Southeast Asia. In addition, China's stock market was confronted by the volatility spillover from the stock crash in 2015. It is worth noting that the volatility clustering produced by these two stock crash is more significant and concentrated than U.S. subprime mortgage crisis.

5. Empirical results and discussion

In this article, four multivariate GARCH models (BEKK-MGARCH, Diag-MGARCH, CCC-MGARCH and DCC-MGARCH) are used to model the dynamic correlation between Chinese and Southeast Asian stock market. The BEKK model serves as a benchmark model, and the other three models can be easily calculated and estimated using the following two steps. Firstly, the residual error is calculated based on the BEKK model and secondly, the calculation of other models obtain correlation coefficients based on the residuals calculated in the first step.

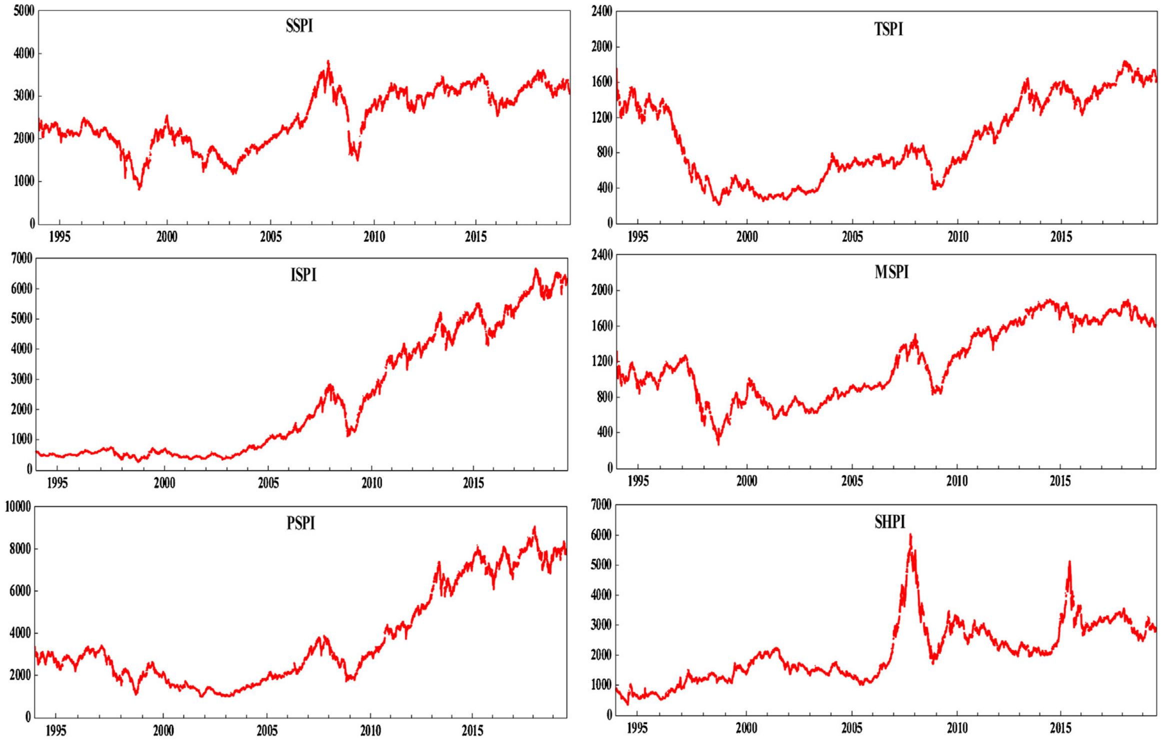

Fig. 1. Time series plots of SSPI, TSPI, ISPI, MSPI, PSPI and SHPI.

Table 1
Summary statistics for daily returns.

Variable	SSPI	TSPI	ISPI	MSPI	PSPI	SHPI
Mean	0.0043	−0.0011	0.0448	0.0039	0.0165	0.0237
Median	0.0088	0.0189	0.0818	0.0184	0.0117	0.0492
Maximum	20.3229	22.6755	16.0037	26.4097	18.5157	28.8610
Minimum	−12.9279	−16.0633	−15.7434	−24.1534	−13.6399	−17.9051
Std. dev.	1.3831	1.6533	1.6714	1.4427	1.5571	2.0770
Skewness	0.4593	0.2996	−0.1430	1.3263	0.3489	1.1012
Kurtosis	19.1121	15.7735	14.1813	61.3741	14.9893	23.6335
Jarque-Bera	57015.32***	35797.36***	27387.15***	747506.60***	31574.60***	94263.79***
ADF test	−70.7149***	−69.2158***	−45.0131***	−33.6926***	−68.4261***	−72.1354***
Q(20)	28.388*	45.29***	72.991***	113.12***	32.886**	56.415***
$Q^2(20)$	1360***	661.63***	1939***	1814.1***	450.03***	35.052**
Observations	5254	5254	5254	5254	5254	5254

Notes: The symbols ***, ** and * indicate the significance level at 1, 5 and 10 percent, respectively.

Table 2
Pearson correlations between daily returns.

Variable	SSPI	TSPI	ISPI	MSPI	PSPI	SHPI
SSPI	1.0000					
TSPI	0.5182***	1.0000				
ISPI	0.5012***	0.4450***	1.0000			
MSPI	0.4858***	0.3993***	0.4111***	1.0000		
PSPI	0.4205***	0.3724***	0.4346***	0.3494***	1.0000	
SHPI	0.1584***	0.0960***	0.1213***	0.0847***	0.1081***	1.0000

Notes: The symbols ***, ** and * indicate the significance level at 1, 5 and 10 percent, respectively.

5.1. Regression results

Table 3 shows the estimated results of four multivariate GARCH models. According to the mean equation, there is a positive and statistically significant result in the own mean spillover effect ($\phi_{11}, \phi_{22}, \phi_{33}, \phi_{44}, \phi_{55}, \phi_{66}$) between Chinese and Southeast Asian stock market. The results indicate that the volatility between Chinese and Southeast Asian stock market depends on their past levels of volatility. For the mean equation of SHPI, the stock markets in Singapore, Thailand, Malaysia and the Philippines all have significant mean spillover effects on the Chinese stock market except for the Indonesian stock market. The estimated coefficients of ϕ_{61} and ϕ_{62} are positive and statistically significant in BEEK and DCC models, while the estimated coefficients of ϕ_{64} and ϕ_{65} are negative and statistically significant in BEEK and DCC models. The results indicate that the log volatility of returns in the stock markets of Singapore and Thailand will have a significant positive spillover effect on the Chinese stock market. The log volatility of returns

Table 3
MGARCH parameter estimates.

	BEKK		Diag		CCC		DCC	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Mean Equation								
ϕ_{10}	0.039***	3.0689	0.0448**	2.0893	0.0631	1.1996	0.0538***	6.0405
ϕ_{11}	0.0006	0.0426	−0.001	−0.0349	−0.0001	−0.0002	0.0119	0.7074
ϕ_{12}	0.0214**	2.0940	0.0412***	3.6095	0.0264	0.2512	0.0161	0.8236
ϕ_{13}	0.0041	0.2731	0.0036	0.3924	0.0176	0.0761	−0.0019	−0.0893
ϕ_{14}	0.0702***	5.1539	0.0431	0.8174	0.0255	0.3687	0.0397*	1.8921
ϕ_{15}	0.0127	1.3395	0.0099**	2.0425	0.0261	0.1385	0.0114	1.4675
ϕ_{16}	−0.0014**	−2.2980	−0.0068	−0.6492	0.0043	0.2227	−0.0074*	−1.9069
ϕ_{20}	0.039**	2.2017	0.0396***	2.8755	0.0874	0.0903	0.0795	1.4211
ϕ_{21}	0.0081	0.5055	−0.0180	−1.0840	−0.0281	−0.0388	0.0023	0.0877
ϕ_{22}	0.0317**	1.9858	0.0878**	2.1418	0.0728	0.1703	0.0519*	1.9193
ϕ_{23}	0.0596***	3.8446	0.0457***	3.5168	0.0541	0.0563	0.0473***	3.9092
ϕ_{24}	0.0648***	3.4961	0.0721***	5.3725	0.0397	0.1186	0.0606*	1.8431
ϕ_{25}	0.0209	1.4550	0.0094	0.6201	0.0238	0.2127	0.0234	1.5066
ϕ_{26}	−0.015***	−2.6312	−0.0123	−0.5574	−0.0117	−0.0476	−0.0194**	−2.3188
ϕ_{30}	0.0849***	5.6418	0.0726***	4.4810	0.0912	0.0847	0.1091***	8.9352
ϕ_{31}	0.0081	0.4995	0.0177	1.1798	−0.0040	−0.0066	0.0144	0.5392
ϕ_{32}	0.0284**	2.4333	0.0396***	3.8689	0.0412	0.0291	0.0269*	1.8030
ϕ_{33}	0.0992***	5.4851	0.1152*	1.7340	0.1379	0.0196	0.0879***	7.3894
ϕ_{34}	0.0499***	2.6593	0.0311	0.8605	0.0324	0.0552	0.0326*	1.7537
ϕ_{35}	0.0211	1.5598	0.0061	0.3687	0.0128	1.5967	0.0123	0.5037
ϕ_{36}	−0.0042	−0.9226	−0.0002	−0.0097	−0.0105	−0.0211	0.0006	0.0129
ϕ_{40}	0.0314***	3.4717	0.0322***	3.3012	0.0471	0.1640	0.0474***	3.2129
ϕ_{41}	0.0245**	2.1670	0.0289***	2.8039	0.0187	0.0408	0.0348	0.6850
ϕ_{42}	0.0164*	1.8159	0.0211	1.1500	0.0259	0.3653	0.0137	0.1290
ϕ_{43}	0.0426***	3.5279	0.0189	1.5514	0.0277	0.0735	0.0279	0.8855
ϕ_{44}	0.0773***	5.3733	0.0746	1.6150	0.0651	0.0618	0.0678*	1.8631
ϕ_{45}	−0.0059	−0.7619	−0.0099	−1.1616	0.0017	0.3586	0.0053	0.4188
ϕ_{46}	−0.0004**	−2.1064	0.0056	0.6155	0.0049	0.0390	−0.0031**	−2.0535
ϕ_{50}	0.0692***	3.5723	0.0578**	2.4132	0.0701***	4.7663	0.0834***	5.5370
ϕ_{51}	0.0808***	5.3064	0.0937***	4.0845	0.0242	0.0478	0.0788***	4.9235
ϕ_{52}	0.0783***	5.8681	0.0836***	7.4767	0.0727	0.5777	0.0706***	5.2370
ϕ_{53}	0.0627***	5.0008	0.051***	3.1635	0.0712	0.7534	0.0471***	3.9478
ϕ_{54}	0.0428**	2.3995	0.0168***	9.0653	0.0658	0.4529	0.0354*	1.7347
ϕ_{55}	0.0170**	2.1540	0.0514***	3.2614	0.0928***	11.3822	0.053***	3.0603
ϕ_{56}	−0.0029	−0.4022	−0.0095	−0.5185	−0.0112	−0.0871	−0.0127	−0.9013
ϕ_{60}	0.0457***	2.6533	0.0414	0.6852	0.0100	0.0184	0.0434**	2.1532
ϕ_{61}	0.0503**	2.4369	0.0303	0.6413	−0.0307	−0.3181	0.0204*	1.7962
ϕ_{62}	0.0319**	2.1534	0.0637***	4.7712	0.0712	0.1363	0.0313***	2.6131
ϕ_{63}	0.0035	0.3738	0.0150	0.3396	0.0389	0.1349	0.0157**	2.4895
ϕ_{64}	−0.037**	−1.9609	−0.0275	−0.9631	−0.0387	−0.0295	−0.052***	−6.5895
ϕ_{65}	−0.0525***	−3.4486	−0.0369	−1.2682	−0.0554	−0.1047	−0.0414**	−3.8111
ϕ_{66}	0.0265**	2.2997	−0.0253**	−2.5441	0.0831	1.2238	0.0624**	2.4008
Variance Equation								
c_{11}	−0.0959***	−7.3668	0.0416***	6.0967	0.045	0.0395	0.0145	1.2146
c_{21}	−0.0639***	−4.1309						
c_{22}	0.0364**	1.9758	0.1349***	28.0349	0.0389	0.0339	0.0824***	3.8433
c_{31}	−0.1198***	−5.4921						
c_{32}	0.0731**	2.1474						
c_{33}	0.0729*	1.9453	0.1424***	34.3219	0.2106	0.1041	0.0045	0.1428
c_{41}	−0.0525***	−5.8972						
c_{42}	−0.0100	−0.5691						
c_{43}	−0.0028	−0.1315						
c_{44}	−0.05***	−6.3002	0.0059***	7.8429	0.0332	0.28	0.0168***	5.9042
c_{51}	−0.1293***	−4.3690						
c_{52}	0.0345	1.0573						
c_{53}	0.0525*	1.6741						
c_{54}	−0.0124	−0.7439						
c_{55}	0.0088	0.3479	0.3485***	14.4921	0.511*	1.737	0.2968***	4.4288
c_{61}	−0.0612**	−2.1467						
c_{62}	0.0144	0.1485						
c_{63}	−0.0680	−0.6991						
c_{64}	−0.0642	−1.5650						
c_{65}	−0.2085***	−3.3760						
c_{66}	−0.0134	−0.1188	1.8361***	6.3164	0.7378***	3.4473	0.1443***	3.3413
α_{11}	0.1876***	10.8046	0.2334***	10.7745	0.1609	0.3552	0.0882***	4.4700
α_{12}	0.0743***	3.7077	−0.0008***	−7.8913	−0.0070	−0.1637	−0.0045	−1.0458
α_{13}	0.0779***	2.8027	0.0373***	5.3260	0.0086	0.0355	−0.0083	−0.9196
α_{14}	0.0282**	2.2610	0.0586***	41.5869	0.0424	0.1284	0.0167**	2.3483
α_{15}	0.0738***	3.0341	−0.009***	−14.9508	0.0001	0.0005	0.0060***	2.8534

Table 3 (*Continued*)

α_{16}	0.0109	0.4543	−0.0001	−0.9556	−0.0001	−0.0606	0.0011**	2.0472
α_{21}	−0.0085	−1.0524	0.0391*	1.8224	0.0080	0.0176	−0.0192	−1.2735
α_{22}	0.0856***	5.6102	0.2109***	16.5844	0.1843	0.8107	0.1540**	2.2723
α_{23}	−0.0012	−0.1319	−0.0019	−0.0652	−0.0114	−0.8739	−0.0051	−0.1615
α_{24}	−0.0012	−0.1462	0.0554**	2.1563	−0.0241	−0.3936	−0.0045	−0.0900
α_{25}	0.0043	0.3023	−0.0106***	−3.1451	0.0016	0.0248	−0.0065	−0.5438
α_{26}	−0.0446	−1.6167	0.0012	0.7488	0.0025	0.2300	0.0012	0.0926
α_{31}	0.0503***	4.2259	0.0884***	4.8753	0.0579	0.2415	−0.0065**	−2.2595
α_{32}	0.0607***	3.6039	0.0271***	12.5270	−0.0077	−0.0924	−0.0032	−0.1340
α_{33}	0.2417***	10.8114	0.1788***	10.5432	0.1948	1.0014	0.1307***	5.1025
α_{34}	0.0071	0.6428	−0.0239***	−8.2973	−0.0294	−0.2610	−0.0142**	−2.0619
α_{35}	0.0593***	3.2673	0.0186***	4.0344	0.0036	0.0151	−0.0048	−0.7859
α_{36}	0.0001	0.0064	0.0001	0.2821	−0.0002	−0.0519	−0.0002	−0.2590
α_{41}	0.0256*	1.8819	0.0209***	26.0676	0.0141	0.0664	0.0053	1.6316
α_{42}	0.0087	0.5246	0.0097***	7.0296	0.0010	0.0061	−0.0033	−1.0029
α_{43}	−0.0423***	−3.0898	0.0035	0.6305	0.0097	0.2674	−0.0017	−1.3928
α_{44}	0.1993***	9.4942	0.1223***	31.9118	0.1361	0.2303	0.1354***	6.2015
α_{45}	−0.0151	−1.0832	0.0004	0.4488	−0.0017	−0.3893	0.005***	12.1296
α_{46}	−0.0053	−0.3945	0.0019***	76.0727	0.0052	1.5701	−0.0002*	−1.8500
α_{51}	0.0027	0.2519	0.0129***	2.7522	0.0404	0.2800	−0.0039	−0.2433
α_{52}	0.0242	1.2801	0.0065	1.4020	0.0191	0.0853	0.0269	0.2697
α_{53}	0.0229	1.3948	−0.0101	−0.9830	0.0081	0.0223	−0.0047	−0.3246
α_{54}	0.0051	0.7352	0.0289	0.9190	0.0733	0.7478	0.0209	0.3534
α_{55}	0.0978***	3.4780	0.139***	19.4872	0.1532	1.0110	0.1204***	5.6343
α_{56}	0.0223	0.6614	0.0036***	9.8181	−0.0006	−0.1459	−0.0011**	−2.4142
α_{61}	−0.0044	−0.7901	0.0193	1.5068	0.0058	0.0564	0.0118	0.7903
α_{62}	0.0119	1.0502	0.0159***	2.7069	0.0136	0.0676	0.0037	1.1624
α_{63}	−0.0033	−0.8273	−0.0269***	−8.1241	−0.019***	−4.6243	−0.0095***	−3.1735
α_{64}	0.0021	0.3879	−0.0003	−0.0523	−0.0041	−0.0889	0.0018	0.4762
α_{65}	−0.0076	−0.8693	0.0111	0.3203	−0.0066	−0.0837	0.0017	0.2755
α_{66}	0.329***	6.8665	0.1137***	13.5641	0.4334*	1.8505	0.3134***	6.3803
b_{11}	0.9809***	299.1796	0.4958***	77.4330	0.6183	0.6759	0.8063***	13.1491
b_{12}	−0.0126***	−3.2805	0.0424***	47.6683	0.0152	0.1360	0.0314***	8.4201
b_{13}	−0.0141**	−2.4024	0.0732***	53.3863	0.0407	0.3137	0.0660	29.8287
b_{14}	−0.0047**	−2.1964	0.0238***	9.4677	0.0961	0.4883	−0.0180	−4.3858
b_{15}	−0.0085**	−2.2112	0.041***	48.0134	0.0229	0.0908	−0.0207**	−2.3872
b_{16}	0.0005	0.1142	−0.0034***	−7.8933	−0.0012	−0.2996	−0.0010	−0.6657
b_{21}	0.0014	1.3373	0.0609***	9.6325	−0.0819	−0.0507	0.1195***	4.9585
b_{22}	0.9956***	618.2709	0.499***	30.2438	0.5903	0.2977	0.6049***	7.4703
b_{23}	0.0017	1.0063	0.0394***	2.6423	0.0495	0.1625	0.0154*	1.9389
b_{24}	0.0006	0.5603	0.1352***	14.3982	0.2493	0.6075	0.2044***	8.0707
b_{25}	−0.0044*	−1.7695	0.1116***	21.1577	0.1281	0.2981	0.0405*	1.8291
b_{26}	0.0024	0.8621	−0.0116***	−2.7862	0.0030	0.0511	0.0032	0.4743
b_{31}	−0.011***	−3.3519	0.1048***	10.2094	0.1762	0.1767	0.2270***	11.0479
b_{32}	−0.0174***	−4.4117	−0.057***	−7.8325	0.0337	0.1492	−0.0176***	−9.1444
b_{33}	0.965***	182.1826	0.6539***	42.9129	0.4860	0.4584	0.6484***	66.9073
b_{34}	−0.0030	−1.0568	0.0771***	9.5055	0.0512	0.1363	0.0266	0.7782
b_{35}	−0.0143***	−3.8194	−0.0174*	−1.7302	0.0044	0.0277	0.0886***	31.8998
b_{36}	−0.0012	−0.3758	−0.0023***	−14.3827	−0.0007	−0.0626	−0.0008	−1.1379
b_{41}	−0.0034	−1.1138	0.0049***	4.0204	0.0168	0.8821	0.0000	0.0017
b_{42}	0.0002	0.0560	−0.0033**	−2.1028	0.0156	0.2209	0.0477***	11.5043
b_{43}	0.0106***	2.9989	−0.0006	−0.4147	−0.0282	−0.6098	0.0089*	1.8513
b_{44}	0.9798***	240.4859	0.8324***	97.1281	0.8341***	5.2362	0.8091***	15.6628
b_{45}	0.0051*	1.7181	−0.0033**	−2.3971	−0.0086	−0.1166	−0.0353***	−10.1875
b_{46}	0.0008	0.2537	0.0004**	2.4667	−0.0049	−0.3561	0.0006	0.0684
b_{51}	−0.0049*	−1.7083	0.0551***	5.6699	0.0139**	2.3001	0.1815***	25.9457
b_{52}	−0.0007	−0.2539	0.0249***	6.8973	0.0011	0.0062	0.0911***	13.5389
b_{53}	−0.0085**	−2.0710	0.0293***	3.4708	−0.0197	−0.1769	0.0654***	3.3755
b_{54}	−0.0024	−1.6437	0.1246***	6.6597	0.1521***	3.9814	−0.0696**	−2.2330
b_{55}	0.9904***	192.8364	0.5413***	203.0798	0.4492	0.7226	0.4598***	67.0379
b_{56}	−0.0007	−0.1280	−0.0177***	−21.0955	−0.0006	−0.0126	−0.0003	−0.3362
b_{61}	0.0007	0.4126	−0.0569***	−5.2591	−0.0781	−0.1645	−0.0673***	−4.1021
b_{62}	−0.0025	−0.8483	0.0712***	10.1559	0.0467	0.2053	0.0151***	8.2381
b_{63}	0.0008	0.9998	−0.0266**	−2.4856	0.0216	0.0915	0.0377***	17.3506
b_{64}	−0.0015	−0.8479	−0.0008	−0.1701	−0.0079	−0.0248	0.0058	0.2768
b_{65}	0.0014	0.6082	−0.0147	−1.3730	0.0742	0.1811	−0.0231***	−6.2377
b_{66}	0.9474***	70.5003	0.4589***	52.6886	0.4683***	7.1904	0.7474***	17.3573
ρ_{16}					0.143***	6.375		
ρ_{26}					0.077	0.731		
ρ_{36}					0.087	0.851		
ρ_{46}					0.083	0.485		
ρ_{56}					0.075	0.612		
DCC(1)							0.0078***	19.126
DCC(2)							0.9895***	1829.52
LogL	−56487.8849		−60548.055		−56908.5055		−56074.3423	
AIC	19.259		20.635		19.403		19.114	
SC	19.413		20.772		19.556		19.253	

Notes: The symbols ***, ** and * indicate the significance level at 1, 5 and 10 percent, respectively.

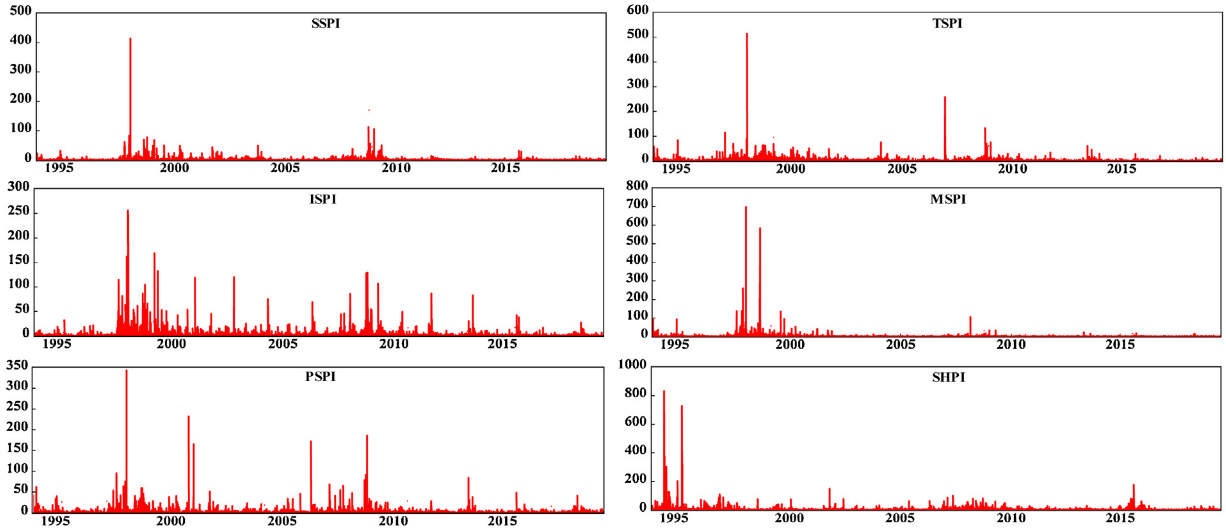

Fig. 2. Squared daily returns of SSPI, TSPI, ISPI, MSPI, PSPI and SHPI.

in Malaysia and the Philippines will have a significant negative spillover effect on the Chinese stock market. On the contrary, the log volatility of returns in the stock market of China will have a negative spillover effect(ϕ_{16}, ϕ_{26}, ϕ_{36}, ϕ_{46}, ϕ_{56}, ϕ_{66})for all the stock markets in Southeast Asia, but only the estimated coefficients of ϕ_{16}, ϕ_{26} and ϕ_{46} are statistically significant in BEEK and DCC models. These results suggest that the log volatility of returns in the stock market of China will have a significant negative spillover effect to the stock markets of Singapore, Thailand and Malaysia.

For the variance equation, matrix element α_{ij} represents the conditional ARCH effect, and its estimated coefficient is used to measure the persistence of short-term volatility. The own conditional ARCH effect ($\alpha_{11}, \alpha_{22}, \alpha_{33}, \alpha_{44}, \alpha_{55}, \alpha_{66}$) is statistically significant under the confidential level of 5 %, which provides lots of evidence for the persistence of short-term volatility in various stock markets. In addition, conditional variance is a function of the volatility impact of self-lag covariance and the lagged return rate of each stock market. From the variance equation, four multivariate GARCH models can measure the short-term volatility spillover among six stock markets. It is worth noting that the estimated coefficient ($\alpha_{16}, \alpha_{36}, \alpha_{46}, \alpha_{56}$) is positive and statistically significant in the DCC model. This result confirms that there is a positive cross-effect and feedback effect between Chinese and Southeast Asian stock markets (except Thailand).

For the variance equation, matrix element b_{ij} represents the conditional GARCH effect, and its estimated coefficient is used to measure the persistence of long-term volatility. According to the variance equation in Table 3, the estimated coefficient is positive and statistically significant, which indicates that each stock market has the persistence of own long-term volatility. Besides, we found that the conditional variance of each variable is also affected by the innovation from at least one other variable except for the own innovation in the past. According to the CCC model, the correlation coefficients (ρ_{16}, ρ_{26}, ρ_{36}, ρ_{46} and ρ_{56}) are positive between Chinese and Southeast Asian stock markets, but only the estimated coefficients ρ_{16} are statistically significant under the confidence level of 1 %. For the DCC model, the DCC estimation parameters (DCC(1) and DCC(2)) are positive and statistically significant under the confidence level of 1 %. The sum of the two estimated parameters (DCC(1) and DCC(2)) is less than 1, indicating that the dynamic conditional correlations are mean reverting and the estimated coefficient is statistically significant. Therefore, these results lead to a rejection of the assumption of CCC for all innovation to stock return. Finally, AIC and SIC criteria both show that the DCC model is the best model to estimate the volatility spillover between China and Southeast Asian stock markets.

Based on the residual error diagnostic test results in Table 4, The BEKK model, Diag model and CCC model shows more evidence of autocorrelation in the squared standardized residuals. Based on the residual diagnostic tests, we found that the DCC model is considered to be the appropriate model to reflect the volatility information and can be used to construct dynamic conditional correlation. Because standardized residuals (Q(20) statistic) do not have statistically significant autocorrelation evidence at 1 % significance level. In addition, Q-square statistic (Q(20) r^2 statistic) also shows that there is no statistically significant GARCH effect at 1 % of the significance level. So we can construct optimal hedge ratios and portfolio weights through estimating conditional volatility from the DCC model.

5.2. *Dynamic conditional correlation*

Fig. 3 shows the time-varying dynamic conditional correlation between China and Southeast Asian stock markets based on the DCC model. The dynamic conditional correlation graph clearly shows that the conditional correlation of sequence variables does not remain unchanged over time, but fluctuates significantly over time. On the whole, the dynamic conditional correlation is positive effect between China and Southeast Asian stock markets. In practical terms, the dynamic conditional correlation do alternate in sign and cover a range of values between -0.15 to 0.45. These periods of negative correlation provide meaningful opportunities for portfolio diversification.

It is worth noting that the dynamic conditional correlation between China and Southeast Asian stock markets reached a peak value during the Asian financial crisis, U.S. subprime crisis and stock market crash in 2015. The results robustly demonstrate that there is a relatively obvious positive spillover effect between China and Southeast Asian stock markets, and that the volatility of Chinese stock market will spill over into Southeast Asian stock market, which shows that there is a relatively obvious co-movement between China and Southeast Asian stock markets. The co-movement is more obvious after CAFTA was fully activated. The results in Table 5 show that the average dynamic conditional correlation between China and Southeast Asian stock market were not more than 0.1 before CAFTA was fully activated, but average dynamic conditional correlation between China and southeast Asian stock market was more than doubled after CAFTA was fully

Table 4
Diagnostic tests for standardized residuals.

	BEKK-GARCH						Diag-GARCH					
	SHPI	SSPI	TSPI	ISPI	MSPI	PSPI	SHPI	SSPI	TSPI	ISPI	MSPI	PSPI
Q(20)*r*	43.92	19.08	56.22	27.12	29.17	27.58	15.40	30.67	25.87	20.89	16.65	30.52
p-values	0.001	0.516	0.00	0.132	0.084	0.12	0.753	0.06	0.17	0.403	0.676	0.062
Q(20)r^2	36.14	44.98	4.64	30.66	39.62	33.35	0.22	12.55	11.66	2.031	2.64	40.72
p-values	0.015	0.001	1.00	0.06	0.006	0.031	1.00	0.896	0.927	1.00	1.00	0.004
	CCC-GARCH						DCC-GARCH					
	SHPI	SSPI	TSPI	ISPI	MSPI	PSPI	SHPI	SSPI	TSPI	ISPI	MSPI	PSPI
Q(20)*r*	47.51	28.28	55.39	30.63	34.79	23.27	12.89	30.91	24.59	25.04	21.79	30.31
p-values	0.00	0.103	0.00	0.06	0.021	0.276	0.882	0.056	0.218	0.215	0.352	0.065
Q(20)r^2	23.28	44.26	14.35	20.81	19.84	7.20	2.23	21.12	18.15	29.66	7.98	20.05
p-values	0.275	0.001	0.812	0.409	0.468	0.996	1.000	0.39	0.578	0.076	0.992	0.455

Notes: Q(20) is the Ljung and Box (1978) test for serial correlation with 20 degrees of freedom.

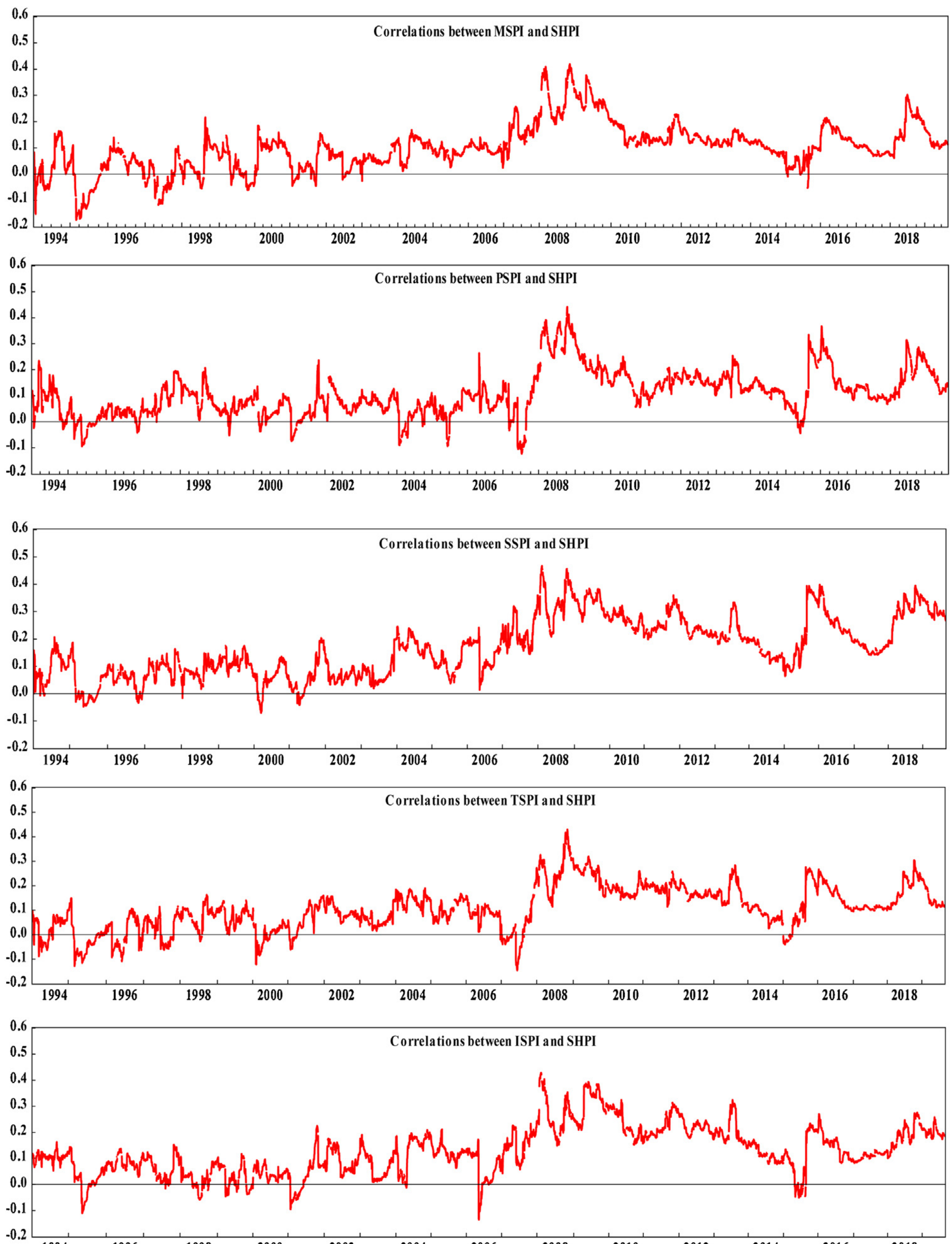

Fig. 3. Time-varying conditional correlations from the DCC model.

Table 5
Average dynamic conditional correlations.

Variable	Pre-CAFTA		Post-CAFTA		Full period
	Sample Period	Average DCC	Sample Period	Average DCC	Average DCC
SSPI/SHPI	1991:01–2009:12	0.0968	2010:01–2019:08	0.2446	0.1455
TSPI/SHPI	1991:01–2009:12	0.0843	2010:01–2019:08	0.1739	0.1138
ISPI/SHPI	1991:01–2009:12	0.0755	2010:01–2019:08	0.1801	0.1099
MSPI/SHPI	1991:01–2009:12	0.0676	2010:01–2019:08	0.1368	0.0904
PSPI/SHPI	1991:01–2009:12	0.0668	2010:01–2019:08	0.1531	0.0952

Table 6
Hedge ratio (long/short) summary statistics.

Variable	Mean	Median	St.Dev	Max	Min
SSPI/SHPI	0.1237	0.1062	0.1013	1.0907	−0.0727
TSPI/SHPI	0.0951	0.0810	0.0973	0.9217	−0.2062
ISPI/SHPI	0.1076	0.0936	0.0990	0.7843	−0.2234
MSPI/SHPI	0.0687	0.0549	0.0799	0.5814	−0.2998
PSPI/SHPI	0.0987	0.0860	0.0941	0.9699	−0.2160
SHPI/SSPI	0.2732	0.2536	0.2131	1.7452	−0.3032
SHPI/TSPI	0.1371	0.1287	0.1335	0.7606	−0.4990
SHPI/ISPI	0.1760	0.1562	0.1591	1.6887	−0.7973
SHPI/MSPI	0.1766	0.1736	0.1684	1.1530	−0.6222
SHPI/PSPI	0.1375	0.1124	0.1440	1.4277	−0.5814

Table 7
Portfolio weights summary statistics.

Variable	Mean	Median	St.Dev	Max	Min
SSPI/SHPI	0.7145	0.7810	0.2034	1.0000	0.0000
TSPI/SHPI	0.6085	0.6503	0.1981	0.9998	0.0000
ISPI/SHPI	0.6153	0.6493	0.2016	1.0000	0.0000
MSPI/SHPI	0.7685	0.8472	0.2050	1.0000	0.0000
PSPI/SHPI	0.6143	0.6312	0.1818	1.0000	0.0000

activated, rising by more than 13 %. Obviously, the barriers of flow of financial capital between China and Southeast Asian countries dropped significantly after CAFTA was fully activated, and this has further deepened the process of China-ASEAN financial integration. On the other hand, it also confirms the positive cross effect and feedback effect between China and Southeast Asian stock markets. In addition, the dynamic conditional correlation between China and Southeast Asian stock market reached low values around May 1995, February 2001, mid-2007 and in the beginning of 2015.

Fig. 3 shows that the dynamic conditional correlation for each pair of sequences peaked in the autumn of 2008, the worst recession since the Great Depression of the 1930s. The time series diagram in Fig. 3 shows that the dynamic conditional correlation (DCC) provides more useful information than the constant conditional correlation (CCC) for each pair of series. It is also worth noting that the dynamic conditional correlation of each pair of series was far greater than the corresponding constant conditional correlation at the onset and duration of the recession in 2008 and 2009. This further confirms the notion that any calculations with the conditional correlations from the constant conditional correlation model are highly erroneous.

5.3. Hedging

We can construct hedge ratios through estimating conditional volatility from the DCC model (Kroner & Sultan, 1993). For instance, a long position in one asset (say asset*i*) can be hedged with a short position in a second asset (say asset*j*). The hedge ratio between asset i and asset j is:

$$\beta_{ijt} = h_{ijt}/h_{jjt}$$

For most of the hedge ratios, computed from the DCC model, the graphs show considerable variability after August 2008 (Fig. 4). For many of the hedge ratios, it is also the case that the maximum value was recorded after August 2008. The exceptions are the SHPI/SSPI, SHPI/ISPI, SHPI/MSPI and SHPI/PSPI hedges where the largest values for these hedge ratios were recorded near the beginning of the sample period.

The average value of the hedge ratio between SHPI and SSPI is 0.2732, while the average value of the hedge ratio between SHPI and TSPI is 0.1371 (Table 6). On the other hand, the average value of the hedge ratio between SHPI and ISPI is 0.1760 and the average value of the hedge ratio between SHPI and MSPI is 0.1766. Lastly but not least, the average value of the hedge ratio between SHPI and PSPI is 0.1375.These results are important in establishing that a $1 long position in Shanghai composite index (SHPI) can be hedged for 27.32 cents with a short position in the FTSE Straits Times Index (SSPI). Similarly, a $1 long position in Shanghai composite index (SHPI) can be hedged for 13.71 cents with a short position in the Thailand SET Index (TSPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 17.6 cents with a short position in the Jakarta Composite Index (ISPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 17.66 cents with a short position in the FTSE Bursa Malaysia Composite Index (MSPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 13.75 cents with a short position in the Manila Composite Index (PSPI). The cheapest hedge is long MSPI and short SHPI. The most expensive hedge is long SHPI and short SSPI. Notice that five of the hedge ratios recorded maximum values in excess of unity.

5.4. Portfolio weights

We can construct optimal portfolio weights by using conditional volatilities from MGARCH models (Kroner & Ng, 1998).

$$\omega_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}$$

$$\omega_{ij,t} = \begin{cases} 0, \; if & \omega_{ij,t} < 0 \\ \omega_{ij,t}, \; if & 0 \le \omega_{ij,t} \le 1 \\ 1, \; if & \omega_{ij,t} > 1 \end{cases}$$

In constructing portfolio weights between two assets, $\omega_{ij,t}$ is the weight of the first asset in a one dollar portfolio of two assets (asset i, asset j) at time t, $h_{ij,t}$ is the conditional covariance between assets i and j and $h_{ij,t}$ is the conditional variance of asset j. The weight of the second asset is $1 - \omega_{ij,t}$. Summary statistics for portfolio weights computed from the DCC model are reported in Table 7. The average weight for the SSPI/SHPI portfolio is 0.7145, indicating that for a $1 portfolio, 71.45 cents should be invested in SSPI and 28.55 cents invested in SHPI. The average weight for the TSPI/SHPI portfolio indicates that 60.85 cents should be invested in TSPI and 39.15 cents invested in SHPI. The average weight for the ISPI/SHPI portfolio indicates that 61.53 cents should be invested in ISPI and 38.47 cents invested in SHPI. The average weight for the MSPI/SHPI portfolio indicates that 76.85 cents should be invested in MSPI and 23.15 cents invested in SHPI. The average weight for the PSPI/SHPI

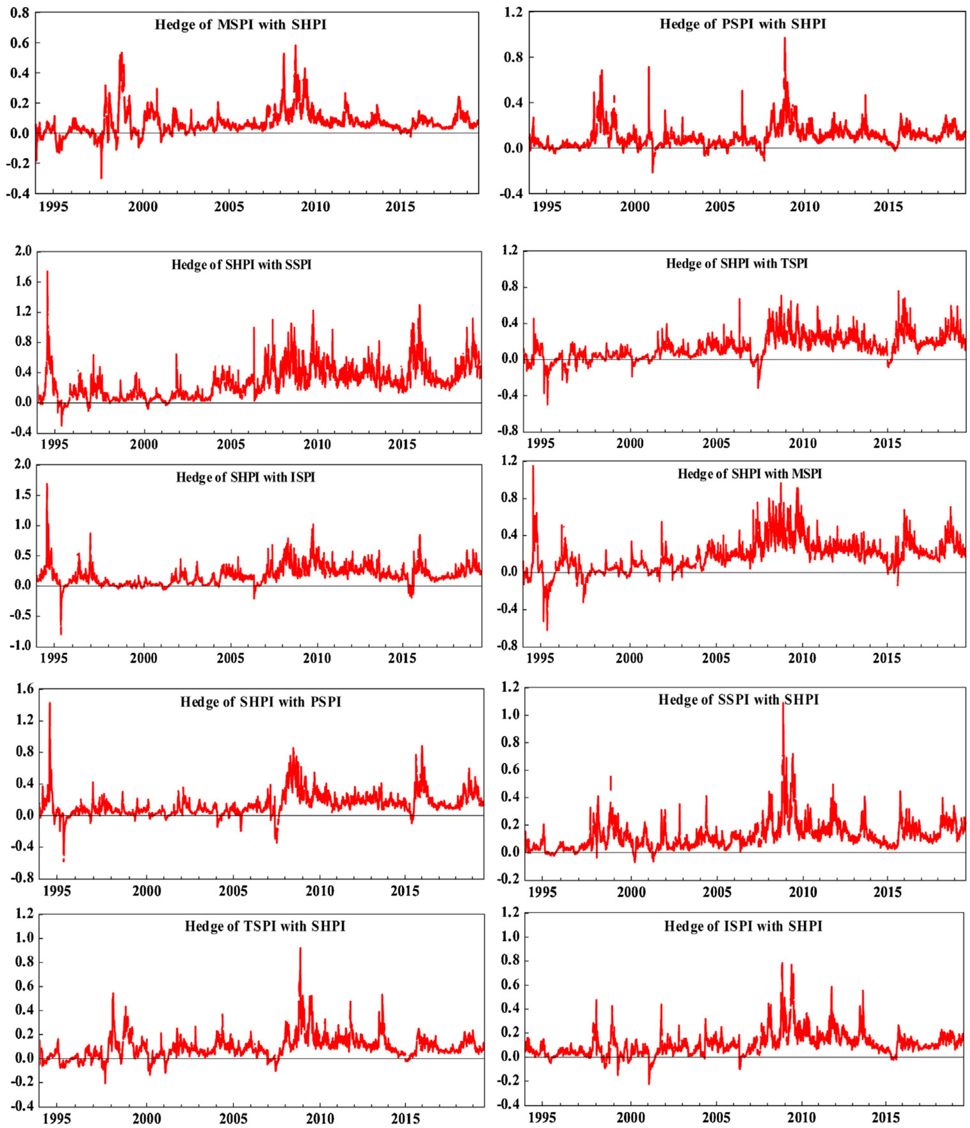

Fig. 4. Time-varying hedge ratios computed from the DCC model.

portfolio indicates that 61.43 cents should be invested in ISPI and 38.57 cents invested in SHPI.

6. Conclusion

Our research uses multivariate GARCH models to model dynamic conditional correlations and the volatility spillovers between Chinese and Southeast Asian stock market. Four multivariate GARCH models (BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation) are compared and contrasted. It was found that the DCC-GARCH model fits the data best and this model was then used to construct hedge ratios and optimal portfolio weights. In conclusion, our study indicates that the dynamic conditional correlation between China and Southeast Asian stock markets is positive in total. Previously, the dynamic conditional correlation between China and Southeast Asian stock markets reached a peak value during the Asian financial crisis, U.S. subprime crisis and stock market crash in 2015. It is worth noting that there is a relatively obvious co-movement between China and Southeast Asian stock markets and this co-movement is more obvious after CAFTA became fully activated.

In addition, we can estimate dynamic hedge ratios by using conditional volatilities from the DCC model. On average, a $1 long position in Shanghai composite index (SHPI) can be hedged for 27.32 cents with a short position in the FTSE Straits Times Index (SSPI). Similarly, a $1 long position in Shanghai composite index (SHPI) can be hedged for 13.71 cents with a short position in the Thailand SET Index (TSPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 17.6 cents with a short position in the Jakarta Composite Index (ISPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 17.66 cents with a short position in the FTSE Bursa Malaysia Composite Index (MSPI). A $1 long position in Shanghai composite index (SHPI) can be hedged for 13.75 cents with a short position in the Manila Composite Index (PSPI).

Finally, we can construct optimal two asset portfolios by using conditional variances and covariances from the DCC model. The average weight for the SSPI/SHPI portfolio is 0.7145, indicating that for a $1 portfolio, 71.45 cents should be invested in SSPI and 28.55 cents invested in SHPI. The average weight for the TSPI/SHPI portfolio indicates that 60.85 cents should be invested in TSPI and 39.15 cents invested in SHPI. The average weight for the ISPI/SHPI portfolio indicates that 61.53 cents should be invested in ISPI and 38.47

cents invested in SHPI. The average weight for the MSPI/SHPI portfolio indicates that 76.85 cents should be invested in MSPI and 23.15 cents invested in SHPI. The average weight for the PSPI/SHPI portfolio indicates that 61.43 cents should be invested in ISPI and 38.57 cents invested in SHPI.

The above empirical results play a significant enlightening role in maintaining the stability of the financial market and inhibiting financial risk in China. The launch of CAFTA and the in-depth implementation of the "one belt and one road" initiative have deepened the connection between Southeast Asian and China's financial markets to some extent. Although China's stock market implements a relatively strict capital access system, it is also necessary to prevent the negative impact of cross-border risk transmission on China's stock market. Therefore, China has to establish a sound stock market early warning mechanism for the government. The financial regulatory authorities should pay close attention to the economic and financial situation of Southeast Asian countries; strictly control the cooperation between Southeast Asian countries and China in financial projects; keep an eye on the capital flow of Southeast Asian countries and China as well as to strictly prevent the severe losses in China's Financial Market caused by the extreme risk situation in Southeast Asian countries. On the other hand, China and Southeast Asian countries should strengthen cooperation, support each other and jointly resist the adverse impact of financial risk spillovers on all countries.

For Southeast Asian countries, they can take advantage of the implementation of CAFTA and "One Belt And One Road" initiative to ride the train of China's rapid economic growth. China and Southeast Asian countries should cooperate in the construction of financial infrastructure, regional financial market development, financial risk prevention and control, and other areas to push the process of China-ASEAN financial integration into a stage of materialization and institutionalization. On the other hand, Southeast Asian countries should deepen their financial market reform, improve the financial market system, and vigorously promote the construction of financial derivatives market. Finally, investors can choose diversified portfolios with low correlation to diversify risks according to the dynamic conditional correlation between the stock markets of China and ASEAN. Stock portfolios of China and Southeast Asian countries can be established for investors, and stock index futures can be used to hedge stock investments of China or Southeast Asian countries, and this can effectively reduce investment risks. In this process, they should pay active attention to the trends of domestic and international stock markets, improve risk awareness, and realize optimal allocation of capital.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A

See Table A1.

Table A1
List of Abbreviations.

Abbreviations	Full Spelling
CAFTA	China-ASEAN Free Trade Area
ASEAN	Association of Southeast Asian Nations
OBOR	One Belt and One Road
SSPI	FTSE Straits Times Index
TSPI	Thailand SET Index
ISPI	Jakarta Composite Index
MSPI	FTSE Bursa Malaysia Composite Index
PSPI	Manila Composite Index
SHPI	Shanghai composite index

References

Abounoori, E., & Tour, M. (2019). Stock market interactions among Iran, USA, Turkey, and UAE. *Physica A: Statistical Mechanics and its Applications*, *524*(6), 297–305.
Alfreedi, A. A. (2019). Shocks and volatility spillover between stock markets of developed countries and GCC stock markets. *Journal of Taibah University for Science*, *13*(1), 112–120.
Bala, D. A., & Takimoto, T. (2017). Stock markets volatility spillovers during financial crises: A DCC-MGARCH with skewed-t density approach. *Borsa Istanbul Review*, *17*(1), 25–48.
Bekiros, S. D. (2014). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC. *International Review of Financial Analysis*, *33*, 58–69.
Cardona, L., Gutiérrez, M., & Agudelo, D. A. (2017). Volatility transmission between US and Latin American stock markets: Testing the decoupling hypothesis. *Research in International Business and Finance*, *39*, 115–127.
Cheng, H., & Glascock, J. L. (2005). Dynamic linkages between the greater China economic area stock markets—Mainland China, Hong Kong, and Taiwan. *Review of Quantitative Finance and Accounting*, *24*(4), 343–357.
Chien, M. S., Lee, C. C., Hu, T. C., & Hu, H. t. (2015). Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. *Economic Modelling*, *51*, 84–98.
Dajčman, S., & Festić, M. (2012). Interdependence between the Slovenian and European stock markets–a DCC-GARCH analysis. *Economic research-Ekonomska istraživanja*, *25*(2), 379–395.
El Ghini, A., & Saidi, Y. (2017). Return and volatility spillovers in the Moroccan stock market during the financial crisis. *Empirical Economics*, *52*(4), 1481–1504.
El Hedi Arouri, M., Bellalah, M., & Nguyen, D. K. (2010). The comovements in international stock markets: New evidence from Latin American emerging countries. *Applied Economics Letters*, *17*(13), 1323–1328.
Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339–350.
Eun, C. S., & Shim, S. (1989). International transmission of stock market movements. *Journal of Financial and Quantitative Analysis*, *24*(2), 241–256.
Güloğlu, B., Kaya, P., & Aydemir, R. (2016). Volatility transmission among Latin American stock markets under structural breaks. *Physica A: Statistical Mechanics and its Applications*, *462*, 330–340.
Gulzar, S., Mujtaba Kayani, G., Xiaofen, H., Rafique, A., & Ayub, U. (2019). Financial cointegration and spillover effect of global financial crisis: A study of emerging Asian financial markets. *Economic research-Ekonomska istraživanja*, *32*(1), 187–218.
Hahm, S. M. (2004). Transmission of stock returns and volatility: The case of Korea. *The Journal of The Korean Economy*, *5*(1), 17–45.
Hung, N. T. (2019). Equity market integration of China and Southeast Asian countries: further evidence from MGARCH-ADCC and wavelet coherence analysis. *Quantitative Finance and Economics*, *3*(2), 201–220.
Hwang, J. K. (2014). Spillover effects of the 2008 financial crisis in Latin America stock markets. *International Advances in Economic Research*, *20*(3), 311–324.
Jain, P., & Sehgal, S. (2019). An examination of return and volatility spillovers between mature equity markets. *Journal of Economics and Finance*, *43*(1), 180–210.
Jebran, K., Chen, S., Ullah, I., & Mirza, S. S. (2017). Does volatility spillover among stock markets varies from normal to turbulent periods? Evidence from emerging markets of Asia. *The Journal of Finance and Data Science*, *3*(1–4), 20–30.
Jeon, B. N., & Von Furstenberg, G. M. (1990). Growing international co-movement in stock price indexes. *Quarterly Review of Economics and Business*, *30*(3), 15–31.
Joshi, P. (2011). Return and volatility spillovers among Asian stock markets. *SAGE Open*, *1*(1), 1–8.
Karunanayake, I., & Valadkhani, A. (2011). Asymmetric dynamics in stock market volatility. *Economic Papers: A Journal of Applied Economics and Policy*, *30*(2), 279–287.
Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, *11*(4), 817–844.
Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, *28*(4), 535–551.

Kundu, S., & Sarkar, N. (2016). Return and volatility interdependences in up and down markets across developed and emerging countries. *Research in International Business and Finance*, *36*, 297–311.

Lee, S. S. P., & Goh, K. L. (2016). Regional and international linkages of the asean-5 stock markets: A multivariate GARCH approach. *Asian Academy of Management Journal of Accounting & Finance*, *12*(1), 49–71.

Liu, C. (2016). Spillover effects in major equity markets: A GARCH BEKK approach. *Open Access Library Journal*, *3*(02), 1–21.

Majdoub, J., & Sassi, S. B. (2017). Volatility spillover and hedging effectiveness among China and emerging Asian Islamic equity indexes. *Emerging Markets Review*, *31*(6), 16–31.

Mathur, I., & Subrahmanyam, V. (1990). Interdependencies among the Nordic and US stock markets. *The Scandinavian Journal of Economics*, *92*(4), 587–597.

Miyakoshi, T. (2003). Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets, Institutions and Money*, *13*(4), 383–399.

Moon, G. H., & Yu, W. C. (2010). Volatility spillovers between the US and China stock markets: Structural break test with symmetric and asymmetric GARCH approaches. *Global Economic Review*, *39*(2), 129–149.

Nishimura, Y., & Men, M. (2010). The paradox of China's international stock market co-movement: Evidence from volatility spillover effects between China and G5 stock markets. *Journal of Chinese Economic and Foreign Trade Studies*, *3*(3), 235–253.

Obadiaru, D. E., Oloyede, J. A., Omankhanlen, A. E., & Asaleye, A. J. (2018). Stock market volatility spillover in west Africa: Regional and global perspectives. *Journal of Applied Economic Sciences*, *13*(6), 1597–1604.

Özdemir, L. (2020). Testing for asymmetric causality between developed and emerging markets. In *Uncertainty and challenges in contemporary economic behaviour*. Emerald Publishing Limited.

Panda, A. K., Nanda, S., & Paital, R. R. (2019). An empirical analysis of stock market interdependence and volatility spillover in the stock markets of Africa and Middle East region. *African Journal of Economic and Management Studies*, *10*(3), 314–335.

Qarni, M. O., & Gulzar, S. (2018). Return and volatility spillover across stock markets of China and its Major Trading Partners: Evidence from Shanghai stock exchange crash. *Business & Economic Review*, *10*(3), 1–20.

Qian, P. Y., & Diaz, J. F. (2017). Volatility integration of global stock markets with the Malaysian stock market: A Multivariate GARCH approach. *Malaysian Journal of Economic Studies*, *54*(1), 83–117.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, *34*(1), 248–255.

Sarwar, S., Khalfaoui, R., Waheed, R., & Dastgerdi, H. G. (2019). Volatility spillovers and hedging: Evidence from Asian oil-importing countries. *Resources Policy*, *61*, 479–488.

Savva, C. S. (2009). International stock markets interactions and conditional correlations. *Journal of International Financial Markets, Institutions and Money*, *19*(4), 645–661.

Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance*, *44*(5), 1115–1153.

Singh, A., & Singh, M. (2017). Co-movement and spillovers: empirical evidence from BRIC equity markets. *China Economic Journal*, *10*(3), 341–361.

Singh, P., Kumar, A., & Deepak, C. A. (2015). Volatility spillover across major equity markets: A critical review of literature. *International Journal of Research in Commerce & Management*, *6*(4), 68–72.

Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. *International Review of Financial Analysis*, *39*, 7–18.

Tastan, H. (2005). *Dynamic interdependence and volatility transmission in Turkish and European equity markets*. Turkish Economic Association Discussion Paper No. 2005/10.

Uludag, B. K., & Khurshid, M. (2019). Volatility spillover from the Chinese stock market to E7 and G7 stock markets. *Journal of Economic Studies*, *46*(1), 90–105.

Umer, U. M., Coskun, M., & Kiraci, K. (2018). Time-varying return and volatility spillover among EAGLEs stock markets: A multivariate GARCH analysis. *Journal of Finance and Economics Research*, *3*(1), 23–42.

Vo, X. V., & Tran, T. T. A. (2020). Modelling volatility spillovers from the US equity market to ASEAN stock markets - ScienceDirect. *Pacific-Basin Finance Journal*, *59*(2), 1012–1019.

Wei, C. C. (2016). Modeling and analyzing the mean and volatility relationship between electricity price returns and fuel market returns. *International Journal of Economics and Finance*, *8*, 55–70.

Xiao, L., & Dhesi, G. (2010). Volatility spillover and time-varying conditional correlation between the European and US stock markets. *Global Economy and Finance Journal*, *3*(2), 148–164.

Yousaf, I., Ali, S., & Wong, W. K. (2020). Return and volatility transmission between world-leading and Latin American stock markets: Portfolio implications. *Journal of Risk and Financial Management*, *13*(7), 148–166.

Zhang, W., Zhuang, X., & Wu, D. (2020). Spatial connectedness of volatility spillovers in G20 stock markets: Based on block models analysis. *Finance Research Letters*, *34*(5), 1012–1022.