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An analysis of dependency of stock markets after unlimited QE announcements during COVID-19 pandemic

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Abstract

Purpose – Unlimited quantitative easing (QE) is one of the monetary policies used to stimulate the economy during the coronavirus disease 2019 (COVID-19) pandemic. This policy has affected the financial markets worldwide. This empirical research aims at studying the dependence among stock markets before and after unlimited QE announcements.

Design/methodology/approach – The copula-based GARCH (1,1) and minimum spanning tree models are used in this study to analyze 14 series of stock market data, on 6 ASEAN and 8 other countries outside the region. The data are divided into two periods to compare the differences in dependence.

Findings – The findings show changes in dependence among the volatility of daily returns in 14 stock markets during each period. After the unlimited QE announcement, the upper tail dependence became more apparent, while the role of the lower tail dependence was reduced. The minimum spanning tree can show the close relationships between stock markets, indicating changes in the connection network after the announcement.

Originality/value – This study allows the dependency to be compared between stock market volatility before and after the announcement of unlimited QE during the COVID-19 pandemic. Moreover, the study fills the literature gap by combining the copula-based GARCH and the minimum spanning tree models to analyze and reveal the systemic network of the relationships.

Keywords Stock markets, QE, GARCH, Copula, Network analysis, COVID-19 pandemic

Paper type Research paper

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has caused a global economic crisis, resulting in a sharp decline in the stock markets. The global stock markets are volatile due to investors' concerns that the pandemic was affecting the global economy (ASEAN Secretariat,

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2020). Liu *et al.* (2020) revealed that the COVID-19 pandemic affected 21 major stock markets worldwide, including Asia, Australia, the Middle East, Europe and the USA, causing volatility along the way. Chopra and Mehta (2022) also revealed the existence of contagious effects on Asian stock markets. The pandemic has caused a global economic recession and uncertainty in the economy, trade and investment. Many countries in advanced economies, emerging markets and developing economies have implemented fiscal and monetary policies to alleviate economic problems. One of the policies used by the world's major central banks to solve economic problems was quantitative easing (QE). The QE monetary policy has been used by central banks such as the US Federal Reserve (Fed) to stimulate the economy and increase the money supply during crises (World Bank, 2020). For example, the Fed purchases predetermined amounts of government bonds or securities on the open market. The Fed started implementing the first QE (QE1) policy in 2008 to address the economic recession during the global financial crisis. They then announced the second round (QE2) in 2010 and the third round (QE3) in 2012 before tapering some of the QE policies in 2013 due to the improved state of the economy. During the COVID-19 pandemic in 2020, the Fed announced QE4 or unlimited QE to address the severe economic recession. The Fed stated that it would purchase unlimited amounts of securities to support the financial market until it reached the desired level of economic stimulus, in contrast to previous QE policies, which involved the purchase of limited assets (Rebucci *et al.*, 2022). Beirne *et al.* (2020) examined the reaction of financial markets across 38 countries. They found that QE measures in advanced economies affected the domestic financial market by lowering bond yields while increasing stock prices. In addition, QE has also affected emerging economies in stabilizing the capital flow dynamics. Therefore, it has become apparent that the COVID-19 pandemic posed a systemic risk to stock markets. In addition, the implementation of QE by the central banks of various countries has affected stock markets worldwide. Stock markets in the ASEAN have also been affected by these factors. Studies undertaken before the COVID-19 pandemic revealed the existence of previous volatility in ASEAN stock markets. Stock markets in the ASEAN Economic Community (AEC) have also been found to have relationships with each other and other stock markets outside the region (Click and Plummer, 2005; Janor and Ali, 2007; Sriboonchitta *et al.*, 2014; Duong and Huynh, 2020; Chitkasame and Tansuchat, 2019; Pongkongkaew *et al.*, 2020; Lim, 2007; Jakpar *et al.*, 2013; Lean and Smyth, 2014).

As mentioned earlier, the COVID-19 pandemic and the implementation of QE implementation have resulted in stock market volatility worldwide. This research aims to analyze the dependence between the volatility of stock market returns both inside and outside the ASEAN. In this study, data before and after the unlimited QE announcement by the Fed were used, at a time when the COVID-19 pandemic was not yet over. In this study, the GARCH (1,1) model (Bollerslev, 1986) was employed to analyze the volatility of daily returns of stock market indices. Next, the copula model (Sklar, 1959; Nelsen, 2006) was used to analyze the dependence between the volatility of the stock returns obtained from the GARCH(1,1) model. After that, Kendall's Tau rank correlation obtained from the copula model was then used to construct the minimal spanning tree (MST) (Millington and Niranjan, 2021). The MST method was employed to cluster the relationship between the volatility of stock markets, showing the connection network and the closeness of the volatility of stock market returns.

This study makes two noteworthy contributions to the existing literature. Firstly, it divides the data into two distinct periods: before (Period 1) and after (Period 2) the announcement of unlimited QE, during the continuing COVID-19 crisis. The analysis results for two time periods were compared with different situations to understand the changes in the relationship between stock market volatility. Secondly, the copula-based GARCH model combined with the minimum spanning tree (MST) model was used to analyze and present the systemic network of the relationship, to obtain a clearer picture of the changes.

The findings of this study highlighted that the relationship between the volatility of daily stock market returns (r) in Period 1 and Period 2 was markedly different. In Period 1, the relationship between stock markets in the lower tail (τ_L) showed greater dependence than other relationships. In Period 2, the upper tail (τ_U) dependence was more apparent than in Period 1, with the role of lower tail (τ_L) dependence being reduced. Moreover, the minimum spanning tree model results revealed patterns of volatility transmission between stock markets and the changes in the relationship between stock markets when the QE policy was implemented. During the period of unlimited QE, stock markets were closer jointly in volatility transmission in such a way that there was a sharp simultaneous rise in the stock market indices.

2. Literature review

In the past, Click and Plummer, 2005 and Janor and Ali, 2007 found that the stock markets of the original member countries in the Associtation of SouthEast Asian Nations (ASEAN), namely Thailand, Indonesia, the Philippines, Singapore and Malaysia were integrated but not yet fully complete.Chitkasame and Tansuchat (2019) also found volatility transmission among the ASEAN stock markets during unusual events. Many studies have demonstrated the potential use of copulas and GARCH models. For example, Sriboonchitta *et al.* (2014) found stock market volatility in Indonesia, the Philippines and Thailand was related and had a tail dependence. These results were consistent with those of Duong and Huynh (2020), who found the left- and right-tail dependence on the volatility of stock markets in Vietnam, Thailand, Singapore, the Philippines, Malaysia and Indonesia. Pongkongkaew *et al.* (2020) found that during the economic boom, there were co-movement dynamics among the stock markets of the Philippines, Indonesia, Malaysia, Thailand and Singapore. Therefore, it is evident that ASEAN stock markets are correlated in normal and volatile market conditions. Other studies have also shown that ASEAN stock markets are correlated with those outside the region. Lim (2007) found that the US stock market significantly influenced the stock markets of Thailand, Indonesia, the Philippines, Singapore and Malaysia. Furthermore, Jakpar *et al.* (2013) identified a co-movement between China and the stock market volatility in the ASEAN-5. Similarly, Lean and Smyth (2014) indicated that the stock markets of Thailand, Indonesia, the Philippines, Singapore, Malaysia, Vietnam and China were cointegrated both in the long and short run.

Previous studies have shown that during the 2008 economic crisis, Asian stock markets became more integrated than in the calm period, with Hong Kong, Japan, Korea and India playing an essential role (Aswani, 2017). Chowdhury *et al.* (2018) showed that ASEAN stock markets form part of the bridge that links stock markets within Asia and outside Asia, including Europe and the US. Thus, ASEAN stock markets face systemic risks, passing them on to stock markets in Asia as well as Hong Kong and China, potentially linking to the risks from outside the region. Furthermore, Rillo (2018) found that ASEAN economies correlate more with the global financial markets than with their regional neighbors. The fact that ASEAN stock markets correlate with those of other countries that play a crucial role in the global economy, such as the US and China, has both advantages and disadvantages. Specifically, the economic growth of these countries can generate growth for ASEAN stock markets. On the contrary, investment fluctuations caused by the economic crisis can also be transmitted from outside the region to the ASEAN stock markets. Previous studies reveal the stock markets of the ASEAN to be related to China's stock market, which has a trade agreement with the ASEAN called the Regional Comprehensive Economic Partnership (RCEP). Thus, the stock markets in other countries involved in trade agreements with the ASEAN, such as Korea, Japan, India, Australia and New Zealand (ASEAN Secretariat, 2016), may have relationships with the ASEAN.

Network analysis is a method used to describe the systemic connection between stock markets. The study of systemic connections between stock markets informs how stock markets are related in a network or group. The systemic or overview relationship between stock markets can also be recognized. Moreover, the connections between stock markets can be grouped (Huang *et al.*, 2016; Long *et al.*, 2017; Isogai, 2017), benefiting investors through risk management. During the COVID-19 pandemic, Zhang *et al.* (2020) studied the linkages of 12 global stock indices. Their findings reveal that the linkages of stock markets are consistent with the COVID-19 situation in each country. In other words, there is co-movement in the stock markets of countries in the same pandemic situation. Aslam *et al.* (2020) used 56 global stock indices to analyze the linkages of stock markets before and during the COVID-19 outbreak. The study results show that the COVID-19 outbreak has dramatically changed the dependence between the stock markets. From these results, the COVID-19 outbreak can be seen as a systemic risk that affects the dependence of stock markets worldwide.

The COVID-19 pandemic and the QE stimulus package impacted stock markets around the world. Before the outbreak of COVID-19, the study of Pastpipatkul *et al.* (2016) found that the use of QE by the Fed had a significant effect on ASEAN financial markets. Zhang *et al.*, (2020) found that the implementation of the unlimited QE program by the Fed has affected stock markets worldwide, causing a rebound in the stock markets affected by the COVID-19 pandemic. Stock market movements have also been more highly correlated. Therefore, it is interesting to study the relationship and systemic connection between the volatility of ASEAN stock markets and those in countries outside the region that play an important role in ASEAN stock markets and economies. Moreover, to examine changes in dependence before and after implementing the unlimited QE program by the Fed.

Our study differs from previous works in terms of the data and methods used in the analysis. The GARCH (1,1) model (Bollerslev, 1986) was used to investigate the marginal distribution of each daily stock index's returns. The data then obtained from the GARCH (1,1) model was then used to analyze the relationship between the volatilities of stock market returns using the copula model (Sklar, 1959; Nelsen, 2006). Sriboonchitta *et al.* (2013) discussed the advantages of the copula model, stating that it can be used to analyze the concordance between data series without normal distribution. The copula model gives excellent flexibility in stock market data analysis. It can also analyze concordance other than linear correlation. The concordance measurement between the data series is in the form of Kendall's Tau, which indicates the level of dependence. The Kendall's Tau value is then used to construct a systemic connection between stock markets using the MST model (Millington and Niranjan, 2021).

3. Methodology

The copula-based GARCH (1,1) was used in this study to investigate the dependence between data series. The model has been proven to be good for a wide range of financial data (Bollerslev, 1986, 1992). The estimation procedures were divided into two main parts. First, the GARCH (1,1) model was used to find the marginal distributions of standardized residuals (Z_t) in each univariate time series data, following Patton (2001, 2006). The most relevant GARCH process is the GARCH (1,1) model. Second, the copula model was used to determine dependence since it has more advantages than the traditional method. It can capture various ranges of dependence structures, such as non-linear relationships and asymmetric and fat tails in extreme events. Copulas can model the dependence between random variables without specifying the distribution of each variable (Chollets *et al.*, 2011). The standardized residuals (Z_t) from the appropriate GARCH (1,1) model in the first step will be transformed using the empirical distribution function referred to as the marginals, $F(x_i)$. These marginals are then used for the copula model.

3.1 GARCH (1,1) model

The generalized autoregressive conditionally heteroscedasticity (GARCH) model is used to estimate the conditional variance of time series data. The generic GARCH model or GARCH (1,1) was used in this study. Many previous studies used the GARCH (1,1) model with the copula model to ascertain the dependence of the financial data, such as stock index and exchange rate returns (Patton, 2001, 2006; Wu *et al.*, 2012; Aloui *et al.*, 2013; Puarattanaarunkorn *et al.*, 2016; Marsila *et al.*, 2021).

Conditional variance equation

$$h_t = \omega_t + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{1}$$

$$\varepsilon_t = z_t\sqrt{h_t}, z_t \sim D(0,1) \tag{2}$$

Equation (1) displays the GARCH (1,1) process where $\omega_t > 0, \alpha \geq 0, \beta \geq 0$ are sufficient to confirm that the conditional variance $h_t > 0$ and $\alpha + \beta < 1$ confirm the stationarity of the analyzed data, following the properties of GARCH (1,1) process. The $\alpha\varepsilon_{t-1}^2$ is the ARCH term or autoregressive conditional heteroskedastic term and α indicates the short-run persistence of shocks, while βh_{t-1} is the GARCH term and β indicates the long-run persistence of shocks. The $\alpha + \beta$ provides a measure for the persistence of the relevant time series. If $\alpha + \beta$ is has a value close to 1, it implies more remarkable persistence in volatility (Chang and McAleer, 2012). In other words, the shocks will affect volatility for a long time or have a long memory.

Equation (2) presents the GARCH variance equation. This innovation ε_t of time series data is defined as the outcome between conditional variance h_t and a standardized residual z_t. The standardized residual z_t is a random variable that is independent and identically distributed (i.i.d). The mean of z_t is equal to 0 and the standard deviation is equal to 1 $(z_t \sim D(0,1))$ for any distribution function (D). Four distribution functions were selected to identify the most appropriate for each data series: normal, skew-normal, student t and skewed student t. Since the exact distribution function of the data series was not known, we selected various functions that could measure the normal distribution, the tail distribution and the skewness (Ghalanos, 2020).

3.2 Copula model

Copula is used to analyze the relationship or concordance between random variables. The random variables data must be adjusted to be in the range of [0,1] with uniform distribution. The marginal distribution of each variable must be known, which can be the same or different. In addition, the random variables must be independent and identically distributed (i.i.d) to be used with the copula model (Patton, 2006). In this study, Kolmogorov-Smirnov (K-S) was used to confirm the uniform distribution and the Box-Ljung test was employed to test for the i.i.d property.

Copula describes the dependence between the marginal distribution of random variables as a joint distribution function. Copula theory is based on Sklar's theorem (Sklar, 1959), as presented in Nelsen (2006), describing the copula theory as follows.

Let X and Y be continuous random variables with the joint function for (X,Y) is

$$H(x,y) = \Pr[X \leq x, Y \leq y] \tag{3}$$

Then, the marginal distributions of X and Y are $F(x) = \mathrm{H}(X,\infty)$ and $G(y) = \mathrm{H}(\infty, Y)$, respectively. According to Sklar's theorem

$$H(x,y) = C(F(x), G(y)) \tag{4}$$

where C is a copula.

If H has continuous marginals F and G, then, the copula in Equation (4) is

$$C(u,v) = H\left(F^{-1}(u), G^{-1}(v)\right) \tag{5}$$

where $F^{-1}(u)$ and $G^{-1}(v)$ are quantile functions. Given a parametric c_θ, then, the joint density c_θ is obtained from

$$c_\theta = \frac{\partial^2 C_\theta(F(x), G(y))}{\partial x \partial y} \tag{6}$$

where θ is the copula parameter. For the estimation of copula parameter, the maximum pseudo-log likelihood by Genest *et al.* (1995) was used. Since we have not known the exact marginal distributions of random variables, the pseudo-observations $F_n(x_i)$ and $G_n(y_i)$ were used for the estimation. The pseudo-observations were obtained by transforming the marginal distribution functions F and G into uniform [0,1] values, by employing the empirical distribution functions, $F_n(x) = \frac{1}{n+1}\sum_{i=1}^{n} \mathrm{I}(x_i \le x), G_n(x) = \frac{1}{n+1}\sum_{i=1}^{n} \mathrm{I}(y_i \le y)$. Furthermore, Equation (6) can be expressed as,

$$c_\theta = \frac{\partial^2 C_\theta(F_n(x), G_n(y))}{\partial x \partial y} \tag{7}$$

Then, we used the maximum pseudo-log likelihood method to estimate copula parameter θ. The pseudo-log likelihood function is presented as $L(\theta) = \sum_{i=1}^{n} \log[c_\theta(F_n(x_i), G_n(y_i))]$.

Many copula families on the CDVine package of the R program (Brechmann and Schepsmeier, 2013) were used in this study to analyze the possible dependence structure and independence of random variables. Each copula family has its different characteristics. The Elliptical copulas were used to analyze the symmetric dependence structure, including Gaussian and Student t copulas. The Archimedean copulas were used for the asymmetric dependence structure, which can capture the strong lower tail and strong upper tail dependences, including Clayton, Gumbel, Frank, Joe, BB1, BB6, BB7 and BB8, survival Clayton, survival Gumbel, survival Joe, survival BB1, survival BB6, survival BB7 and survival BB8. We will select a suitable copula family that is the best to capture the dependence structure of the data by employing the Akaike Information Criterion (AIC) of Akaike (1973). Furthermore, the dependence in the form of Kendall's Tau correlation τ was measured to compare the relationship size of each copula family.

3.3 Minimum spanning tree

The minimum spanning tree (MST) model is widely used to analyze the connection between stock markets to understand the overall relationship (Huang *et al.*, 2016; Long *et al.*, 2017; Zhang *et al.*, 2020; Aslam *et al.*, 2020). The MST model constructed from the Pearson correlation coefficient may be faulty due to the non-normal distribution and outlier of the analyzed data. However, the MST model constructed from Spearman's or Kendall's Tau values is more accurate. The tree structure is also more stable than the one constructed from the Pearson correlation coefficient (Millington and Niranjan, 2021). In this study, Kendall's Tau values obtained from the copula model were used to construct an MST for clustering stock markets that are close in the volatility transmission of daily returns of stock indices. The MST is a topological method for visualizing the systemic relationship between stock markets and is convenient for analyzing complex data. The stock markets with the most consistent changes will be displayed according to their direct linking positions in the connection network, so the systemic relationship of the movements between stock markets can be visualized. Direct-connected markets tend to experience more consistent changes than non-directly connected markets.

Therefore, it is beneficial for investors to manage their investment risks and understand the interconnected phenomena of the stock market in order to improve policy formulation or plan stock markets-related works.

To model the MST, a distance matrix (d_{ij}) must first be constructed using the equation presented by Mantegna (1999).

$$d_{ij} = \sqrt{2(1 - c_{ij})} \tag{8}$$

In this study, c_{ij} refers to Kendall's Tau correlation obtained from the copula model. There are three Kendall's Tau value types: τ, τ_U and τ_L, showing the concordance between the volatility of the stock market indices i and j. The distance matrix is denoted as d_{ij} is the used to create the MST with Kruskal's algorithm, as mentioned by Millington and Niranjan (2021).

Equation (9) represents the normalized tree length (*NTL*) values in the MST structure. This formula is derived from the study by Onnela *et al.* (2002). The *NTL* values are used to study market conditions at different times. In other words, they show the overall relationship of the entire network. A low *NTL* value means a high systemic relationship between markets.

$$NTL_{Period}^{Type} = \left(\frac{1}{N-1}\right)\sum e_{ij} \tag{9}$$

where *Type* is used to indicate the type of *NTL*, divided into three types, generated based on Kendall's Tau value either, τ, τ_U, or τ_L. *Period* denotes the study duration: before or after the unlimited QE announcement. N is the number of stock markets and e_{ij} represents the distance between stock markets i and j in the MST structure.

4. Data

Time series data on 14 stock market indices were used for analysis. in this case covering two periods. Period 1: January 1, 2019–March 23, 2020 (before the unlimited QE announcement) and Period 2: March 24, 2020–April 28, 2021 (after the unlimited QE announcement). Almost all the data series were taken from the Thomson Reuters Datastream, except for the Standard and Poor's/NZX 50 obtained from Investing.com. Each data series in Period 1 and Period 2 consisted of 320 and 287 observations, respectively. The data used in this study consisted of the daily closing prices, as presented in Table 1.

The COVID-19 outbreak was announced as a global pandemic on March 11, 2020, by the World Health Organization (WHO). The outbreak situation has caused fluctuations in global stock markets (ASEAN Secretariat, 2020). Figure 1 shows the daily closing prices of 14 stock market indices, pointing out that in Period 1 (before the unlimited QE announcement), stock market indices declined sharply as a result of the announcement by the WHO. On March 23, 2020, unlimited QE was announced by the Fed (Rebucci *et al.*, 2022). Following this announcement, all stock market indices immediately rose, even at a time when COVID-19 showed no signs of ending. This shows that unlimited QE has a significant influence on stock markets.

The daily returns on the stock market index (R_t) are calculated from $R_t = \ln(P_t) - \ln\ (P_{t-1})$. P_t and P_{t-1} represent the stock market indexes on days t and t-1, respectively. Figure 2 shows the volatility of R_t on 14 stock markets.

Table 2 shows the descriptive statistics of R_t in Periods 1 and 2. In Period 1, the means of R_t on most markets are negative, except for China. The skewness values of R_t on all markets are

Variables	Stock market indices	Location
Thai	Bangkok SET	Thailand
Malay	FTSE Bursa Malaysia Top 100	Malaysia
Sing	Straits Times Index	Singapore
Indo	IDX Composite	Indonesia
Phi	Philippines Stock Exchange I (PSEI)	Philippines
Viet	Hochiminh Stock Exchange Vietnam All Share	Vietnam
India	Standard and Poor's BSE (Sensex) 30 Sensitive	India
Hong	Hang Seng	Hong Kong
China	Shanghai Stock Exchange A Share	China
Japan	Nikkei 225 Stock Average	Japan
Korea	Korea Stock Exchange Composite (KOSPI)	Korea
Aus	Standard and Poor's/Australian Stock Exchange 200	Australia
New	Standard and Poor's/NZX 50	New Zealand
USA	Standard and Poor's 500 Composite	United States

Table 1. Description of variables

negative. This indicates that in Period 1, negative returns of R_t may be more common than positive ones. In Period 2, the means of all markets are positive, with their skewness values being higher than those in Period 1 and mostly positive. It can be said that an increase in all stock market indices occurs in Period 2 compared to Period 1. The kurtosis values of all stock markets in Period 2 decreased from Period 1, indicating that the R_t changes in Period 2 do not dramatically fluctuate from the mean as in Period 1 and the values of R_t are more distributed than those in Period 1.

Based on the descriptive statistics of both periods, it can be said that after the unlimited QE announcement, the stock market indices in Period 2 changed in an upward trend. In addition, the standard deviation (*SD*) values show that the volatility in most markets increased during Period 2 but decreased in Thailand, China and the USA.

In the next step of the analysis, data series of each stock market were analyzed by the GARCH (1,1) model to determine the volatility of the daily returns of stock market indices (r). The dependence between the volatility (r) of 14 stock markets was then analyzed by the copula and MST models.

5. Empirical results

5.1 Results of GARCH (1,1) model

Before using the GARCH (1,1) model to capture the volatility of each time series data, the Augmented Dickey–Fuller test (ADF) was applied to test the stationarity of time series data in Period 1: 1 January 1, 2019–March 23, 2020 and Period 2: March 24, 2020–April 28, 2021. The results showed that all the data series for the period were stationary with p-values of less than 0.01. Furthermore, the ARCH-LM tests revealed that all the return data series exhibited heteroskedasticity or time-varying variances. The p-values of ARCH-LM tests were less than 0.01 level. Therefore, the GARCH model was considered appropriate for capturing the volatility of time series data.

The GARCH (1,1) model results in Period 1 showed that 14 stock market return series existed with short-run α and long-run β persistence. All showed statistical significance parameters α and β at the 1% level. Moreover, the coefficients $\alpha + \beta$ were close to 1, with values ranging from 0.915 to 0.999, indicating that a shock effect would remain for a long time or has a long memory in conditional variance. For Period 2, the estimated coefficients showed that the parameter α of the return data series was significant at the 1%, 5% and 10% levels, except for Australia. The parameter β of 14 stock market return series was highly significant

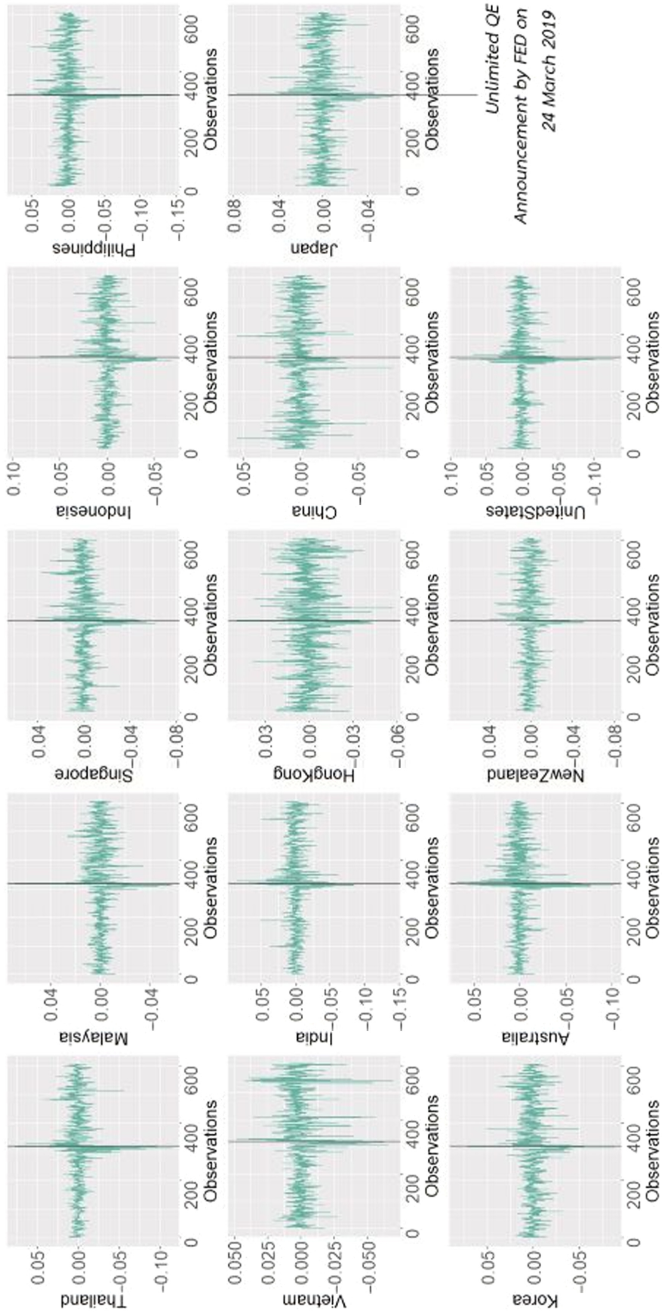
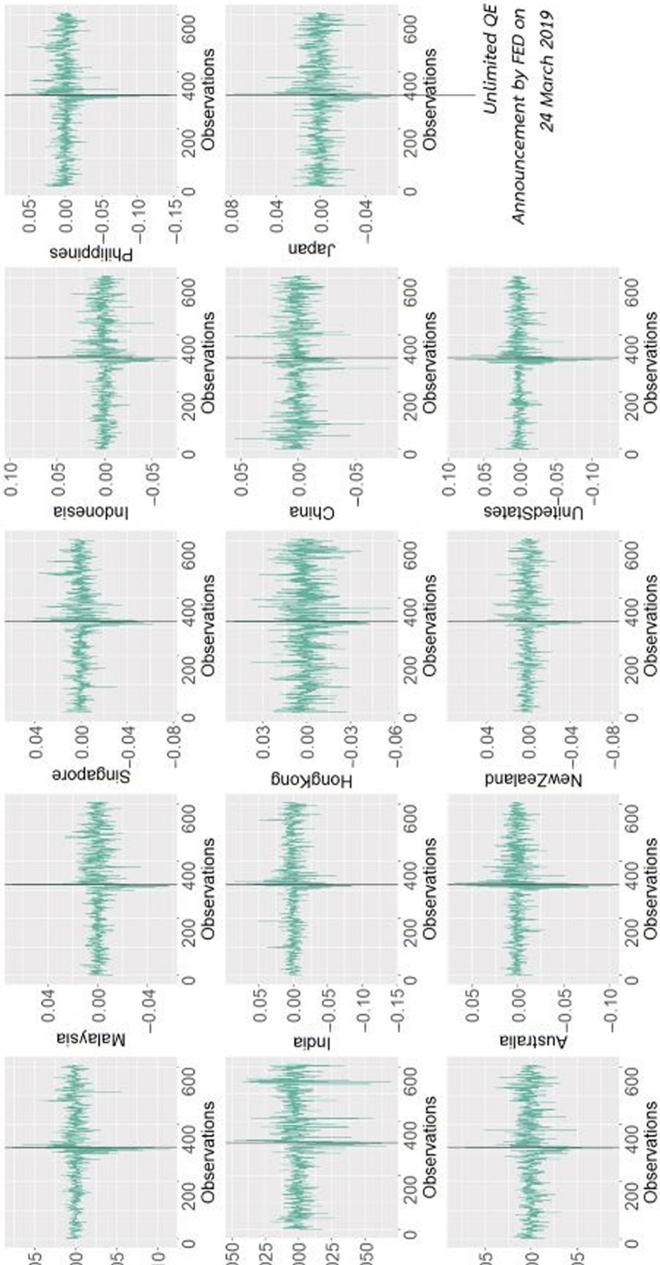


Figure 1.
Fourteen stock market indices from 1 January 2019 to 28 April 2021

Source(s): Authors



Source(s): Authors

Figure 2.
Daily return in 14 stock market indices from 1 January 2019 to 28 April 2021

Table 2.
Descriptive statistics of daily returns

Stock market	Mean		Median		Max		Min		SD		Skew		Kurtosis	
	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
Thai	−0.0013	0.0015	0.0000	0.0003	0.0765	0.0647	−0.1143	−0.0559	0.014	0.012	−3.59	0.49	29.78	4.68
Malay	−0.0009	0.0011	0.0000	0.0005	0.0676	0.0272	−0.0570	−0.0338	0.009	0.009	−0.97	−0.04	23.82	0.76
Sing	−0.0010	0.0013	0.0000	0.0001	0.0423	0.0589	−0.0764	−0.0455	0.010	0.011	−2.78	0.89	17.61	5.66
Indo	−0.0014	0.0014	0.0000	0.0000	0.0289	0.0970	−0.0681	−0.0514	0.010	0.014	−2.21	1.22	10.57	9.20
Phi	−0.0014	0.0011	0.0000	0.0000	0.0330	0.0717	−0.1432	−0.0733	0.015	0.015	−4.32	0.32	33.42	4.08
Viet	−0.0009	0.0024	0.0003	0.0030	0.0201	0.0481	−0.0650	−0.0688	0.010	0.014	−2.74	−1.03	13.90	4.58
India	−0.0010	0.0023	0.0000	0.0023	0.0559	0.0859	−0.1410	−0.0612	0.015	0.015	−3.72	0.39	32.62	5.57
Hong	−0.0005	0.0010	0.0000	0.0007	0.0493	0.0436	−0.0498	−0.0572	0.012	0.013	−0.56	−0.30	3.10	1.96
China	0.0002	0.0009	0.0000	0.0000	0.0545	0.0555	−0.0803	−0.0460	0.012	0.011	−1.07	0.14	8.03	3.59
Japan	−0.0005	0.0019	0.0000	0.0001	0.0258	0.0773	−0.0627	−0.0462	0.011	0.014	−1.37	0.75	5.88	5.26
Korea	−0.0010	0.0027	0.0001	0.0022	0.0718	0.0825	−0.0877	−0.0488	0.013	0.014	−1.41	0.56	12.38	4.88
Aus	−0.0007	0.0015	0.0009	0.0009	0.0566	0.0677	−0.1020	−0.0544	0.013	0.013	−3.09	0.33	20.39	4.41
New	−0.0001	0.0014	0.0009	0.0001	0.0216	0.0694	−0.0795	−0.0265	0.010	0.011	−3.27	1.30	20.57	6.30
USA	−0.0004	0.0022	0.0008	0.0018	0.0888	0.0897	−0.1277	−0.0608	0.016	0.014	−2.26	0.67	21.92	7.68

Note(s): P1 is Period 1; P2 is Period 2 at the 1% level. The coefficients $\alpha + \beta$ were close to 1 with values ranging from 0.885 to 0.997. Therefore, a shock effect on the conditional variance for a long time was indicated, as in Period 1.

5.2 Dependence between the volatility of daily stock market returns in period 1

The copula model was used to analyze the dependence between the volatility of daily stock market returns (r) extracted from the GARCH (1,1) model. The empirical results in Table 3 show that each pair-copula had different appropriate copula families for describing the dependence structures. Furthermore, three types of Kendall's Tau correlations were used to measure the dependence between data series. The τ values indicated concordance between the data series r, τ_U and τ_L at the upper and lower tails, respectively. As can be observed from Table 3, the volatility of stock market returns (r) in Period 1 (January 1, 2019–March 23, 2020) exhibited by almost every market was related. Most interestingly, they had an asymmetric relationship with lower tail dependence.

The findings of this study revealed a dependence among ASEAN stock markets, with most having an asymmetric relationship when considering the copula family. Some pair-copulas had both upper and lower tail dependence, while others demonstrated only lower tail dependence. For example, pair-copulas of Thai-Sing ($\tau = 0.3$, $\tau_U = 0.33$, $\tau_L = 0.22$); Thai-Malay ($\tau = 0.23$, $\tau_U = 0.05$, $\tau_L = 0.3$); Indo-Phi ($\tau = 0.34$, $\tau_L = 0.42$); Malay-Sing ($\tau = 0.33$, $\tau_L = 0.4$). These findings indicate volatility transmission among stock markets intra-ASEAN rather than the outer region.

The volatility of ASEAN stock markets was related to those outside the region except for the stock markets of Malaysia and the Philippines, which showed no relation to the volatility of the USA stock market. For example, pair-copulas of Sing-Hong ($\tau = 0.46$, $\tau_L = 0.54$) was the most closely related; Sing-Korea ($\tau = 0.4$, $\tau_U = 0.09$, $\tau_L = 0.2$); Sing-Japan ($\tau = 0.34$, $\tau_U = 0.16$, $\tau_L = 0.16$); Sing-Aus ($\tau = 0.3$, $\tau_L = 0.45$); Sing-China ($\tau = 0.27$, $\tau_L = 0.4$). The lower tail dependences were relatively high for Sing-Hong, Sing-Aus and Sing-China.

Notably, the volatility of the Singapore stock market was most closely related to the volatility of the stock markets outside the region. Moreover, Hong Kong, Japan and Korea were found to have the strongest relationships with the ASEAN stock markets. Countries involved in trade agreements with the ASEAN, namely China, Korea, Japan, India, Australia and New Zealand, were related to the volatility of ASEAN stock markets. In terms of the US stock market, we found concordance with the stock markets of Thailand and Singapore in all values of τ, τ_U and τ_L. However, India-New and New-US, were independent.

5.3 Dependence between the volatility of daily stock market returns in period 2

The volatility of stock market returns (r) in almost all markets was found to be related and most had asymmetrical relationships in Period 2 (Table 4). Period 2 ranges from March 24, 2020, to April 28, 2021, the period after the unlimited QE announcement by the Fed. During Period 2, an increase in the upper tail dependence was exhibited among the ASEAN stock markets compared to Period 1, even though the COVID-19 pandemic had not yet ended, indicating greater liquidity in the ASEAN stock markets after the unlimited QE announcement. Investment in various stock markets can be observed in Figure 1 along with the values of τ_U.

As in Period 1, volatility transmission still existed among ASEAN stock markets according to the results in Table 4. For example, pair-copulas of Sing-Indo ($\tau = 0.26$, $\tau_U = 0.21$, $\tau_L = 0.11$); Sing-Malay ($\tau = 0.25$, $\tau_U = 0.30$, $\tau_L = 0.11$); Malay-Thai ($\tau = 0.22$, $\tau_U = 0.29$); Malay-Phi ($\tau = 0.24$, $\tau_U = 0.30$); Sing-Phi ($\tau = 0.17$, $\tau_U = 0.22$).

Table 3.
Results of pair-copulas in period 1

	Thai	Malay	Sing	Indo	Phi	Viet	India	Hong	China	Japan	Korea	Aus	New	USA
Thai	*Fam*	*SBB7*	*BB7*	*SJ*	*CT*	*SJ*	*CT*	*SBB7*	*G*	*SGB*	*BB7*	*SJ*	*SJ*	*SBB7*
	$\boldsymbol{\tau}$	0.23	0.3	0.19	0.21	0.15	0.22	0.28	0.19	0.19	0.24	0.12	0.11	0.17
	$\boldsymbol{\tau}_U$	0.05	0.33	0	0	0	0	0.18	0	0	0.22	0	0	0.03
	$\boldsymbol{\tau}_L$	0.3	0.22	0.37	0.27	0.31	0.28	0.33	0	0.24	0.19	0.26	0.24	0.21
Malay	*SBB7*	*Fam*	*SGB*	*SBB8*	*SGB*	*SGB*	*SGB*	*SGB*	*CT*	*SGB*	*BB7*	*SGB*	*SJ*	*Ind*
	0.23	$\boldsymbol{\tau}$	0.33	0.3	0.32	0.21	0.21	0.3	0.15	0.23	0.3	0.26	0.14	
	0.05	$\boldsymbol{\tau}_U$	0	0	0	0	0	0	0	0	0.22	0	0	
	0.3	$\boldsymbol{\tau}_L$	0.4	0	0.4	0.27	0.27	0.38	0.14	0.3	0.35	0.33	0.29	
Sing	*BB7*	*SGB*	*Fam*	*SGB*	*CT*	*SJ*	*CT*	*SGB*	*CT*	*St*	*SBB1*	*CT*	*CT*	*BB7*
	0.3	0.33	$\boldsymbol{\tau}$	0.26	0.25	0.22	0.22	0.46	0.27	0.34	0.4	0.3	0.21	0.18
	0.33	0	$\boldsymbol{\tau}_U$	0	0	0	0	0	0	0.16	0.09	0	0	0.15
	0.22	0.4	$\boldsymbol{\tau}_L$	0.33	0.34	0.42	0.29	0.54	0.4	0.16	0.2	0.45	0.27	0.09
Indo	*SJ*	*SBB8*	*SGB*	*Fam*	*SGB*	*SJ*	*CT*	*BB7*	*G*	*St*	*SGB*	*CT*	*CT*	*SJ*
	0.19	0.3	0.26	$\boldsymbol{\tau}$	0.34	0.15	0.19	0.23	0.18	0.22	0.23	0.18	0.14	0.1
	0	0	0	$\boldsymbol{\tau}_U$	0	0	0	0.19	0	0.12	0	0	0	0
	0.37	0	0.33	$\boldsymbol{\tau}_L$	0.42	0.31	0.23	0.18	0	0.12	0.3	0.2	0.11	0.22
Phi	*CT*	*SGB*	*CT*	*SGB*	*Fam*	*SJ*	*CT*	*BB7*	*CT*	*BB7*	*SGB*	*SJ*	*SGB*	*Ind*
	0.21	0.32	0.25	0.34	$\boldsymbol{\tau}$	0.14	0.16	0.23	0.14	0.18	0.25	0.17	0.19	
	0	0	0	0	$\boldsymbol{\tau}_U$	0	0	0.12	0	0.17	0	0	0	
	0.27	0.4	0.34	0.42	$\boldsymbol{\tau}_L$	0.29	0.17	0.24	0.12	0.07	0.31	0.34	0.24	
Viet	*SJ*	*SGB*	*SJ*	*SJ*	*SJ*	*Fam*	*CT*	*SGB*	*G*	*St*	*SGB*	*SGB*	*SJ*	*SJ*
	0.15	0.21	0.22	0.15	0.14	$\boldsymbol{\tau}$	0.15	0.24	0.21	0.22	0.23	0.22	0.13	0.09
	0	0	0	0	0	$\boldsymbol{\tau}_U$	0	0	0	0.15	0	0	0	0
	0.31	0.27	0.42	0.31	0.29	$\boldsymbol{\tau}_L$	0.14	0.31	0	0.15	0.3	0.28	0.26	0.2
India	*CT*	*SGB*	*CT*	*CT*	*CT*	*CT*	*Fam*	*SGB*	*SJ*	*SGB*	*CT*	*CT*	*Ind*	*CT*
	0.22	0.21	0.22	0.19	0.16	0.15	$\boldsymbol{\tau}$	0.25	0.15	0.18	0.18	0.17		0.12
	0	0	0	0	0	0	$\boldsymbol{\tau}_U$	0	0	0	0	0		0
	0.28	0.27	0.29	0.23	0.17	0.14	$\boldsymbol{\tau}_L$	0.32	0.3	0.24	0.21	0.19		0.08
Hong	*SBB7*	*SGB*	*SGB*	*BB7*	*BB7*	*SGB*	*SGB*	*Fam*	*BB1*	*St*	*St*	*SGB*	*CT*	*G*
	0.28	0.3	0.46	0.23	0.23	0.24	0.25	$\boldsymbol{\tau}$	0.42	0.35	0.45	0.25	0.13	0.2
	0.18	0	0	0.19	0.12	0	0	$\boldsymbol{\tau}_U$	0.30	0.21	0.2	0	0	0
	0.33	0.38	0.54	0.18	0.24	0.31	0.32	$\boldsymbol{\tau}_L$	0.44	0.21	0.2	0.32	0.09	0

(*continued*)

Table 3.

	Thai	Malay	Sing	Indo	Phi	Viet	India	Hong	China	Japan	Korea	Aus	New	USA
China	*G*	*CT*	*CT*	*G*	*CT*	*G*	*SJ*	*BB1*	*Fam*	*FR*	*SBB8*	*CT*	*CT*	*BB8*
	0.19	0.15	0.27	0.18	0.14	0.21	0.15	0.42	$\boldsymbol{\tau}$	0.3	0.3	0.21	0.12	0.13
	0	0	0	0	0	0	0	0.30	$\boldsymbol{\tau_U}$	0	0	0	0	0
	0	0.14	0.4	0	0.12	0	0.3	0.44	$\boldsymbol{\tau_L}$	0	0	0.27	0.08	0
Japan	*SGB*	*SGB*	*St*	*St*	*BB7*	*St*	*SGB*	*St*	*FR*	*Fam*	*St*	*G*	*CT*	*SGB*
	0.19	0.23	0.34	0.22	0.18	0.22	0.18	0.35	0.3	$\boldsymbol{\tau}$	0.39	0.31	0.14	0.13
	0	0	0.16	0.12	0.17	0.15	0	0.21	0	$\boldsymbol{\tau_U}$	0.2	0	0	0
	0.24	0.3	0.16	0.12	0.07	0.15	0.24	0.21	0	$\boldsymbol{\tau_L}$	0.2	0	0.11	0.18
Korea	*BB7*	*BB7*	*SBB1*	*SGB*	*SGB*	*SGB*	*CT*	*St*	*SBB8*	*St*	*Fam*	*SGB*	*SGB*	*SGB*
	0.24	0.3	0.4	0.23	0.25	0.23	0.18	0.45	0.3	0.39	$\boldsymbol{\tau}$	0.27	0.15	0.16
	0.22	0.22	0.09	0	0	0	0	0.2	0	0.2	$\boldsymbol{\tau_U}$	0	0	0
	0.19	0.35	0.2	0.3	0.31	0.3	0.21	0.2	0	0.2	$\boldsymbol{\tau_L}$	0.34	0.2	0.21
Aus	*SJ*	*SGB*	*CT*	*CT*	*SJ*	*SGB*	*CT*	*SGB*	*CT*	*G*	*SGB*	*Fam*	*BB7*	*SGB*
	0.12	0.26	0.3	0.18	0.17	0.22	0.17	0.25	0.21	0.31	0.27	$\boldsymbol{\tau}$	0.31	0.1
	0	0	0	0	0	0	0	0	0	0	0	$\boldsymbol{\tau_U}$	0.17	0
	0.26	0.33	0.45	0.2	0.34	0.28	0.19	0.32	0.27	0	0.34	$\boldsymbol{\tau_L}$	0.39	0.14
New	*SJ*	*SJ*	*CT*	*CT*	*SGB*	*SJ*	*Ind*	*CT*	*CT*	*CT*	*SGB*	*BB7*	*Fam*	*Ind*
	0.11	0.14	0.21	0.14	0.19	0.13		0.13	0.12	0.14	0.15	0.31	$\boldsymbol{\tau}$	
	0	0	0	0	0	0		0	0	0	0	0.17	$\boldsymbol{\tau_U}$	
	0.24	0.29	0.27	0.11	0.24	0.26		0.09	0.08	0.11	0.2	0.39	$\boldsymbol{\tau_L}$	
USA	*SBB7*	*Ind*	*BB7*	*SJ*	*Ind*	*SJ*	*CT*	*G*	*BB8*	*SGB*	*SGB*	*SGB*	*Ind*	*Fam*
	0.17		0.18	0.1		0.09	0.12	0.2	0.13	0.13	0.16	0.1		$\boldsymbol{\tau}$
	0.03		0.15	0		0	0	0	0	0	0	0		$\boldsymbol{\tau_U}$
	0.21		0.09	0.22		0.2	0.08	0	0	0.18	0.21	0.14		$\boldsymbol{\tau_L}$

Note(s): Fam is family of copula; Ind is independence; CT is Clayton; FR is Frank; G is Gaussian; St is Student t; SJ is survival Joe; SGB is survival Gumbel; SBB1 is survival BB1; SBB7 is survival BB7 and SBB8 is survival BB8

Table 4.
Results of pair-copulas in period 2

	Thai	Malay	Sing	Indo	Phi	Viet	India	Hong	China	Japan	Korea	Aus	New	USA
Thai	*Fam*	*GB*	*G*	*SBB1*	*GB*	*GB*	*SBB1*	*G*	*G*	*FR*	*G*	*FR*	*BB8*	*G*
	τ	0.22	0.31	0.19	0.16	0.09	0.32	0.33	0.19	0.23	0.27	0.21	0.18	0.13
	τ_U	0.29	0	0.01	0.21	0.12	0.08	0	0	0	0	0	0	0
	τ_L	0	0	0.18	0	0	0.32	0	0	0	0	0	0	0
Malay	*GB*	*Fam*	*BB7*	*BB1*	*GB*	*Ind*	*GB*	*BB7*	*G*	*G*	*SBB7*	*GB*	*BB7*	*G*
	0.22	τ	0.25	0.21	0.24		0.22	0.23	0.17	0.23	0.25	0.14	0.11	0.1
	0.29	τ_U	0.3	0.13	0.3		0.29	0.19	0	0	0.12	0.18	0.08	0
	0	τ_L	0.11	0.11	0		0	0.19	0	0	0.3	0	0.02	0
Sing	*G*	*BB7*	*Fam*	*BB1*	*GB*	*SGB*	*G*	*St*	*St*	*BB1*	*BB7*	*St*	*G*	*SBB7*
	0.31	0.25	τ	0.26	0.17	0.16	0.32	0.41	0.21	0.35	0.37	0.3	0.14	0.16
	0	0.3	τ_U	0.21	0.22	0	0	0.33	0.08	0.35	0.44	0.11	0	0.12
	0	0.11	τ_L	0.11	0	0.22	0	0.33	0.08	0.1	0.3	0.11	0	0.07
Indo	*SBB1*	*BB1*	*BB1*	*Fam*	*G*	*CT*	*St*	*SBB8*	*SBB8*	*St*	*St*	*FR*	*SCT*	*SCT*
	0.19	0.21	0.26	τ	0.23	0.11	0.24	0.26	0.2	0.24	0.28	0.26	0.1	0.11
	0.01	0.13	0.21	τ_U	0	0	0.2	0	0	0.11	0.09	0	0.04	0.06
	0.18	0.11	0.11	τ_L	0	0.06	0.2	0	0	0.11	0.09	0	0	0
Phi	*GB*	*GB*	*GB*	*G*	*Fam*	*FR*	*G*	*G*	*Ind*	*GB*	*G*	*FR*	*G*	*Ind*
	0.16	0.24	0.17	0.23	τ	0.11	0.19	0.17		0.11	0.18	0.14	0.09	
	0.21	0.3	0.22	0	τ_U	0	0	0		0.15	0	0	0	
	0	0	0	0	τ_L	0	0	0		0	0	0	0	
Viet	*GB*	*Ind*	*SGB*	*CT*	*FR*	*Fam*	*Ind*	*St*	*SGB*	*SGB*	*St*	*Ind*	*Ind*	*Ind*
	0.09		0.16	0.11	0.11	τ		0.19	0.16	0.14	0.16			
	0.12		0	0	0	τ_U		0.07	0	0	0.03			
	0		0.22	0.06	0	τ_L		0.07	0.21	0.19	0.03			
India	*SBB1*	*GB*	*G*	*St*	*G*	*Ind*	*Fam*	*SBB7*	*SBB7*	*G*	*G*	*G*	*G*	*G*
	0.32	0.22	0.32	0.24	0.19		τ	0.31	0.15	0.24	0.29	0.21	0.13	0.14
	0.08	0.29	0	0.2	0		τ_U	0.18	0.03	0	0	0	0	0
	0.32	0	0	0.2	0		τ_L	0.38	0.17	0	0	0	0	0
Hong	*G*	*BB7*	*St*	*SBB8*	*G*	*St*	*SBB7*	*Fam*	*SBB7*	*BB1*	*G*	*BB1*	*G*	*SCT*
	0.33	0.23	0.41	0.26	0.17	0.19	0.31	τ	0.37	0.33	0.45	0.26	0.17	0.14
	0	0.19	0.33	0	0	0.07	0.18	τ_U	0.25	0.22	0	0.27	0	0.12
	0	0.19	0.33	0	0	0.07	0.38	τ_L	0.47	0.29	0	0.03	0	0

(*continued*)

Table 4.

	Thai	Malay	Sing	Indo	Phi	Viet	India	Hong	China	Japan	Korea	Aus	New	USA
China	*G*	*G*	*St*	*SBB8*	*Ind*	*SGB*	*SBB7*	*SBB7*	*Fam*	*SGB*	*G*	*G*	*G*	*G*
	0.19	0.17	0.21	0.2		0.16	0.15	0.37	$\boldsymbol{\tau}$	0.2	0.28	0.16	0.1	0.12
	0	0	0.08	0		0	0.03	0.25	$\boldsymbol{\tau_U}$	0	0	0	0	0
	0	0	0.08	0		0.21	0.17	0.47	$\boldsymbol{\tau_L}$	0.26	0	0	0	0
Japan	*FR*	*G*	*BB1*	*St*	*GB*	*SGB*	*G*	*BB1*	*SGB*	*Fam*	*BB1*	*St*	*GB*	*GB*
	0.23	0.23	0.35	0.24	0.11	0.14	0.24	0.33	0.2	$\boldsymbol{\tau}$	0.41	0.39	0.15	0.13
	0	0	0.35	0.11	0.15	0	0	0.22	0	$\boldsymbol{\tau_U}$	0.39	0.31	0.2	0.18
	0	0	0.1	0.11	0	0.19	0	0.29	0.26	$\boldsymbol{\tau_L}$	0.23	0.31	0	0
Korea	*G*	*SBB7*	*BB7*	*St*	*G*	*St*	*G*	*G*	*G*	*BB1*	*Fam*	*G*	*FR*	*SCT*
	0.27	0.25	0.37	0.28	0.18	0.16	0.29	0.45	0.28	0.41	$\boldsymbol{\tau}$	0.34	0.18	0.14
	0	0.12	0.44	0.09	0	0.03	0	0	0	0.39	$\boldsymbol{\tau_U}$	0	0	0.11
	0	0.3	0.3	0.09	0	0.03	0	0	0	0.23	$\boldsymbol{\tau_L}$	0	0	0
Aus	*FR*	*GB*	*St*	*FR*	*FR*	*Ind*	*G*	*BB1*	*G*	*St*	*G*	*Fam*	*GB*	*Joe*
	0.21	0.14	0.3	0.26	0.14		0.21	0.26	0.16	0.39	0.34	$\boldsymbol{\tau}$	0.23	0.11
	0	0.18	0.11	0	0		0	0.27	0	0.31	0	$\boldsymbol{\tau_U}$	0.29	0.23
	0	0	0.11	0	0		0	0.03	0	0.31	0	$\boldsymbol{\tau_L}$	0	0
New	*BB8*	*BB7*	*G*	*SCT*	*G*	*Ind*	*G*	*G*	*G*	*GB*	*FR*	*GB*	*Fam*	*GB*
	0.18	0.11	0.14	0.1	0.09		0.13	0.17	0.1	0.15	0.18	0.23	$\boldsymbol{\tau}$	0.19
	0	0.08	0	0.04	0		0	0	0	0.2	0	0.29	$\boldsymbol{\tau_U}$	0.24
	0	0.02	0	0	0		0	0	0	0	0	0	$\boldsymbol{\tau_L}$	0
USA	*G*	*G*	*SBB7*	*SCT*	*Ind*	*Ind*	*G*	*SCT*	*G*	*GB*	*SCT*	*Joe*	*GB*	*Fam*
	0.13	0.1	0.16	0.11			0.14	0.14	0.12	0.13	0.14	0.11	0.19	$\boldsymbol{\tau}$
	0	0	0.12	0.06			0	0.12	0	0.18	0.11	0.23	0.24	$\boldsymbol{\tau_U}$
	0	0	0.07	0			0	0	0	0	0	0	0	$\boldsymbol{\tau_L}$

Note(s): Fam is Family of copula; Ind is independence. CT is Clayton. FR is Frank. G is Gaussian. GB is Gumbel. St is Student t. SJ is survival Joe. SCT is survival Clayton. SGB is survival Gumbel. SBB1is survival BB1. SBB7 is survival BB7. SBB8 is survival BB8

Volatility transmission was also found between four ASEAN member states: Thailand, Malaysia, Singapore, Indonesia and other countries outside the ASEAN. However, stock market volatility in the Philippines was not correlated with that of China and the USA.

For example, pair-copulas of Sing-Hong (τ = 0.41, τ_U = 0.33, τ_L = 0.33); Sing-Korea (τ = 0.37, τ_U = 0.44, τ_L = 0.3); Sing-Japan (τ = 0.35, τ_U = 0.35, τ_L = 0.1); Sing-China (τ = 0.21, τ_U = 0.08, τ_L = 0.08); Sing-USA (τ = 0.16, τ_U = 0.12, τ_L = 0.07). This finding obviously showed that the volatility in the Singapore stock market was most closely connected to the volatility of stock markets outside the ASEAN. In particular, the stock markets in Hong Kong, Japan and Korea were most closely related in terms of volatility to those in the ASEAN, according to their dependence values. The volatility of stock markets in countries involved in trade agreements with the ASEAN was related to those in the ASEAN, except for Phi-China, Viet-Aus and Viet-New. For US stock market volatility, concordance was found to exist with the stock markets of Singapore in all values of τ, τ_U and τ_L, as in Period 1. Moreover, dependence was exhibited between the volatility in the stock markets of India, Hong, China, Japan, Korea, Australia, New Zealand and the USA.

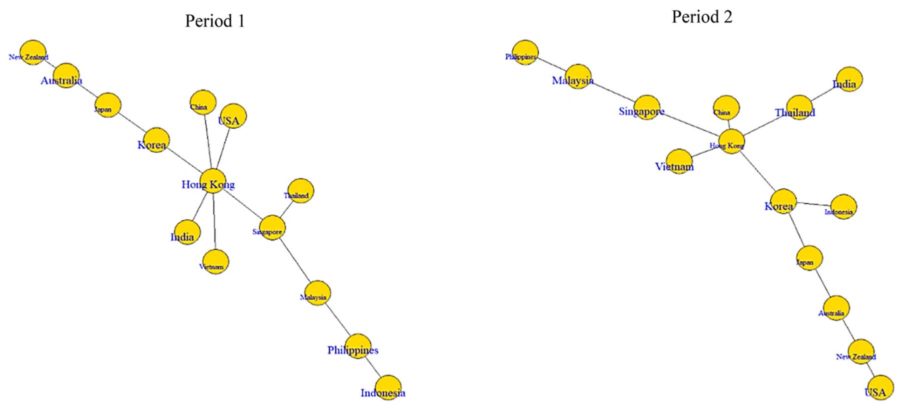
5.4 Results of minimum spanning tree model

The values of Kendall's Tau correlation from the copula model, τ, τ_U and τ_L, presented in Table 5, were used to analyze the minimum spanning tree model (MST). The MST model provided a clear picture of the relationship between stock market volatility intra-ASEAN and extra-ASEAN. Stock markets with closer relationships will have a direct connection. The results shown in Figures 3–5 are divided into three parts based on Kendell's Tau correlation values.

Table 5.
Results of normalized tree length

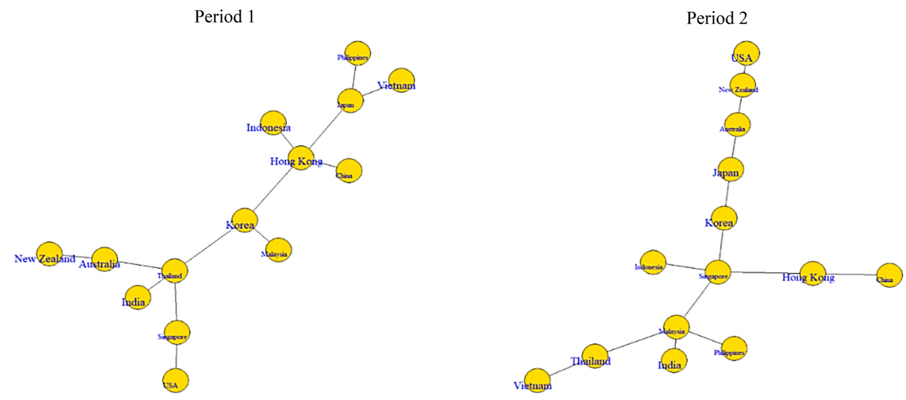
Type is Kendall's tau	NTL_{Before}	NTL_{After}	Change
τ	1.1537	1.1787	Increasing = 0.0250
τ_U	1.2805	1.1906	Decreasing = 0.0899
τ_L	1.1059	1.2224	Increasing = 0.1165

Note(s): *NTL* is normalized tree length values. *before* is period 1, *after* is period 2



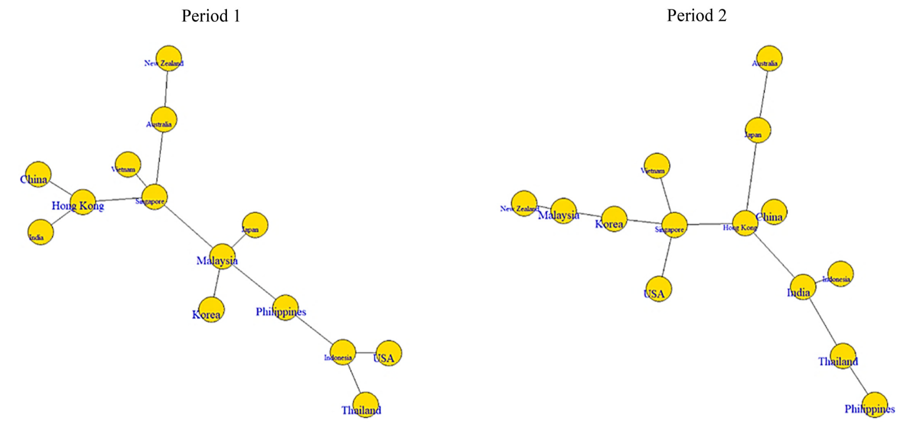
Source(s): Authors

Figure 3.
Minimum spanning trees based on τ



Source(s): Authors

Figure 4. Minimum spanning trees based on τ_U



Source(s): Authors

Figure 5. Minimum spanning trees based on τ_L

5.4.1 The minimum spanning tree networks based on τ. According to the MST networks based on the τ value in Figure 3, there is a high level of concordance in the volatility in directly connected markets. In Period 1, the volatility of various stock markets in the ASEAN were connected and in the same cluster. The sum of all pair-copulas of τ values in Figure 3 for Period 1 is 4.32. The stock markets closely related to each other were directly connected. The Singapore stock market was a bridge that connected the volatility between the intra-ASEAN and outside regional stock markets by linking to the Hong Kong stock market. The Hong Kong stock market direct connects to many other stock markets, such as China, the USA, India, Vietnam and Korea. Thus, it also provided a bridge, connecting the volatility between the intra and extra-ASEAN regional stock markets.

In Period 2, the Hong Kong stock market still had a direct connection with many markets and played a role as a bridge like in Period 1. The stock markets of ASEAN member states did not cluster as in Period 1 and were more independent from each other. The sum of all pair-copulas of τ values in Figure 3 for Period 2 is 4.06, indicating greater independence of each market. However, the stock markets of Singapore, Malaysia and the Philippines continued to cluster in both periods. The stock markets of advanced economies, such as New Zealand, Australia, Japan, Korea and Hong Kong, were similarly connected in both periods.

Therefore, the empirical results from the MST model before and after the unlimited QE announcement allow us to know which stock market segments or pairs continue to exhibit clustering. These findings signify the integration between the markets.

5.4.2 The minimum spanning tree networks based on τ_U. In the MST networks based on τ_U (Figure 4), in Period 1, there was a relatively low density in the connection of each market in upper tail dependence. Specifically, in the direct connection, no clustering was exhibited in the same region and there were many edges. During Period 2, there was apparent clustering based on region and border proximity. In addition, the sum of all pair-copula τ_U values in Periods 1 and 2 were 2.31 and 3.84, respectively. This indicates greater the upper tail dependence between the markets in Period 2 than during Period 1.

5.4.3 The minimum spanning tree networks based on τ_L. According to Figure 5, the stock markets in the ASEAN were directly interconnected in Period 1. The stock markets of Australia and New Zealand were also connected. The Singapore stock market acted as a bridge to connect the volatility between ASEAN stock markets and those outside ASEAN. In Period 2, there was relatively low density in the connection of stock markets in the lower tail dependence of the MST. As for the direct connection, there was no clustering like in Period 1. Australia and New Zealand stock markets were not directly connected and ASEAN stock markets being more independent than in Period 1. The sum of all pair-copulas of in Periods 1 and 2 were 5.02 and 3.21, respectively, indicating decreasing values in Period 2, compared to Period 1.

5.4.4 The normalized tree length. The normalized tree length (NTL) values in the MST structure are used to study market conditions at different times (Onnela *et al.*, 2002). The values of NTL show the overall relationship of the entire network. A low NTL value means a high systemic relationship between markets.

According to Table 5, the NTL values of τ and τ_L increased from Period 1 to Period 2, implying that the systemic relationship between stock markets of the whole network decreased in τ and τ_L. However, the NTL value of τ_U decreased, so the systemic relationship of the whole network increased on τ_U.

6. Conclusion

This research investigated the dependence between the volatility of daily returns on 14 stock market indices (r). *In Period 1*, the results of the GARCH model (1,1) indicate that a shock effect will remain for a long time or has a long memory in conditional variance. The results from the copula model show that the volatility of daily returns in almost all markets is related with most having an asymmetric relationship. Stock market volatility is prominently in the form of lower tail dependence (τ_L). The empirical results indicate that stock markets in countries with close borders and within the same economic region usually have a high level of dependence. In Period 2, the implementation of unlimited QE in advanced economies has helped to stabilize the capital flow dynamics in emerging economies (Beirne *et al.*, 2020). Cortes *et al.* (2022) found that implementing the Fed's measures to reduce tail risks in domestic equity markets has positively affected the international equity markets in both advanced and emerging economies.

The MST model results indicate a systemic relationship between the volatility of daily returns in all 14 markets. The stock markets of countries with close borders and located in the same region are directly connected in the MST network. Moreover, lower tail dependence is more prominent than other forms, implying a sharp simultaneous decline in stock market indices. This relationship pattern appears more prominent than others during Period 1.

According to the results, almost all markets are related to each other in both Periods 1 and 2. This finding is consistent with previous studies in that ASEAN stock markets are intra-regionally integrated. Moreover, they are also integrated with the stock markets outside the region. The value of τ, τ_U and τ_L of the Hong Kong–Singapore copula-pair is higher than those of other stock market pairs because Hong Kong and Singapore are the business funding markets and centers of financial services in the region. The environment in these two countries also facilitates investment. Therefore, these two markets move together and are directly connected in the MST network.

The significant highlight of this research finding is the change in dependence and connection network between stock markets before and after the unlimited QE announcement. In terms of policy implications, the MST model results are useful for risk management in international investment. For example, during periods of poor stock market performance, recession trends, or when the markets are sensitive to bad news, investors should invest in different stock markets, rather than in the same cluster in the network. This is because, during a stock market crash, those in the same cluster or directly connected in the network will fall together with a higher level of concordance compared to other market pairs not closely related. When stock markets continue to rise, investors can invest in those directly connected in the network because stock markets in the same cluster will rise simultaneously during a market boom. The level of dependence between stock markets is one indicator that can indicate the degree of successful cooperation in the economic development of free trade zones while benefiting investors in risk management.

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