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Research article

Equity market integration of China and Southeast Asian countries: further evidence from MGARCH-ADCC and wavelet coherence analysis

Ngo Thai Hung*

University of Finance-Marketing, Ho Chi Minh City, Vietnam

* **Correspondence:** Email: hung.nt@ufm.edu.vn; Tel: +36306675042.

Abstract: This paper investigates the short-term and long-term dynamics between China and four Southeast Asian countries (Vietnam, Thailand, Singapore and Malaysia) during period 2008–2018. Our empirical research is based on the Generalized Autoregression Conditional Heteroscedasticity-Asymmetric Dynamic Conditional Covariance (MGARCH-ADCC) model and the wavelet coherence technique which allow us to estimate the time-varying correlation and the co-movement in both time-frequency spaces of stock markets of China and its neighboring countries. The results of the study reveal that stock markets of China and its trading partners are relatively integrated after the global financial crisis of 2008, frequency changes in the pattern of the co-movements and a positive linkage throughout the sample period. Specifically, the conditional correlation of stock returns between China and Singapore is more significantly influenced by negative innovations than by positive shocks to return. Furthermore, the study provides evidence of significant coherence between both the variables for almost the entire studied period in long scale. Therefore, these findings are positive signs for the Chinese and international investors to diversify their portfolio among the stock markets of China and its trading partners.

Keywords: stock market integration; China; wavelet coherence; GARCH-ADCC; Southeast Asian

JEL codes: G15, F36, C40

1. Introduction

The behavior of stock market co-movement is a controversial issue in finance literature because it has a significant practical implication for the portfolio's allocation and hedging strategy design (Aloui and Hkiri, 2014). Specifically, current debated matters, China's economy has become the main engine of global economic growth over the last decades and its influence on the neighboring countries, which has received much attention from academic researchers and practitioners. As per Sznajderska (2019), the influence of China on the Asia region would be considered because China is a central point of the Asian supply chains, the slowdown of the Chinese economy could cause distress for Asian countries. Further, a stronger than expected downturn in the Chinese economy might increase uncertainty in global financial markets, cause the depreciation of the Chinese renminbi. Recent crises have proved that turbulence in China's financial market results in capital outflows from emerging markets and depreciation of their currencies. Therefore, an understanding of the correlations and interactions between China and various financial markets is indispensable for investors, financial institutions, and governments.

Recent literature focused on the correlations between China and other financial markets (Sznajderska, 2019; Bissoondoyal-Bheenick et al., 2018; Zhou et al., 2012). The cited papers reveal that the volatility of the Chinese markets has a significant impact on other markets. For example, Kirkulak Uludag and Khurshid (2019) find that significant volatility spillover from the Chinese stock market to the E7 and G7 stock markets. Roni et al. (2018) state the Asian territory markets shock start to significantly increase the volatility in the Chinese market. Lau and Sheng (2018) confirm that the positive return spillovers between China and developed markets are mostly unidirectional. Sehgal et al. (2018) show that China known as a state-of-the-art equity market infrastructure should take the lead to facilitate the process of stock development and share its best experiences to other member countries of the region. Therefore, we would say that China has emerged as a global economic power, that recently has a great impact on the world equity markets.

In recent years, several articles have been implemented for the interconnectedness of other markets. For example, Khan et al. (2018) assess the linkages of Pakistan stock exchange with emerging and developed financial markets from 1997 to 2014. The findings indicate that Pakistan stock exchange has a negative impact on China stock markets. Kao et al. (2018) provide evidence that there is an interdependence between emerging markets (Russia, South Africa, and China) and East Asian stock markets (Indonesia and the Philippines). Aggarwal and Raja (2019) examine the co-integration among the stock markets of BRIC countries (Brazil, Russia, Indian and China), and find that there exists one long-run cointegrating nexus between these stock markets. In addition, the study also confirms the existence of a stable long-run causal relationship between the variables, especially the index of China can explain on average 0.5 percent of the forecast error variance of Indian index. Prasad et al. (2018) state that the US is the largest contributor of volatility spillovers to other markets, while the large emerging markets of India, China, Brazil and Mexico are somewhat separated and move as volatility receivers for a majority of the study period. Lee (2019) concludes that Asian stock markets generally move together and become more integrated. More importantly, China stock market is not in sync with any other Asian financial markets in the sample. Li and Zeng (2018) analyze the dependence structure between the CSI 300 index return, the S&P 300 index return and the Association of South East Asian Nations (ASEAN). The paper shows that three types of stock returns have apparent time-varying properties. Specifically, the dependence between China and the ASEAN stock market is more sensitive to the financial crisis and there is difference dependence between China-ASEAN and China-US.

On the empirical side, this primary investigation issue has been firmly grasped in the international finance literature and different empirical methodologies including cointegration approach (Chien et al., 2015), multivariate VAR (Huyghebaert and Wang, 2010), univariate and multivariate GARCH-type family, error correction models (Kirkulak Uludag and Khurshid, 2019; Roni et al., 2018; Fang and Bessler, 2018; Lau and Sheng, 2018; Hung, 2018) and copula theory (Sehgal et al., 2018) were executed to shed light on stock market co-movement and risk management. In general, they concluded that stock market co-movement varies over time.

Moreover, several studies employed the MGARCH-DCC to capture the dynamic conditional correlation among stock markets. For example, Joyo and Lefen (2019) analyze the co-movements and the portfolio diversification between the stock markets of Pakistan and its top trading partners, namely China, Indonesia, Malaysia, the United Kingdom, and the United States, and point out that the integration among stock markets decreases substantially after the period of financial crises. In a same vein, Chiang and Chen (2016) examine the dynamic conditional correlations of stock returns between China and international markets, suggest that stock-return correlations across markets are time-varying and exhibit a structural change triggered by an upward shift in China's adoption of financial liberalization. Rizvi and Arshad (2014) investigate the volatility and correlation of Islamic financial markets, and provide evidence of a low moving correlation between the conventional and Islamic indices for twelve years. In addition, several investigations employ MGARCH-ADCC model to examine the interrelation among bond, foreign exchange, and commodity markets (Cappiello et al., 2006; Tamakoshi and Hamori, 2013; Toyoshima et al., 2012). Therefore, it is worthwhile to use the MGARCH-ADCC model to analyze the interrelatedness between China and four Southeast Asian stock markets.

However, the dissimilarity between short and long-term investor behavior should be taken into consideration in a co-movement analysis. Therefore, it might be very necessary for portfolio managers to look into the frequency domain so as to provide a better understanding of stock market co-movement behavior at the frequency level (Aloui and Hkiri, 2014). In addition, an analysis in the frequency domain is much less found in the empirical finance literature. Ramsey and Zhang (1996) employ the wavelet approach as pioneers to systematically explain some relationships between several macroeconomic variables. In the last 20 years, with the development of financial econometrics, the increasing number of papers have used the wavelet technique to explore the nexus between economic variables. For example, Aloui and Hkiri (2014) study the short-term and long-term dependencies between stock market returns for the Gulf Cooperation Council Countries, and note an increasing strength of dependence among the GCC markets during the global financial crisis. In this vein, Najeeb et al. (2015) show an effective portfolio diversification opportunities between Islamic equity returns existing mainly for short holding periods and the markets seem to be highly correlated yielding minimal portfolio diversification benefits. More importantly, the wavelet has been used in a large number of papers in connection with energy commodities such as Nagayev et al. (2016), Raza et al. (2017), Raza et al. (2019), Yang et al. (2016), Yang et al. (2017), and Cai et al. (2017). Overall, wavelets are considered as a powerful mathematical approach for signal processing which can give straightforward insight into co-movement among international stock markets via a decomposition of the time series into their time scale element (Aloui and Hkiri, 2014; Yang et al., 2017).

Current paper differs from the previous literature in that we are the first to use a battery of econometric models combined to capture the dynamic and multi-time scale nature of the interconnection between China and four stock markets in Southeast Asian countries. First, the multivariate generalized autoregressive conditional heteroskedasticity asymmetric dynamic conditional correlation (MGARCH-ADCC) model is employed to capture the evolution of volatilities and correlations between the Chinese with the Vietnamese, Thailand, Malaysia and Singapore stock markets. Second, we use the wavelet coherence analysis for the investigation of the time series in the time-frequency domain to uncover the dynamics of correlations between variables. Several main reasons why we incorporate MGARCH-ADCC model into wavelet coherence technique are because MGARCH-ADCC can capture variations in correlations and volatilities in higher frequency level in a more productive and better snapshot. Wavelet can evaluate the co-movement between the assets on medium and high scales (Nagayev et al., 2016; Yang et al., 2016, Yang et al., 2017). As a result, these models formally issue a more in-depth and robust analysis that reinforces a better understanding of the study under consideration. This type of analysis may be extremely important that investors, portfolio managers, and policymakers understand the dynamic interactions between China and four stock markets in Southeast Asian countries. To the best of our knowledge, this is the first empirical work conducting the econometric models combined to explore the dynamic connectedness between the stock markets in China and four countries in Southeast Asia.

Since little work has been done in this area (Caporale et al., 2015), this paper provides a novel perspective on the literature on financial integration and liberalization. From the abovementioned studies, the most used techniques for connectedness analysis between financial markets are cointegration tests and vector error correction models, which do not imply the underlying time-varying change in the lead-lag structure. Therefore, the primary objective of this research is to provide a fresh new look into the characteristic of stock market dynamic correlation in these countries. For simplicity, we examine the time-frequency relationship between China and four stock markets in Southeast Asian countries using MGARCH-ADCC model alongside with wavelet coherence framework in this paper. As stated above, these approaches are promising techniques for analyzing in-depth and instantaneous interrelatedness between stock market returns. As a result, the purpose and primary contribution of this current investigation is to fill this gap.

This paper is organized as follows. Section 2 outlines the methodology and data used in this study. Section 3 discusses our substantive results and discussion. Section 5 concludes with some relevant implications.

2. Materials and method

2.1. The asymmetric dynamic conditional correlation model (MGARCH-ADCC)

The dynamic conditional correlation (DCC) is employed. Engle (2002) introduced this estimator to capture the dynamic time-varying behavior of conditional covariance. The conditional covariance matrix H_t is now defined as,

$$\mathrm{H}_t = D_t P_t D_t \tag{1}$$

where $D_t = diag\sqrt{\{\mathrm{H}_t\}}$ is the diagonal matrix with conditional variances along the diagonal, and P_t is the time-varying correlation matrix.

A GARCH (1,1) specification of each conditional variance can be written as,

$$h_{ii,t} = c + a_i z_{i,t-1}^2 + b_i h_{ii,t-1} \tag{2}$$

where c is a $n \times 1$ vector, a_i and b_i are diagonal $(n \times n)$ matrices. $z_t = r_t / \sqrt{h_{it}}$, r_t are a $k \times 1$ vector of stock returns, $r_t \mid \zeta_{t-1} \sim N(0, H_t)$. z_t are used to estimate the correlation parameters. The evolution of the correlation in DCC model proposed by Engle (2002) is given by

$$Q_t = (1 - \alpha - \beta)\bar{P} + \alpha z_{t-1} z_{t-1}^{'} + \beta Q_{t-1} \tag{3}$$

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

where $P_t = E[z_t z_t^{'}]$ and α and β are scalars that $\alpha + \beta < 1$. $Q_t^* = [q_{iit}^*] = [\sqrt{q_{iit}}]$ is a diagonal matrix with the square root of the i th diagonal element of Q_t on its i th diagonal position.

The asymmetric dynamic conditional correlation ADCC was developed by Cappiello et al. (2006), and the evolution of the asymmetric generalized DCC model can be written as

$$Q_t = \left(\bar{Q} - A^{'}\bar{Q}A - B^{'}\bar{Q}B - G^{'}\bar{N}G\right) + A^{'}z_{t-1}z_{t-1}^{'}A + B^{'}Q_{t-1}B + G^{'}\eta_{-1}\eta_{-1}G \tag{5}$$

where $\bar{Q}$ and $\bar{N}$ are the unconditional correlation matrix of ε_t and η_t , $\eta_t = I[z_t < 0] \circ \varepsilon_t (I[.])$ is a $k \times 1$ indicator function that takes a value of 1 if the argument is true and 0 otherwise, while "$\circ$" describes the Hadamard product, and $\bar{N} = E[\eta_t \eta_t^{'}]$. The asymmetric DCC (ADCC) is obtained when the matrix A, B and G are replaced by scalars (α , β and g).

2.2. Wavelet coherence

In order to complement the MGARCH-ADCC models, the Wavelet Coherence approach allows us to evaluate the co-movement between China and four stock markets in Southeast Asian countries in both time-frequency spaces. The wavelet technique used by Grinsted et al. (2004), utilizes a bivariate framework, which is based on a continuous wavelet transform, allowing for different forms of localization. As per Nagayev et al. (2016), the wavelet method allows us to analyze correlation patterns between financial data during various regimes without having to sub-divide the data into different sample periods. A brief note on wavelet coherence is defined as follows:

$$R_n^2(S) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right).S(s^{-1}\left|W_n^Y(s)\right|^2} \tag{6}$$

where S is a smoothing operator. Smoothing is achieved by convolution in time and scale.

$$S(W) = S_{scale}\left(S_{time}\left(W_n(s)\right)\right) \tag{7}$$

where S_{scale} and S_{time} illustrate smoothing on the wavelet scale axis and in time, respectively. Smoothing operator we use in this study is the Morlet wavelet, so the more suitable definition is given by Torrence and Webster (1999):

$$S_{time}(W) = \left(W_n(s) * c_1^{\frac{-t^2}{2s^2}}\right)\Bigg|_s \quad \text{and} \quad S_{time}(W)_s = \left(W_n(s) * c_2\Pi\left(0.6s\right)\right)_s\Big|_n \tag{8}$$

where c1 and c2 are normalization constants and Π is the rectangle function, the scale decorrelation length for the Morlet wavelet is 0.6

The wavelet coherence coefficient measures the local linear correlation between two stationary time series at each scale and ranges $R_n^2(s) \in [0,1]$.

$W_n^{XY}(s)$ is the cross-wavelet power. It can be seen as the local covariance between the two time series at each scale. Given time series $x(t)$ and $y(t)$, the cross-wavelet power can be written as

$$W_n^{XY}(s) = W_n^X(s)W_n^{*Y}(s) \tag{9}$$

where $W_n^X(s)$ and $W_n^{*Y}(s)$ are continuous wavelet transforms of two time series $x(t)$ and $y(t)$. The symbol * represents a complex conjugate.

The wavelet coherence phase is defined as

$$\phi_n^{XY}(s) = \tan^{-1}\left(\frac{I\left\{S\left(s^{-1}W_n^{XY}(s)\right)\right\}}{R\left\{S\left(s^{-1}W_n^{XY}(s)\right)\right\}}\right) \tag{10}$$

where I and R are the imaginary and real parts of smooth power spectrum.

2.3. Data

The study is conducted using daily closing price of the Chinese, Vietnamese, Singapore, Thailand and Malaysian indices, abbreviated as SSE (the Shanghai Stock Exchange Composite Index), VNI (Vietnam Ho Chi Minh Stock Index), STI (the Straits Times Index), SET (Thai composite stock market index), KLCI (Kuala Lumpur Composite Index) respectively. The data are daily observations for period from September 2008 to July 2018. Stock market data are extracted from Bloomberg Terminal. According to Hung (2018), daily data capture more precise information content of changes in stock prices than doing with weekly or monthly data as well as better able to capture the dynamics between time series variables. These indices are matched in pairs of two with an aggregate of four pairs: China-Vietnam, China-Thailand, China-Singapore, China-Malaysia. In this study, we are going to measure China's influence on Southeast Asian markets only, which are known as the Asian emerging stock markets (Hung, 2019) except for Singapore known as developed stock market (Yarovaya et al., 2016). Yilmaz (2010) put forward the rapidly developing financial markets in this region, these countries started to play an increasingly pivotal role in the global financial market. Continuously compounded returns r_t are calculated by taking the difference in the logarithm of two consecutive prices.

Table 1 reports the statistical properties of the data as well as unit root and ARCH test for the full sample. In general, the sample means of returns are low and greater than 0. The lowest return occurs in the Singapore stock market (0.0096 %), and the highest return occurs in Thailand (0.0453%) in the sample period from September 2008 to July 2018. In terms of standard deviations, the volatility of stock markets is somewhat high, the Chinese stock market is the most volatile market with the highest standard deviation (1.6317%). The measures for skewness and kurtosis demonstrate that stock returns are negatively skewed and highly leptokurtic. This departure from normality is formally confirmed by the Jarque-Bera test statistics. Augmented Dickey – Fuller and Phillips-Perron test reveal that the null hypothesis of unit root for all the return series is rejected at the 1% significance level. Finally, ARCH test results provide evidence of autocorrelation in return series in all stock markets. It is clear from the table that the null hypothesis of no ARCH effect is rejected, so the existence of ARCH effect illustrates that MGARCH-ADCC models can perfectly be adopted.

Table 2 highlights pair wise correlation coefficients between variables under investigation. All the coefficients are positive which shows that stock markets move in the same direction. As unexpected, high correlation is not observed among concerned variables. The correlation between Vietnam and China stock returns is the lowest, while the correlation between Singapore and Thailand is the highest. Static correlation does not show the variations in the correction over the period. We implemented more detailed correlation with MGARCH-ADCC model.

The price and return movements of all five variables are plotted in Figure 1. The time series graphs of the stock prices data illustrate the changing mean and variance throughout the sample period of 2008–2018. Overall, all price series show both increasing and decreasing trends during the research period. The Shanghai Stock Exchange Composite Index exhibited highly fluctuating movements with sharp spikes in 2015 and 2016. Additionally, the graph of the return series also shown that the volatility of The Shanghai Stock Exchange Composite Index was high at the same year, which was caused by the European stock market collapse and the bank save the euro (Drometer and Oesingmann, 2015). The rest of the return series are relatively low. Hence, the results of preliminary tests make the MGARCH-DC model appropriate for the examination.

Table 1. Descriptive statistics of index returns.

	Thailand	Malaysia	China	Singapore	Vietnam
Mean	0.0453	0.0234	0.0110	0.0096	0.0256
Median	0.0846	0.0395	0.0716	0.0260	0.0955
Maximum	7.5487	4.7227	9.0344	9.2451	9.8187
Minimum	−10.0994	−5.1242	−8.9058	−12.9278	−8.2822
Std. Dev	1.2623	0.7198	1.6317	1.1738	1.5030
Skewness	−0.5944	0.0074	−0.5349	−0.2422	−0.2460
Kurtosis	10.3381	10.2238	7.7807	18.3086	6.000
Jarque-Bera	4890.6*	4618.2*	2124.0*	20761.0*	818.2*
PP test	−42.691*	−40.029*	−44.214*	−43.884*	−39.124*
ADF test	−42.664*	−40.179*	−44.216*	−43.887*	−38.954*
ARCH test	220.8008*	39.8115*	104.4249*	180.475*	141.078*
Observations	2124	2124	2124	2124	2124

Notes: * denotes significance at the 1% level. All returns are expected in percentages. ADF and PP test represents the augmented Dickey and Fuller test and Phillips Perron test of stationarity respectively. ARCH test is employed to test the presence of ARCH effect in data sets.

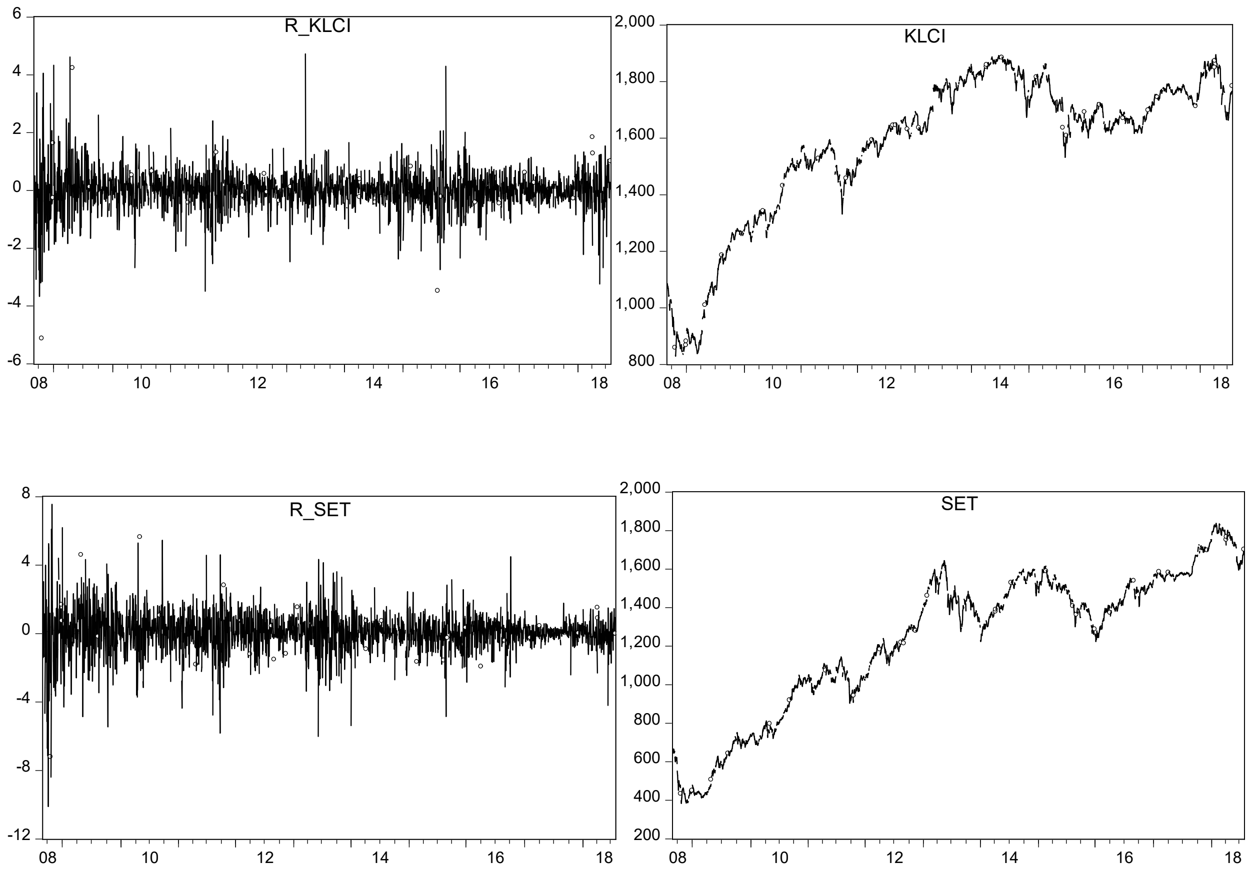

Figure 1. Daily stock prices and percentage returns.

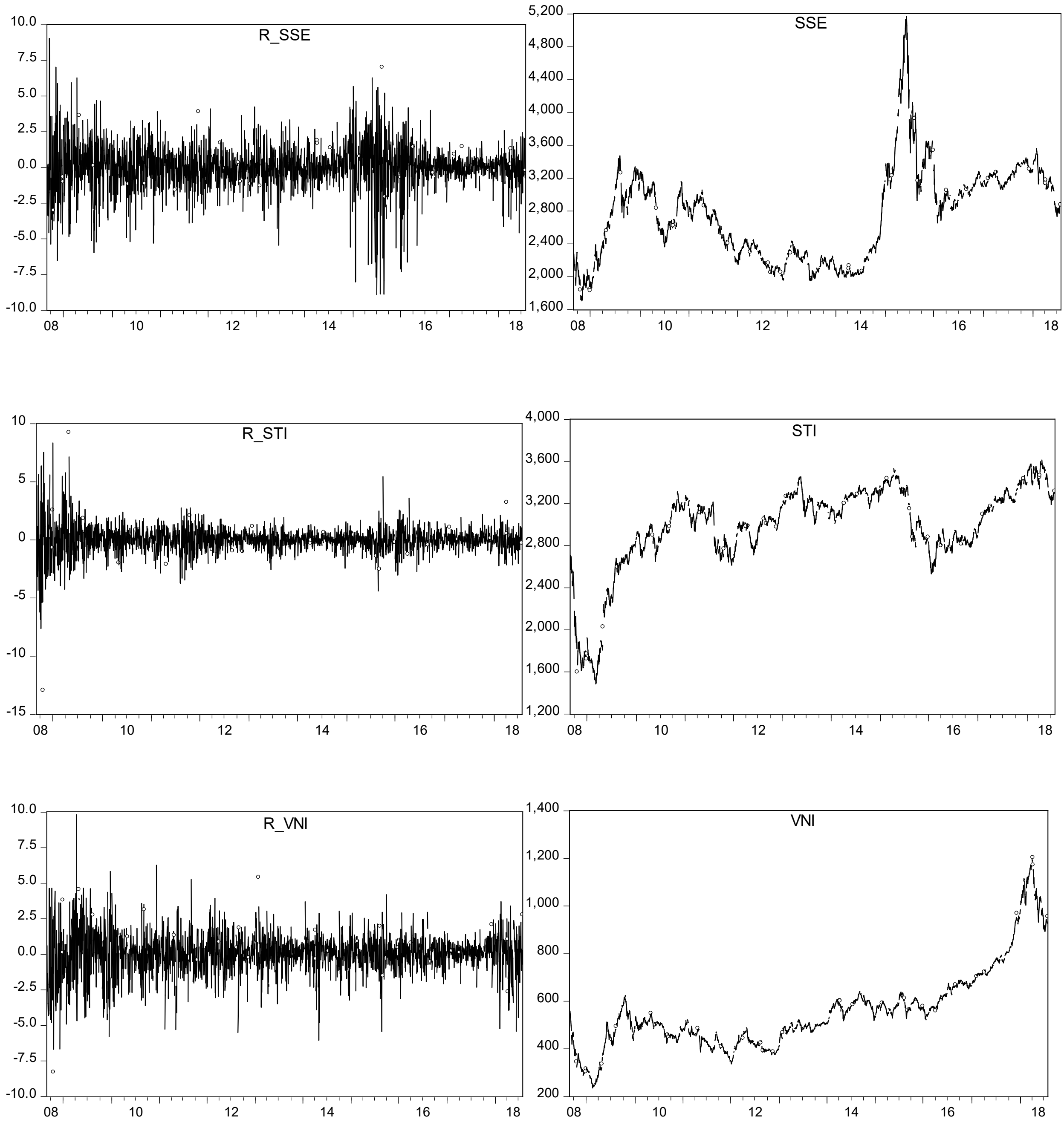

Figure 1. *Continued.*

Table 2. Correlation matrix between index returns.

	China	Thailand	Malaysia	Singapore	Vietnam
China	1				
Thailand	0.2763	1			
Malaysia	0.2846	0.5017	1		
Singapore	0.3457	0.5903	0.5853	1	
Vietnam	0.1570	0.2041	0.2593	0.2140	1

Table 3. Univariate GARCH.

	Coefficient	Std. Error	t-statistics	Prob
SSE				
C(M)	0.013810	0.024150	0.571838	0.5674
C(V)	0.007601	0.001780	4.269626	0.0000
ARCH	0.048300	0.004023	12.00679	0.0000
GARCH	0.949075	0.003546	267.6763	0.0000
VNI				
C(M)	0.052867	0.023598	2.240263	0.0251
C(V)	0.030578	0.005631	5.430234	0.0000
ARCH	0.114797	0.009445	12.15434	0.0000
GARCH	0.876189	0.008339	105.0756	0.0000
SET				
C(M)	0.077085	0.018197	4.236077	0.0000
C(V)	0.015314	0.002587	5.920179	0.0000
ARCH	0.110533	0.008774	12.59729	0.0000
GARCH	0.885546	0.008671	102.1300	0.0000
KLCI				
C(M)	0.034224	0.012299	2.782740	0.0054
C(V)	0.011896	0.001600	7.432852	0.0000
ARCH	0.110731	0.007264	15.24472	0.0000
GARCH	0.870318	0.008490	102.5104	0.0000
STI				
C(M)	0.032802	0.016526	1.984851	0.0472
C(V)	0.008087	0.001514	5.341116	0.0000
ARCH	0.061335	0.006442	9.520499	0.0000
GARCH	0.928647	0.006510	142.6595	0.0000

Notes: C(M): constant in mean equation, C(V) constant in variance equation.

Table 4. Behavior of the residual product.

Residuals	ARCH(5)	ARCH(10)	Q(20)	Q(30)	Q(40)	Q(50)	Q(60)
SSE*VNI	1.105175	2.151955	18.548	24.277	31.094	41.948	49.464
	(0.9536)	(0.9950)	(0.551)	(0.759)	(0.843)	(0.890)	(0.982)
SSE*SET	0.117794	0.229652	10.613	16.145	22.524	29.624	38.031
	(0.9998)	(1.00000)	(0.956)	(0.981)	(0.988)	(0.990)	(0.998)
SSE*KLCI	2.829913	3.096732	22.373	31.989	40.011	51.470	56.102
	(0.7262)	(0.9791)	(0.751)	(0.813)	(0.840)	(0.853)	(0.861)
SSE*STI	4.13525	5.72991	27.312	34.176	44.934	51.239	57.592
	(0.3212)	(0.5411)	(0.127)	(0.274)	(0.375)	(0.542)	(0.731)

Note: numbers in parentheses are probability. Q (n) denotes the n^{th} order Ljung Box test for serial correlation. ARCH test is employed to test the presence of ARCH effect.

3. Results

As the first step, we explore the interrelatedness between China stock market and four countries in Southeast Asia using MGARCH-ADCC model to track the time-varying characteristics of the variables in terms of volatility and correlations. We then employ the wavelet coherence analysis to examine the nexus between the selected variables on a multi-scale, time-frequency domain. The following table indicates the model parameters from the MGARCH-ADCC.

Caporin and McAleer (2013) point out that the dynamic conditional correlations are real or apparent, apart from taking into consideration the coefficients of α and β, the conditional variance may be estimated as GARCH(1,1). Therefore, the standardized residuals may have remaining heteroskedasticity. This simply means that fitting standardized residuals, the diagonal term of the DCC representation will capture the dynamics. In this study, the standardized residuals can be used to verify the persistence of dynamics in the conditional correlations. First, we have generated volatility residual series from a specific GARCH model for each variable separately. Second, the product of the standardized residuals between two variables has been employed to evaluate that whether the heteroskedasticity exists or not. It is clear from Table 3 and Table 4 that there is no ARCH effect for al series considered at 1% significant level. As a result, modelling the ADCC specifications can successful capture the dynamic conditional correlation between financial stock markets in these countries.

As we can see from Table 5 that both α and β are statistically significant for the pairs of stock markets with China stock market over the sample period. The volatility persistence is measured by $(\alpha+\beta)$. In parallel, GARCH parameters are statistically significant, indicating that the volatility transmission is bi-directional between the variable pairs in all cases. Similarly, the ARCH parameters are also significant for all cases. It is clear that $\beta > \alpha$, suggesting that the current variances are more influenced by the past return innovations. The coefficient of α reflects the effect of the past shocks on current conditional correlation, while the β captures the impact of past correlation. The sum of the parameters α and β is close to one. This means that the process described by the model is not mean reverting. Put another way, after the innovations occurred in the markets, the dynamic correlation will not return to the long-run unconditional level. In addition to the high conditional volatility, the most key point in the present study is the significant time-varying correlation. Both α and β are mostly significant, and the conditional correlation highlights high persistence for all cases during the study period. In contrast, the estimates on the parameter of asymmetric term (g) are insignificant for most of the combinations. These results are commonly seen in similar studies such as Cappiello et al. (2006), Toyoshima et al. (2012), this simply means that the conditional correlation of China stock market on Vietnam, Thailand and Malaysia stock markets is not necessarily impacted more significantly by negative shocks than by positive shocks to the changes of Chinese market. However, it should be noted that the estimates are statistically significant for the correlations between SSE and STI at the 5% significant level: negative innovations play a prominent role than positive innovations in driving the dynamic conditional correlation between these stock markets. The next step of this section is to use the model estimates to plot the conditional correlations for the pairs of stock markets with China stock market under investigation.

As shown in Figure 2, the conditional correlations between China stock returns and four Southeast Asian countries are fluctuant with outliers. In all cases, the plot shows that the DCC climbs within the range of 0 to 0.6, exhibiting a positive linkage between China stock returns and four Southeast Asian countries throughout the sample period. Overall, quite a volatile movement is evident when we take a look at graphs of time-varying correlations between China stock returns and four Southeast Asian countries, and there are trends apparent with the European stock market collapse period around 2014–2016 as a turning point. Figure 2 reveals that the correlation between China and the rest of other countries has trended upwards. Specifically, a similar pattern is established for the correlations between China and Singapore after the global financial crisis except for the period between 2013 and 2015, where we observed a huge decrease in correlation. A similar pattern, but in a smaller degree, is observed for the correlation between China with Thailand and Vietnam respectively. However, the correlation between China and Malaysia seems to remain stable with a band of 0.1–0.5 for the whole period except for the period between 2011 and 2016. Therefore, we can conclude that this is an influence coming from China. Put differently, there exists the co-dependency of both the China stock market and other selected countries. The findings are consistent with previous studies of Sznajderska (2019) and Bissoondoyal-Bheenick et al. (2018).

Table 5. Estimation results of MGARCH-ADCC model.

		SSE-VNI	SSE-SET	SSE-KLCI	SSE-STI
GARCH	c_1	0.007504685*	0.610708504*	0.0094812387**	0.008892188**
	c_2	0.029670186*	0.035344983*	0.0140911174*	0.009378393*
	a_1	0.052118254*	0.214971017*	0.0548994431*	0.052995702*
	a_2	0.113982045*	0.138527501*	0.1154022580*	0.069640489*
	b_1	0.946254099*	0.558406727*	0.9427060475*	0.944318529*
	b_2	0.877951549*	0.846323172**	0.8611625815***	0.920178456*
ADCC	α	0.015393236***	0.009741759**	0.0173757986***	0.010382551*
	β	0.904785305*	0.500000031***	0.8942952632*	0.859509823*
	g	−0.002161813	0.009374760	0.0204979462	0.035690209***
	ARCH-LM	51.69 (0.22881)	43.07 (0.55413)	39.88 (0.68814)	43.89 (0.51907)

Notes: p-Values are given in parentheses.

*Estimated coefficients are significant at 1% levels.

** Estimated coefficients are significant at 5% levels.

***Estimated coefficients are significant at 10% levels.

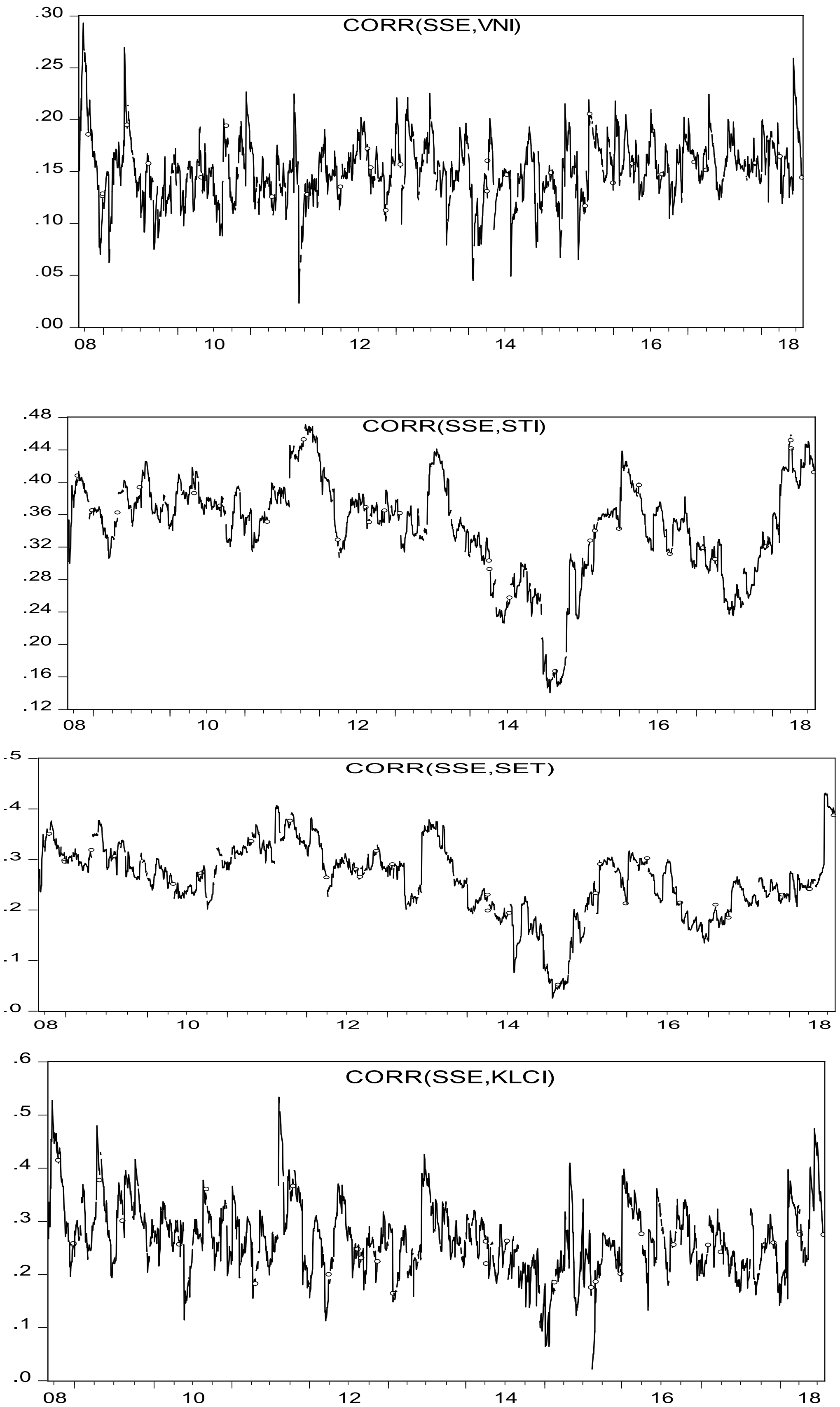

Figure 2. Time-varying correlations between China stock returns and four Southeast Asia countries.

The diagnostic test is documented in the last rows of Table 3, where the ARCH-LM tests are reported. It clearly indicates that there are no problems of ARCH effect for all selected variables during the study period providing some indications of good specification in each model. However, MGARCH-ADCC model does not reveal the lead or lag structure amongst variables (Jain and Biswal, 2016). To supplement our analysis and address this issue, we employed the cross-wavelet transform to seek for regions in time-frequency space in which the time series display high common power. The different intercorrelation structures are elaborated in the following sections.

3.2. Wavelet coherence

We are now turning to the stock market co-movement, we use the wavelet coherence transform to measure the dynamic connectedness between China stock market and four Southeast Asian countries (Vietnam, Singapore, Thailand and Malaysia). Figure 3 below illustrates the estimated wavelet coherence and the phase difference for all examined pairs under investigation.

For a simple interpretation, we can perceive that time is displayed on the horizontal axis and frequency is shown on the vertical axis - regions in time-frequency space where two concerned variables co-vary are located by wavelet coherence. Regions with significant interconnection are presented by warmer colors (red), while lower dependence between variables is signified by colder colors (blue). Cold regions beyond the significant areas show frequencies and time with no dependence in the series. Both the frequency and the time intervals where the pairs of concerned variables move together significantly can be identified. An arrow in the wavelet coherence plots displays the lag phase connections between the examined variables. A zero phase difference explains that the two variables move together on a particular scale. Arrows point to the right (left) when the return series are in phase (anti-phase), simply meaning that they move in the same direction when the two series are in phase, and they move in the opposite direction when the two series are in anti-phase. Arrow pointing to the right-down or left-up describe that crude oil and gold returns lead the Chinese financial markets, while arrows pointing to the right-up or left-down show that crude oil and gold returns are leading (Nagayev et al., 2016; Yang et al., 2017). In addition, wavelet coherence plots can provide straightforward insights into the behavior over time of the interactive relationships amongst the variables and across frequency. Regarding the statistical significance, it is delimitated by the bold black line for the significance level of 5%.

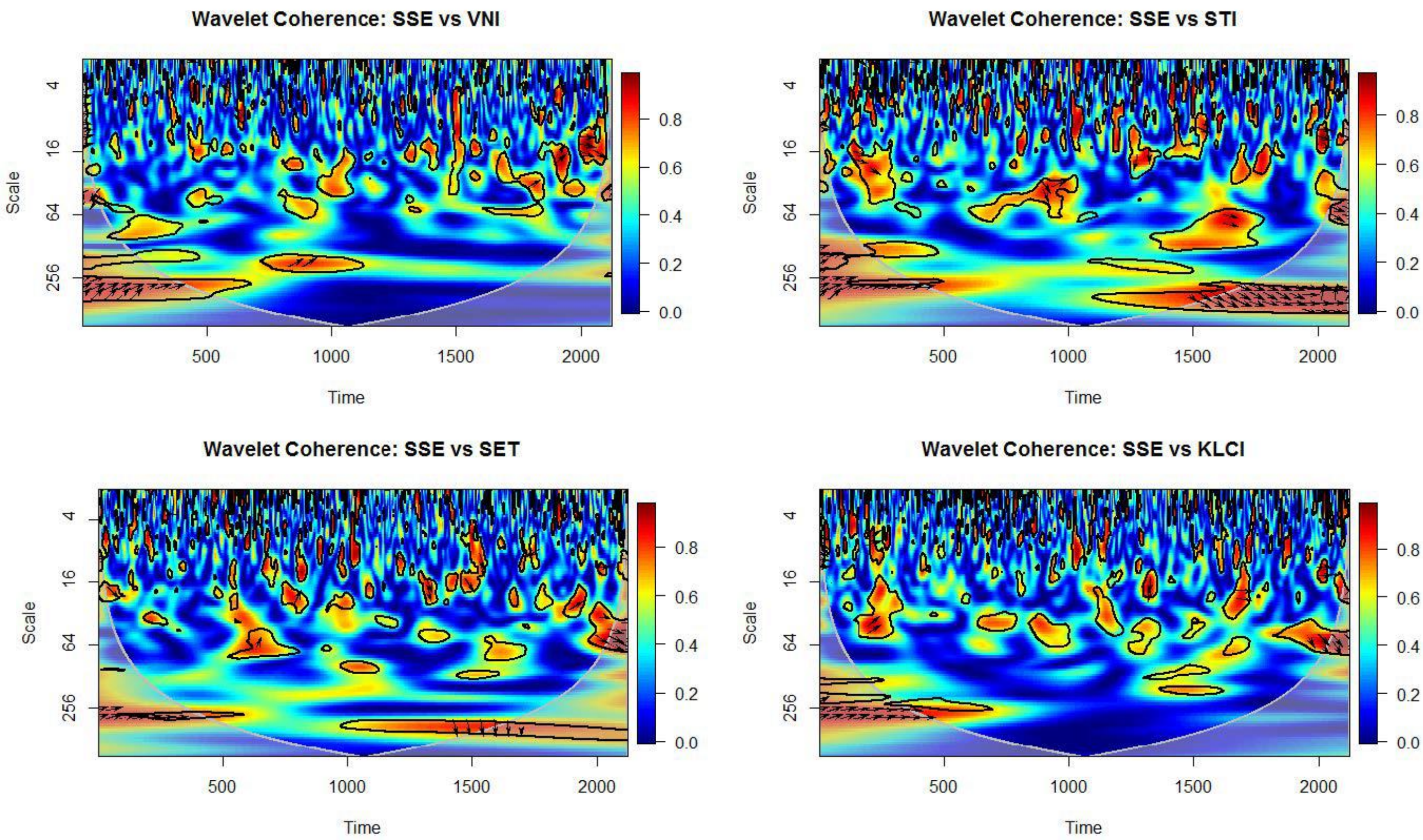

Figure 3. Wavelet coherence results. **Notes:** This figure represents the wavelet coherence of China stock market (SSE) and four Southeast Asian countries (VNI, STI, KLCI and SET) pairs. Time and frequency are presented on the horizontal (time period from September 2008 to July 2018, with 500 = 2008–2010, 1000 = 2011–2013, 1500 = 2014–2016, 2000 = 2017–2018) and the vertical axis, respectively. Frequency is covered to days. The warmer the color of a region, the greater the coherence is between the pairs. The solid black line isolates the statistical significance area at the level of 5%.

First of all, we can easily observe that the dynamics of the interactive linkages between China and the selected financial markets are varying rapidly over time, we can also see that the dynamics change in frequency. The results of the pair of the SSE and VNI display that in the period of 2010–2012 and in 2016, the arrows are right up indicating that variables are in phase with SSE lagging. However, the arrows are left down suggesting that the variables are the out-phase relationship and showing leading and lagging simultaneously in the market. For almost the entire research period in the long scale, the study evidences the moderate coherence between China and Vietnam stock markets. Interestingly, the results of a long period have failed to find bidirectional causality between the variables.

We continue observing the case of China and Singapore stock markets. In the small period in 2011, 2016, 2018, the arrows are right down indicating that SSE and STI were exhibiting in phase connectedness with both leading and lagging simultaneously in the market. Overall, during the time frame, the two variables are both showing cyclic effects with SSE leading and anti-cyclic effects with STI leading the casual influence. This finding is opposite the research of Huyghebaert and Wang (2010). Similar results for the case of China and Thailand stock markets, but the arrows tend to be right up and down revealing that variables are in phase relationship with SSE and SET lagging respectively. Further, no causality can be concluded between China with Singapore and Thailand in any small and long period. Finally, we take into account China and Malaysia stock markets. In a small scale, the identified patterns are not showing in any visible arrow. By contrast, the longtime zone is not able to create any strong variance pattern. In a medium scale, few small patterns of causality are found.

Summarizing all, the estimates of the MGARCH-ADCC model alongside with the wavelet coherence analysis are not the notable difference of the interplay between China with Vietnam, Singapore, Thailand and Malaysia stock markets over the sample period. Our results collaborate with some previous literatures. For instance, Zhou et al. (2012) put forward that the volatility of the Chinese market has had a significant positive influence on other Asian markets since 2005. Huyghebaert and Wang (2010) investigate the long-run and short-run casual linkages among seven major stock exchanges in East Asia, provide evidence of China stock market generally respond to worldwide shocks before the Asian financial crisis. Li and Giles (2015) highlight significant unidirectional shock and volatility spillovers from the US market to China. Chien et al. (2015) investigate the dynamic process of convergence among cross-border stock markets in China and ASEAN-5 countries, and show that the regional financial integration between China and ASEAN-5 has gradually increased. Majdoub and Sassi (2017) examine the volatility spillover between China and Asian Islamic stock markets, and reveal that a significant positive and negative return spillover from China to selected Asian Islamic stock market and bidirectional volatility spillovers between China, Korea and Thailand Islamic market showing evidence of short-term predictability on Islamic Chinese stock market movements. Chiang and Chen (2016) study the dynamic correlations between Chinese stock returns and those of six major and geographically close Asian partner and find that China has a significant impact on the Asian stock markets. Fang and Bessler (2018) look into the impact of China B-share on major Asian stock market, confirm that the China market shows strong negative impact and is highly responsible for leading most markets down during the crash.

From a financial view, the increasing of China and other stock market return coherence and its interdependence are viewed as a continuous level of correlation as well as the non-persistence of a significant stock market interactive relationship. Our findings strongly support some previous analogous articles including among others; Paramati et al. (2018), Lau and Sheng (2018) and Bai et al. (2018).

From a practical side, our result justifies the comment by the public press that China stock market plays a prominent role and put on view significant influence on most stock markets in Southeast Asia. Put another way, the increasing importance if the Chinese stock market has improved rapid development in financial openness. Based on these findings, the present study suggests that the stock market of China and four Southeast Asian countries have become more interdependent and therefore the opportunity for international portfolio diversification has remarkable reduced (Fang and Bessler, 2018). In addition, policymakers in these countries need to be aware of the economic changes because these variables will adequately reflect on their stock market performance and interrelatedness. Further, our article also provides positive connotations for the issue of bilateral trade connectedness and stock market interaction.

4. Conclusion

The assessment of the interactive relationship between China and the world equity market is considered as one of the major debated issues in empirical finance, so the current study carries out MGARCH-ADCC model alongside with the wavelet coherence analysis to provide a fresh novel look to the time-varying intercorrelation between China and four Southeast Asian countries (Vietnam, Thailand, Singapore and Malaysia). The noteworthy results of this study can be summarized as follows:

Firstly, the findings of the significant time-varying correlation between the two series imply that MGARCH-ADCC framework might be a suitable estimation for examining the nexus. Additionally, it reveals that the Chinese stock market profoundly impacts four nations in Southeast Asia. Specifically, the fluctuations were small after the global financial crisis, which suggests stability throughout the rest of the period. Figure 2 shows clearly a positive conditional correlation for most of the markets. Further, we find evidence of asymmetric dynamic conditional correlation for the pair of SSE and STI, this implies that the conditional correlation of stock returns between China and Singapore tends to be more influenced by joint negative innovations than by positive shocks.

The wavelet coherence analysis indicates that co-movement depends on both frequency and time. For almost over the sample period in a long scale, the study provides strong evidence of coherence between both the series. Further, the interesting part of coherence is the non-persistent of bidirectional causality in the longtime scale. The arrows in this long region are pointing both right up and right down indicating that our variables are highlighting in phase linkage with mutually leading and lagging the market.

Finally, the findings provide a better understanding of the time-frequency causality between stock markets in China and Southeast nations, which is significant implications for investors, portfolio managers to invest in the Chinese markets as well as its neighboring countries.

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Conflict of interest

The author declares no conflict of interest in this paper.

References

Aloui C, Hkiri B (2014) Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis. *Econ Model* 36: 421–431.

Aggarwal S, Raja A (2019) Stock market interlinkages among the BRIC economies. *Int J Ethics Syst* 35: 59–74.

Bissoondoyal-Bheenick E, Brooks R, et al. (2018) Volatility spillover between the US, Chinese and Australian stock markets. *Aus J Manage* 43: 263–285.

Bai S, Cui W, Zhang L (2018) The Granger causality analysis of stocks based on clustering. *Cluster Comput*, 1–6.

Cai XJ, Tian S, Yuan N, et al. (2017) Interdependence between oil and East Asian stock markets: Evidence from wavelet coherence analysis. *J Int Financ Mark Inst Money* 48: 206–223.

Cappiello L, Engle RF, Sheppard K (2006) Asymmetric dynamics in the correlations of global equity and bond returns. *J Financ Econ* 4: 537–572.

Chien M, Lee C, Hu T, et al. (2015) Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. *Econ Model* 51: 84–98.

Caporale G, Ali F, Spagnolo N (2015) Oil price uncertainty and sectoral stock returns in China: A time-varying approach. *China Econ Rev* 34: 311–321.

Chiang T, Chen X (2016) Empirical analysis of dynamic linkages between China and international stock markets. *J Math Financ* 6: 189.

Caporin M, McAleer M (2013) Ten things you should know about the dynamic conditional correlation representation. *Econometrics* 1: 115–126.

Drometer-Oesingmann K (2015) Household Debt in Central and Eastern Europe CEE. In CESifo Forum, München: ifo Institut–Leibniz-Institut für Wirtschaftsforschung an der Universität München. 16: 82–84.

Engle R (2002) Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J Bus Econ Stat* 20: 339–350

Fang L, Bessler D (2018) Is it China that leads the Asian stock market contagion in 2015? *Appl Econ Lett* 25: 752–757.

Grinsted A, Moore J, Jevrejeva S(2004) Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Process Geophys* 11: 561–566.

Hung N (2019) Return and volatility spillover across equity markets between China and Southeast Asian countries. *J Econ Financ Administrative Sci*.

Hung N (2018) Volatility Behaviour of the Foreign Exchange Rate and Transmission Among Central and Eastern European Countries: Evidence from the EGARCH Model. *Global Bus Rev.*

Huyghebaert N, Wang L (2010) The co-movement of stock markets in East Asia: Did the 1997–1998 Asian financial crisis really strengthen stock market integration? *China Econ Rev* 21: 98–112.

Jain A, Biswal P (2016) Dynamic linkages among oil price, gold price, exchange rate, and stock market in India. *Resour Policy 49*: 179–185.

Joyo A, Lefen L (2019) Stock Market Integration of Pakistan with Its Trading Partners: A Multivariate DCC-GARCH Model Approach. *Sustainability* 11: 303.

Kumar D (2014) Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness. *IIMB Manage Rev* 26: 5–16.

Kao W, Kao T, Changchien C, et al. (2018) Contagion in international stock markets after the subprime mortgage crisis. *Chin Econ* 51: 130–153.

Khan F, Bangash R, Khan M (2018) Dynamic Linkage among Pakistan, Emerging and Developed Equity Market. *FWU J Social Sci* 112.

Li Y, Giles D (2015) Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. *Int J Financ Econ* 20: 155–177.

Li B, Zeng Z (2018) Time-varying dependence structures of equity markets of China, ASEAN and the USA. *Appl Econ Lett* 25: 87–91.

Lee B (2019) Asian financial market integration and the role of Chinese financial market. *Int Rev Econ Financ* 59: 490–499.

Lau C, Sheng X (2018) Inter-and intra-regional analysis on spillover effects across international stock markets. *Res Int Bus Financ* 46: 420–429.

Majdoub J, Sassi S (2017) Volatility spillover and hedging effectiveness among China and emerging Asian Islamic equity indexes. *Emerg Mark Rev* 31: 16–31.

Nagayev R, Disli M, Inghelbrecht K, et al. (2016) On the dynamic links between commodities and Islamic equity. *Energy Econ* 58: 125–140.

Najeeb S, Bacha O, Masih M (2015) Does heterogeneity in investment horizons affect portfolio diversification? Some insights using M-GARCH-DCC and wavelet correlation analysis. *Emerg Mark Financ Trade* 51: 188–208.

Prasad N, Grant A, Kim S (2018) Time varying volatility indices and their determinants: Evidence from developed and emerging stock markets. *Int Rev Financ Anal* 60: 115–126.

Paramati S, Zakari A, Jalle M, et al. (2018) The dynamic impact of bilateral trade linkages on stock market correlations of Australia and China. *Appl Econ Lett* 25: 141–145.

Raza S, Shah N, Sharif A (2019) Time frequency relationship between energy consumption, economic growth and environmental degradation in the United States: Evidence from transportation sector. *Energy*.

Raza S, Sharif A, Wong WK, et al. (2017) Tourism development and environmental degradation in the United States: Evidence from wavelet-based analysis. *Curr Issues Tour* 20: 1768–1790.

Ramsey J, Zhang Z (1996) The application of wave form dictionaries to stock market index data. In *Predictability of complex dynamical systems,* Springer, 189–205.

Rizvi S, Arshad S (2014) An empirical study of Islamic equity as a better alternative during crisis using multivariate GARCH DCC. *Islamic Econ Stud* 130: 1–27.

Roni B, Abbas G, Wang S (2018) Return and Volatility Spillovers Effects: Study of Asian Emerging Stock Markets. *J Syst Sci Inf* 6: 97–119.

Kirkulak Uludag B, Khurshid M (2019) Volatility spillover from the Chinese stock market to E7 and G7 stock markets. *J Econ Stud* 46: 90–105.

Sehgal S, Pandey P, Deisting F (2018) Stock market integration dynamics and its determinants in the East Asian Economic Community Region. *J Quant Econ* 16: 389–425.

Sznajderska A (2019) The role of China in the world economy: evidence from a global VAR model. *Appl Econ* 51: 1574–1587.

Torrence C, Webster P (1999) Interdecadal changes in the ENSO–monsoon system. *J clim* 12: 2679–2690.

Tamakoshi G, Hamori S (2013) An asymmetric dynamic conditional correlation analysis of linkages of European financial institutions during the Greek sovereign debt crisis. *Eur J Financ* 19: 939–950.

Toyoshima Y, Tamakoshi G, Hamori S (2012) Asymmetric dynamics in correlations of treasury and swap markets: Evidence from the US market. *J Int Financ Mark Inst Money* 22: 381–394.

Yarovaya L, Brzeszczyński J, Lau C (2016) Volatility spillovers across stock index futures in Asian markets: Evidence from range volatility estimators. *Financ Res Lett* 17: 158–166.

Yilmaz K (2010) Return and volatility spillovers among the East Asian equity markets. *J Asian Econ* 21: 304–313.

Yang L, Cai XJ, Zhang H, et al. (2016) Interdependence of foreign exchange markets: A wavelet coherence analysis. *Econ Model* 55: 6–14.

Yang L, Cai XJ, Hamori S (2017). Does the crude oil price influence the exchange rates of oil-importing and oil-exporting countries differently? A wavelet coherence analysis. *Int Rev Econ Financ* 49: 536–547.

Zhou X, Zhang W, Zhang J (2012) Volatility spillovers between the Chinese and world equity markets. *Pac-Basin Financ J* 20: 247–270.