THE STOCK MARKET VOLATILITY BETWEEN CHINA AND ASEAN COUNTRIES ASSOCIATION STUDIES BASED ON COMPLEX NETWORKS

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ABSTRACT

By constructing the volatility network of stock market indexes in China and ASEAN, the mechanism of transnational market risk transmission and the characteristics of key nodes are analysed. Finding the volatility network is a good description of the linkage and tightness of the various share index volatility. The COVID-2019 led to a significant increase in convergence of behaviour patterns of major country share indexes, and significant differences in node changes and topological features of the volatility network. A few share indexes in Singapore and Thailand are key nodes and the source of market risk in the transnational stock market. Dynamic analysis shows that the evolution of share index volatility network reflects that the overall risk of volatility network changes with time, the information link structure of the market changes with time, and major emergencies break the original structure and trigger the information connection in the market. The findings of this paper have important implications for understanding the characteristics of transnational risk transmission between the stock markets of China and ASEAN.

KEYWORDS

China and ASEAN, Stock market, Share index volatility network, Complex networks

1. INTRODUCTION

In November 2021, the partnership of China and ASEAN was upgrade from a "strategic partnership" to a "comprehensive strategic partnership". With the economic and trade contacts between China and ASEAN have become closer and closer, the cross-border capital flows and the asset allocation which have cause by the cross-border investment and speculation have become increasingly active, also the co-movement and risk transmission of the stock market volatility in various countries has been growing. In this context, the major sudden emergency of China and ASEAN easily increases the systematic risk of stock markets and the difficulty for international capital to manage the risk of portfolio investment in the stock market. Understanding the changes in the static and dynamic correlation structure of the stock market volatility between China and ASEAN, that helps for identifying risk transmission mechanisms and key markets and grasping the rules of stock market risk transmission and adding the risk factors into stock valuation. Furthermore, this also can predict cross-border capital flow and the assets allocation direction, and provide the basis for formulating risk management plans of market shocks caused by international investment capital transfers, that has great significance for the pricing of financial derivatives and the government to formulate reasonable financial regulatory policies. This paper constructs a static and dynamic network of stock market volatility

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between China and ASEAN, focuses on answering the following questions: **What are the characteristics of the correlation structure of core stock market indexes between China and ASEAN? What is the mechanism of cross-border transmission of market risk and the characteristics of key nodes? How does the correlation structure between stock markets change over time?**

Compared with the existing literature, the main contribution of this study is the correlation research of multivariate time series analysis is very important for financial markets. In the topics of asset pricing, asset allocation, volatility transmission and risk management, the correlation between risk factors is crucial. This paper aims to study the characteristics of the association structure and the co-movement pattern in the stock market of China and ASEAN, and to deeply understand the diffusion of the market volatility risk from key nodes to other nodes. Based on a long-term sample of the share index volatility network, which provide a solid foundation for the analysis of the complexity and dynamic time-varying nature of share index volatility structure in China and ASEAN, the research of this paper finds that the volatility network can better depict the linkage characteristics and tightness of the share index volatility in various countries. The COVID-2019 shock led to a significant increase in convergence of behaviour patterns of major country stock indexes, and significant differences in node changes and topological features of the volatility network. The share index volatility network of major countries reflects clustering and homogeneity based on geographical distribution. A few share indexes of Singapore and Thailand are key nodes and sources of market risk in cross-border stock markets. Dynamic analysis shows that the evolution of the share index volatility network embodies the overall risk of the volatility network changes over time. Major sudden emergencies may lead to a significant increase in the correlation level of share index volatility. Also, the information link structure of the market changes over time, and the major sudden emergency break the original structure and trigger information links in the market.

The rest of the paper consists of the following. Section 2 summarizes the literature from three aspects. Section 3 introduces the design and method of the research. Data description and descriptive statistics are in Section 4. Section 5 is empirical research results and analysis. The last section concludes the paper.

2. RELATED WORK

The research of this paper is the expansion and deepening of the stock market co-movement. The research topic and method are mainly related to the literature in three aspects.

2.1. The Co-Movement Between China and the International Stock Market

Since China's stock market started late, many scholars believe that China's stock market and the world's stock market are isolated. However, with the acceleration of the internationalization process of China's stock market, many scholars began to study the co-movement between China and the international stock market. For example, Huang et al. used the Johansen maximum likelihood method to conduct an empirical test on the share index of the U.S., Hong Kong, Taiwan, China, and Japan. They found that the linkage of the Nikkei 225 Index to the stock markets of Hong Kong and Taiwan is far less than the impact of the U.S. Dow Jones Industrial Index on the stock markets of these two regions, but there is no linkage between the U.S. and Japanese stock markets to the Chinese stock markets.[1] Miyakoshi studied the linkage between the Japanese and American stock market and the stock markets of seven countries in the Asia Pacific region, believed that the American stock market had a guiding role in China's yield, while Japan had a volatility spill over effect on China's stock market, and there was no yield impact.[2]

Hongquan Zhu conducted a causal link test on the stock markets of Hong Kong, Shanghai and Shenzhen, found that there was no volatility of the yield rate between the Shanghai Shenzhen stock markets and the Hong Kong stock markets.[3]Wu Zhenxing and Xu Ning used the cointegration method to test the relation between Shanghai Composite Index and six major foreign indexes, and concluded that the Shanghai Composite Index only has a long-term cointegration relationship with the Dow Jones Index, Hang Seng Index and Singapore Index.[4] Zhang Biqiong found that the stock markets of Hong Kong, London and New York have volatility spill over effects on Shanghai and Shenzhen used the EGARCH model.[5]Wang Zhifen and Zhang Xueling used cointegration and Granger causality test to study the linkage effect of China's mainland stock market, Hong Kong stock market and the U.S. stock market.[6]They found that the long-term equilibrium relationship and Granger causality among the three major indexes in the U.S. and China stock markets had changed before and after the subprime crisis, and there was no fluctuation synergy for a period of time after the subprime crisis.

2.2. The Co-Movement between China and ASEAN Stock Markets

Since the establishment of the ASEAN Free Trade Area in 2010, the economic contact between China and ASEAN has been further deepened. Many scholars have studied the co-movement of the stock market between them. Teng KT et al. studied the cycle synchronization of stock market, found that China's linkage with ASEAN-5 stock market was enhanced by using the analysis of synergy index and rolling synergy index.[7] Mandigma discussed the linkage of the stock market for China and ASEAN during the subprime crisis. Taking the subprime crisis as the boundary, the paper found that Japan, South Korea had a greater linkage with the five ASEAN countries before the subprime crisis, while China and the five ASEAN countries had a smaller linkage. However, since 2008, the linkage between China and ASEAN countries has been growing.[8] Teng Kee Tuan et al. studied the linkage of the stock markets between China and ASEAN through the synergy index, found that the stock market linkage of China and ASEAN has been growing since the establishment of the ASEAN Free Trade Area.[9][8] HH Lean and R Smyth studied the cointegration relationship of stock market between China and ASEAN, found that the impact was rapid in a short time and there was a cointegration relationship for a long time.[10] Lei C et al. analysed the dynamic correlation coefficient between China and the ASEAN-5, and found that there was a cointegration relationship from 1994 and 2002.[11] Chien M S et al. studied the dynamic convergence of cross-border stock markets between China and ASEAN from 1994 to 2002, found that there was at most one cointegration vector in the stock market of China and ASEAN.[12]When KT Teng et al. studied the linkage between the stock markets of China and ASEAN, they found that the linkage between the two countries was on the rise in the short term, especially Thailand and Indonesia, which had stronger linkage with China, but the linkage between the stock markets of China and ASEAN was not strong in the long term.[13] Mao Wei and Hao Mengyu analysed the linkage of stock markets between China and ASEAN, and found that there was no cointegration relationship between the Shanghai Composite Index with the stock indexes of Malaysia, Singapore, the Philippines, Indonesia and Thailand. However, the Shanghai Composite Index and the Singapore share index are causality, and there is a one-way causality with the Thai and Malaysian share index, furthermore, there is no Granger causality with the Philippine and Indonesian share indexes.[14]

2.3. The Complex Networks Application of the Stock Market

Since traditional econometric models cannot accurately describe the correlation between financial markets, scholars began to use complex networks to check the correlation between them. Mantegna first proposed to build a complex network of stock correlation, analyzed the stock related index using cross correlation network analysis tools MST and HT, and gave the optimal portfolio strategy.[15] Engsted and Tanggaard constructed a complex network of British and

American stock markets to study the correlation characteristics of the stock markets of them.[16] Boginski used the threshold method to analyze the statistical properties of the stock market network, and found that the degree distribution of the stock market has power law characteristics, and has factional groups.[17] Li Ping, Wang Binghong constructed a complex network for the Hong Kong stock market, found that was not a random network.[18] Huang Weiqiang et al. used 1080 constituent stocks of Shanghai Composite Index and Shenzhen Index to build a stock related network using MST and PMFG, and analyzed the topological nature of the network.[19] Huang used the APM model to study the Chinese stock market, and analyse that the network is vulnerable to attacks, but more robust than the random network.[20]Aste et al. constructed a correlation network using PMFG based on 395 American stocks from 1996 to 2009, found that the 2007 US subprime crisis changed the network structure.[21] Namaki, Shirazi et al. established a stock market network in various thresholds for the Iranian stock market by using the threshold method to analyse the statistical characteristics of the network structure.[22] Nobi, Lee and Kim used the APM model to analyse the impact of the 2008 financial crisis on the global stock market network, and found that the financial crisis changed the topology of the global network.[23] Deng Chao used simulation methods to systematically analyse the financial contagion risk model basing on Watts cascade dynamic theory of complex networks.[24] Ouyang Hongbing and Liu Xiaodong used MST and PMFG methods to analyse the financial market network, which can dynamically identify the systematic importance of nodes in the financial network.[25] Under the background of the financial crisis, Liu Weizong and Zhang Wei used the threshold method to construct the global stock market network, and found that the network changed dynamically and cooperatively with the crisis process.[26]Xie Chi and Hu Xuejing built a dynamic correlation network of the stock market, and discussed dynamic evolution characteristics and market robustness.[27]

In summary, firstly, when studying the linkage between China and the international stock market, previous studies usually divided the time into several sub samples, the segmentation method is subjective. For example, divided by the 2008 US Subprime Crisis. Second, scholars generally focus on the linkage between the stock markets of China and developed countries, and the study of stock markets of ASEAN is shortage. Third, ASEAN usually are taken as a whole when studying the linkage of stock markets between China and ASEAN. However, the linkage between China and those countries is not consistent, the linkage can explore respectively. Fourth, the data sample of the existing co-movement empirical analysis usually takes month as the unit, and few uses high-frequency daily data. Based on predecessors, this paper takes daily frequency data as the research object to better capture the internal structure that is difficult to capture by low-frequency data, such as, weekly frequency and monthly frequency. The research on the correlation structure of stock market volatility in China and ASEAN is of unique significance.

3. PROPOSED METHOD

The research is carried out by the following steps: 1. Taking the core index as nodes, and using the volatility cross-correlation matrix to define edges, to construct the stock market volatility network of China and ASEAN-9. 2. Using the eigenvector centrality represents the network centrality of share index volatility, to identify the core-periphery position of stock markets and key node characteristics. 3. Investigating time-varying characteristics and the stability of the volatility network structure.

3.1. Share Index Volatility Network

The topological structure of complex network can effectively extract the complex correlation structure between the share index volatility, while retaining basic characteristics of data sets and reducing the complexity of data. The priority of constructing the stock market volatility network is the correlation definition of the stock market network. Pearson correlation coefficient usually uses to define the network,[15]and has extensive application in the literature of network analysis. For avoiding falling into the lengthy discussion of the effectiveness comparison between various related methods, we directly use Pearson correlation coefficient to construct the minimum spanning tree (MST), focus on the correlation structure of share index volatility and key market nodes and so on.

$N = \{i|i = 0, \ldots, n\}$ is the set of n share indexes, and the i is the share index of each country. Based on N set, we define $P_i(t)$as the closing price of the i-th share index at the t-th period, and the return rate$r_i(t)$ of the i-th share index after the time interval (Δt)can be calculated by the formula:

$$r_i(t) = ln(P_i(t)) - ln(P_i(t-1)) \quad (1)$$

To calculate the volatility of share indexes, we use Garman & Klass to construct logarithmic price changes based on daily frequency data interval, and use daily frequency data to calculate the realized volatility (variance) of each proxy index, that is, "realized volatility of daily interval price difference". The algorithm is as follow:

$$\begin{aligned}\hat{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ -2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \quad (2)\end{aligned}$$

As the formula 2, the H_{it}, L_{it}, O_{it}, C_{it} are the daily highest, lowest, opening and closing prices of the logarithmic index respectively for the i-th index at t-th day. The realized volatility calculated based on the daily frequency interval price is constructed by using the key characteristics of the price of the day, such as the opening price, closing price, maximum price and minimum price. Compared with the traditional realized volatility which calculated based on the daily minute level high-frequency sampling data, the "realized volatility of daily interval price difference" not only achieve similar effects and simplify the calculation procedures of the traditional approach, but also have strong immunity to market microstructure.[28] In addition, since the daily frequency data generally has good availability, the sample can be obtained in a long-time range as much as possible.

Then, we calculate Pearson correlation coefficient of realized volatility of any two assets $i$and j.

$$C_{ij}^T = \frac{\sum_{t=1}^T (r_i(t) - \overline{r_i(t)})(r_j(t) - \overline{r_j(t)})}{\sqrt{\sum_{t=1}^T (r_i(t) - \overline{r_i(t)})^2 \sum_{t=1}^T (r_j(t) - \overline{r_j(t)})^2}} \quad (3)$$

The correlation coefficient is treated by measuring distance to make it conform to the European distance axiom: (1) $d_{ij} = 0$if and only if$i = j$; (2)$d_{ij} = d_{ji}$;(3) $d_{ij} \leq d_{ik} + d_{kj}$.

$$d_{ij} = \sqrt{2(1 - C_{ij}^T)} \quad (4)$$

The d_{ij} is the distance between the assets i and j.[15]
The MST is mainly used to filter the network for redundant links, extract important link information from the financial market.[15] For a financial market network with N nodes, all possible links are $N(N-1)/2$. The MST selects the $N-1$ stronger link, which corresponds to the shortest path of all vertices on the graph, redundant links do not appear in the MST. In this paper, Prim algorithm is used to construct the MST.

3.2. Network Centrality of the Stock Market Volatility

Network centrality is a key index to measure the statistical characteristics of the network, which can quantify the importance of nodes in a given network. According to the share index volatility network constructed in3.1section, the volatility network with $n$share indexes can be expressed as$G = \{N, \quad \omega\}$, which is composed of nodes$N = (1,2, \ldots, n)$and edges ω, Nisthe set of share index volatility. If the volatility of the node $i$and $j$have relation, then there is $(i,j) \in \omega$. In order to extract the information of the volatility network, converting it into the adjacency matrix$\Omega = [\Omega_{ij}]$.Asthe non-weight undirected network, there is $\Omega \in [0,1]$.When $(i,j) \in \omega$, there is $\Omega_{ij} \neq 0$.Since $(i,j) \in \omega \Leftrightarrow (j,i) \in \omega$, there is $\Omega = \Omega^T$.

The index of network centrality measurement mainly includes degree centrality, betweenness centrality, closeness centrality and eigenvector centrality.[29] The degree centrality is used to calculate the number of share indexes that linked to a country's share index, which reflecting the position of the country's share index in the global stock market. The meaning is intuitive, the larger the value of nodes the more share index relation to it. Besides, betweenness centrality is also a key index to measure network centrality. The larger value, the higher the central position of the share index in the network. In addition, closeness centrality index is the reciprocal of the sum of the shortest distances from the share index to all other share indexes multiplied by the number of other share index nodes. For this measurement, the higher value, the closer to the central of the network, the more important it is in the network. Finally, the eigenvector centrality is defined as the proportion sum of the centrality of adjacent node$i$, which is expressed as$v_i = \lambda^{-1} \Sigma_j \Omega_{ij} v_j$, node$i$ acquires a highereigenvector centrality by connecting to many other nodes or nodes with a high centrality. Since the centrality of eigenvector can absorb the quantity and quality information of adjacent nodes. Eigenvector centrality can most accurately reflect the key nodes of the market.

3.3. Dynamic Network of Stock Market

In the past ten years, stock markets both of China and ASEAN have been affected by sudden shocks. Thus, the structure of the volatility network of the stock market is not stable and has characteristics of changing over time. In order to study the evolution characteristics of the network structure, by the cross-correlation matrix, we use the sliding time window to calculate the mean, standard deviation and other indexes by the cross-correlation matrix, and the performance change over time for the network average degree and other statistical characteristics. Following are specific procedures: 100 observations are calculated each time, measuring them recursively, moving along the time scale, and the window step is 1. Then, we get a total of 1415 windows as the complete example.

We calculate moments of the correlation matrix for each time window, mainly evaluating the mean value and the standard deviation of the correlation matrix and the statistical characteristics of the generalized time-varying correlation matrix of the stock market network, and then evaluating the network evolution and stability. The moment of the correlation matrix is defined as follows:

$$\text{Mean value:}\overline{C(t)} = \frac{2}{N(N-1)} \sum_{i=1,j=1}^{T} C_{ij}^{T}(t) \quad (5)$$

Similar with the definition of mean value of correlation coefficient, the definition of variance, skewness and kurtosis is as follow:

$$\text{Variance:}S_2(t) = \frac{2}{N(N-1)} \sum_{i=1,j=1}^{T} (C_{ij}^{T}(t) - \overline{C_{ij}^{T}(t)})^2 \quad (6)$$

Wherein, $\overline{C(t)}$is the average value of the correlation matrix on the$t$ trading day, and $C_{ij}(t)$is the correlation coefficient of assets $i$and assets $j$on the $t$trading day.

4. Data Description and Descriptive Statistics

Our research object is the stock market index of China and ASEAN-9 (see Table 1), which have the time range from March 1, 2016 to November 22, 2021 with a total of 1515 observations. The research scope includes 10 countries' stock market indexes: China (CSI300), Laos (LXS), Singapore (SGX), Thailand (SET), Vietnam (VN), Malaysia (FTSE), the Philippines (PSEI), Cambodia (CSX), Japan (N225), and South Korea (KRX). The reasons for choosing them are mainly based on the availability of data and the closeness of the stock market of various countries. As some of the ASEAN-9 lack of stock market indexes, and considering Japan and South Korea are geographically close to China and ASEAN, they may have close association with the stock markets of China and ASEAN, so this paper brings them into the scope of research. The closing price and trading volume of share indexes of various countries are from Wind Financial Terminal. However, the trading time of share indexes in those countries does not correspond to each other. If we simply adopt the "common time window" method to process data, namely, deleting the share index data that cannot be matched by the trading time, and a large amount of data will be lost. Therefore, we use the moving median with a window length of 10 trading days to replace and complete the missing values of share indexes in those countries.

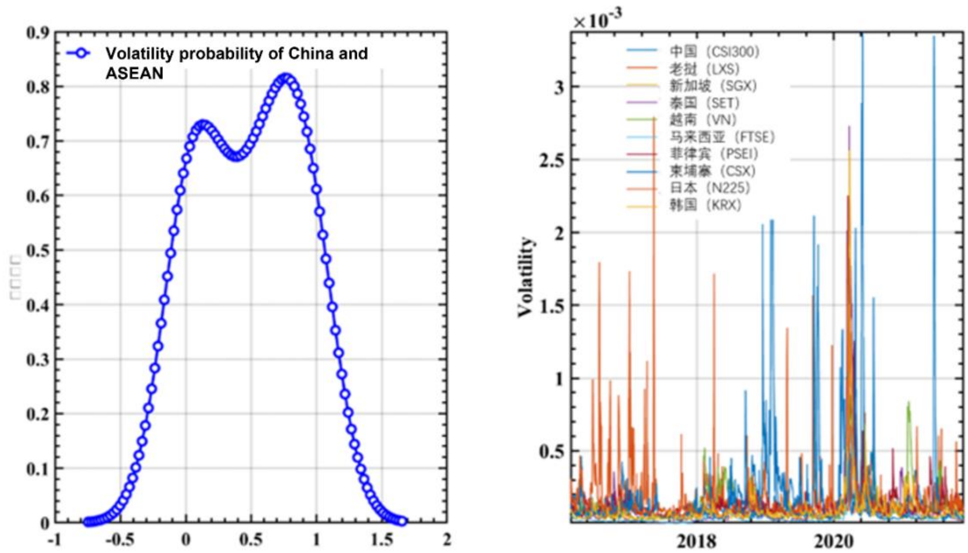

Figure 1. Probability distribution of volatility and volatility trend of stock market index (3/1/2016 to 11/22/2021)

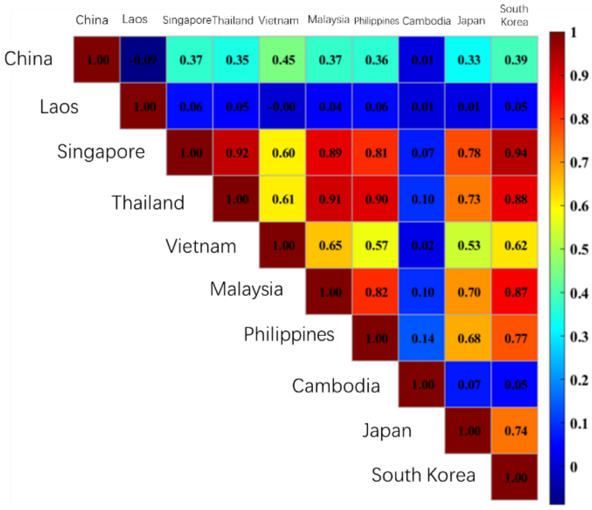

Figure 2. Volatility correlation chart of the share index (3/1/2016 to 11/22/2021),red and blue block relatively represents strong and weak correlation.

In order to further study the changes in the volatility correlation of the stock markets of China and ASEAN by the impact of major emergencies, we used the idea of event research method to analyse the COVID-2019. We use the dataset we mention above with difference time range which October 15, 2019 to January 5, 2021, and divide it to 3 sub-sample by time. Due to the widespread impact of the COVID-2019 on the world, the World Health Organization (WHO) declared it as a global pandemic on March 11, 2020. Based on this, the 3 sub-sample is divided as follow: (1) Before the outbreak: October 15, 2019 to March 10, 2020; (2) Outbreak period: March 11, 2020 to August 7, 2020; (3) Duration of epidemic: August 10, 2020 to January 5, 2021. All of the sub-sample have 102 trading days.[1]

As shown in Figure 1, selected the trend of share index volatility of China and ASEAN-9in the whole sample. In the first half of 2020, the wave of share index volatility of almost all countries were amplified, and China, South Korea, Singapore and the Philippines leading the way among all countries, that is closely related to the epidemic situation. Figure 2 shows the correlation chart of the stock index volatility of China and ASEAN-9.The share index volatility of countries which have more developed stock market among them, under the full sample state, have close relation with the other country in static linkage of the share index volatility. In the correlation chart, the share index volatility of Singapore, Japan and South Korea with other countries fall into a red block which is strong correlation block. In addition, the linkage between stock markets of ASEAN is generally obvious, but the static linkage of the share index volatility between China and the other 9 countries is not close.

[1]In this paper, we also use the time node of the outbreak of the epidemic in China to divide the event: (1) Before the outbreak: October 15, 2019 to February 10, 2020. (2) Outbreak period: February 11, 2020 to August 7, 2020. (3) Duration of epidemic: August 10, 2020 to January 5, 2021. Due to space limitation, the detailed results by the sample division can be obtained from the author.

5. EMPIRICAL TEST

5.1. Static Structure of Share Index Volatility Network

Firstly, we investigate the overall structure of the share index volatility network between China and ASEAN-9. This structure can reflect the correlation structure of share index volatility in various countries. We gave the MST of the share index volatility network of China and ASEAN-9 under the full sample in Mar 1, 2016 to Nov 22, 2021. In the MST, which integrates the entire sample information and reflects the normal state of the stock market correlation. Furthermore, the link mode of the market intuitively reflects the connection and tightness between the markets, and the link presents a clustered correlation structure of the stock market. Specifically, China, Vietnam, Malaysia and Thailand form Group 1, Philippines and Cambodia form Group 2, and Singapore, Laos, Japan and Korea form Group 3. The stock market of countries in the group are more likely to influence each other. It is easy to find that those groups are related to the level of national economic development and the stock market development. The stocks markets of relatively developed countries tend to form clusters, such as Japan and Singapore. The stock markets of developing countries with a relatively high level of economic development, such as China, Vietnam, Malaysia and Thailand, belong to the same group. The most backward markets in the sample form a group.

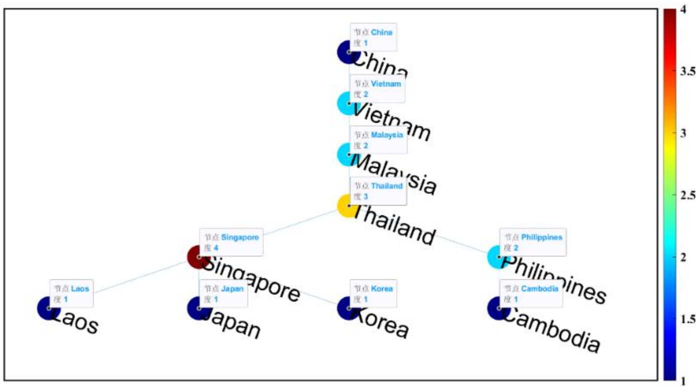

Figure 3. MST and network degree centrality of the stock market index volatility network in China and ASEAN-9 (Mar 1, 2016 to Nov 22, 2021)

Secondly, as a further study, we investigated the difference in the overall structure of the share index volatility network before, during and after the COVID-2019. The average cross correlation coefficient is given in Table 1. Table 1 shows that the COVID-2019 made the overall correlation of the stock market between China and ASEAN-9 have significantly increased. Also, during the outbreak, the average cross correlation was about 42% higher than before, and about 132% higher than after. This means that the convergence tendency of the behaviour patterns for the share index in the 10 countries increased significantly under the sudden impact. That highlight the importance of the major sudden emergencies research on the research of the overall structure in stock market. The continuous impact is basically within the time range of the epidemic outbreak defined in this paper. In addition, the average cross correlation falls rapidly after the event, even lower than the level before the event.

Table 1. Cross correlation list of share index volatility network of China and ASEAN-9

Country、Time	Index	Cross correlation of standardized volatility		
		Mean	**Minimum**	**Maximum**
Stock Market of China and ASEAN-9	Full samples	0.4018	-0.0197	0.9692
	Before the outbreak	0.4721	-0.5716	0.9143
	Outbreak period	0.6716	-0.1940	0.9877
	Duration of epidemic	0.2889	-0.6155	0.9529

5.2. Impact of Stock Market Volatility Network

The network centrality of share index volatility network reflects the importance of nodes. For the research of important of market, we first analysed the degree centrality. A degree is defined as the number of links of a given node. The higher degree of given market, the higher amount of market has association with it, the higher importance of the market. As the Figure 3, we used different colour to represent the degree centrality of the node of the share index volatility network in the MST of 10 countries. As the results, the key node was Singapore (D=4), and the secondary key node was Thailand (D=3).The centrality of the volatility network is an important basis for identifying key nodes in the stock market. The more centrality of the share index, the deeper it is embedded into the market network, the greater the impact on the market. Then, the most central key node is the first to be impacted, which is the source of market risk and transmits the volatility information to the share index that are directly related to it.

Also, we investigated the betweenness centrality which provides different perspectives for measuring market centrality. The betweenness centrality for a node is defined as the number of shortest paths through it, which represents the transit effect of a market. The result similar with the degree centrality, that the share index volatility of Singapore (B=21) and Thailand (B=26) had the largest betweenness centrality, and Thailand was the largest one. The fact reflects that, in the share index volatility network, both Thailand and Singapore share indexes are the key role for link in the MST.

Furthermore, we analysed the closeness centrality which is the reciprocal of the average distance between a node and all other nodes, and reflects the closeness of a node to other nodes in the network. The results similar with previous analysis, that is, Thailand (C=0.063) and Singapore (C=0.055) where the share indexes with the largest closeness centrality respectively.

Finally, in the share index volatility network, the importance of a node depends on the number of its neighbour nodes (namely, the degree of the node), and also depends on the importance of its neighbour nodes. The more important the neighbour nodes, the more important the node is. The eigenvector centrality can absorb the quantity and quality information of the neighbour nodes. The eigenvector centrality proved once again that Singapore (V=0.202) and Thailand (V=0.183) were the key nodes of the network.

From the geographical perspective, the share indexes of Singapore and Thailand ware the key nodes can be understandable. Singapore is the financial center and logistics center of Asia and even the world, and Thailand is the central region of the entire ASEAN. As the share index of key node, the systematic risk of the stock market generally spreads to the node with lower centrality through the key node with the highest centrality, and finally spreads to nodes of peripheral countries. As the perspective of risk prevention and control, grasping this communication mechanism to track and monitor the high centrality nodes of share index in a targeted manner during the outbreak of major sudden emergencies, that can deploy risk prevention measures in a timely manner. In addition, combining the centrality propagation law can intervene or even designing the "firewall" mechanism transmission path in advance. Those will help to mitigate the transmission risk of market fluctuations which caused by large fluctuations in other countries' markets.

Table 2. Influence of share index volatility network in China and ASEAN-9

Share Index Name	Degree centrality (D)	Betweenness centrality (B)	Closeness centrality (C)	Eigenvector centrality (V)
China（CSI300）	1	0	0.029	0.0269
Laos（LXS）	1	0	0.038	0.090
Singapore（SGX）	**4**	**21**	**0.055**	**0.202**
Thailand（SET）	**3**	**26**	**0.063**	**0.183**
Vietnam（VN）	2	8	0.038	0.060
Malaysia（FTSE）	2	14	0.050	0.108
Philippines（PSEI）	2	8	0.045	0.102
Cambodia（CSX）	1	0	0.033	0.045
Japan（N225）	1	0	0.038	0.090
Korea（KRX）	1	0	0.038	0.090

Table 3. Topological characteristics of share index volatility networks in China and ASEAN-9

Network	Node	Edge	Eigenvector centrality	Degree centrality	Degree index γ
Before the outbreak	10	9	0.0135	2.0526	3.26
Outbreak period	10	9	0.0131	1.7368	3.5
Duration of epidemic	10	9	0.0146	1.6842	3.07

Generally, the financial market network belongs to scale-free network, which has the network characteristics follows the power law distribution. The degree of a node in the network is defined as the sum of the connected edges of the node, which means if there are$k$ edges for a node, the degree is$k$. A degree distribution$p(k)$ reflects the degree distribution of each node in the network structure. If the node degree distribution follows thePower-law distribution, then there is the distribution relation :$p(k) \sim k^{-\gamma}$, which indicate that the network is scale-free or has scale-free structure. There are some studies find the financial network is the scale-free structure. The topological properties of scale-free networks are related to the degree index. Generally, the degree index that less than 2 is abnormal in network, and the number of links at the largest hub node grows faster than the size of the network. Also, when the degree index is between 2 and 3 and greater than 3, they are scale-free networks and random networks, respectively. In this case, the first and second moment of the degree distribution are limited. When the degree index is greater than 3, scale-free networks and random networks have no significant difference. In Table 3, the result shows that the degree indexγ of China and ASEAN-9 was in the range of [3.07, 3.26] before, during and after the epidemic, which indicated that this was a scale-free network, and the degree index$\gamma$of China and ASEAN-9 increased to varying degrees during the epidemic outbreak.

5.3. Dynamic Structure of Stock Market Volatility Network

The evolution characteristic of the share index volatility network reflects that the overall risk of the volatility network changes with time. We use the sliding time window technology[2] to calculate the time-varying mean, standard deviation, skewness and kurtosis of the time-varying cross correlation matrix for the share index volatility network of 10 countries, as well as the eigenvector centrality for all countries.

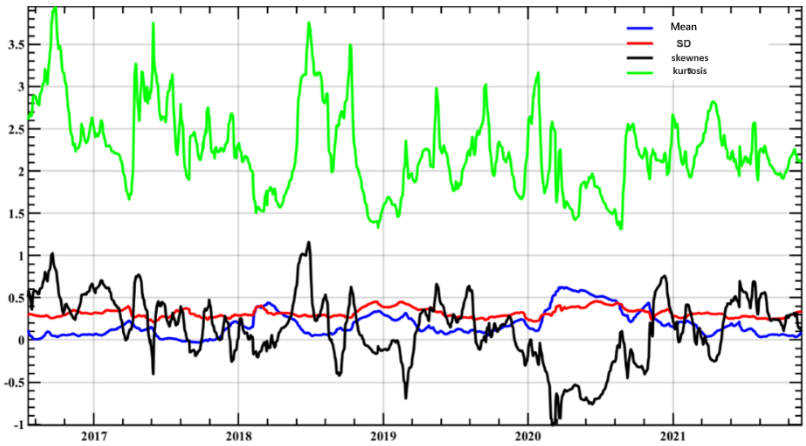

Figure 4. Dynamic structure of the share index volatility network of China and ASEAN-9 (Mar 1, 2016 to Nov 22, 2021)

As shown in Figure 4, dynamic network analysis shows that the overall risk is time-varying. The average cross correlation coefficient of the share index volatility risen rapidly in the major sudden emergencies. The more prominent is the Sino-US trade friction in 2018, the Brexit of the U.K. and the COVID-2019 around 2020. Especially, the impact of COVID-2019was the biggest that reached the highest for the correlation of the share index volatility of 10 countries within the sample range. In the first half of 2020, there was a sudden change in the overall market correlation level, which shows a sharp rise and decline driven by the major sudden emergencies. In addition, the Sino-US trade friction in 2018 and the Brexit also led to turbulence in the stock markets of China and ASEAN, which was directly reflected in the sharp rise in the correlation of share index volatility. The facts above show that the information link structure of the market changed over time under the impact of COVID-2019. Since the network structure was affected by the source of the impact and the first affected share index, major sudden emergencies broke the original structure and triggered the information link in the market.

As for the evolution of eigenvector centrality of China and ASEAN-9 over time, we focused on how the importance of share indexes of major countries changes during the COVID-2019. The more was key node of the market for a country, the more it can become the source of market risk under external shocks. The average time-varying eigenvector centrality (V) of China and ASEAN-9 was shown in Table 2.

As shown in Figure 5 and 6, during the COVID-2019, the time-varying centrality of major countries evolved with the volatility of the share index risen. This indicates that the information link structure between share indexes is variable. During the outbreak of COVID-2019, the

[2]The size of the sliding time window is balanced between excessive noise and excessive smoothing. The window size is set to 100 days. 100 observations are calculated each time and these measurements are estimated recursively. The window moves along the time scale with a window step of 1. A total of 2092 observations were selected from Mar 1, 2016 to Nov 22, 2021. According to the above procedures, we get a total of 1991 windows as the complete example.

centrality of Singapore, Thailand and Japan increased significantly, which means that the market fluctuation information mainly came from these countries which played a leading role in influencing stock market volatility of other countries at that time. In addition, there were differences in the rhythm of the centrality evolution of those countries, such as Laos and Cambodia, had not significantly changed for their share index during the outbreak which defined in this paper. But the centrality of them has increased significantly in the second half of 2020, which is related to the relative lag in the outbreak of the epidemic and the lag in the confirmation of the epidemic data. For example, China and Japan had earlier outbreak of the epidemic so the stock market is not closely linked to the stock market of other countries. The relative instability and the difference rhythm of the change of the stock market centrality in various countries in the network structure, that reflected the instability feature of the co-movement of the share index volatility network.

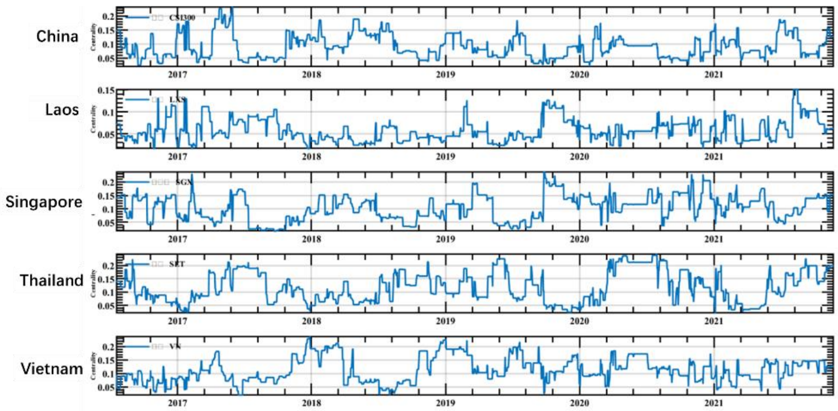

Figure 5. Dynamic structure of eigenvector centrality in major countries (Jan 2006 to Mar 2021)

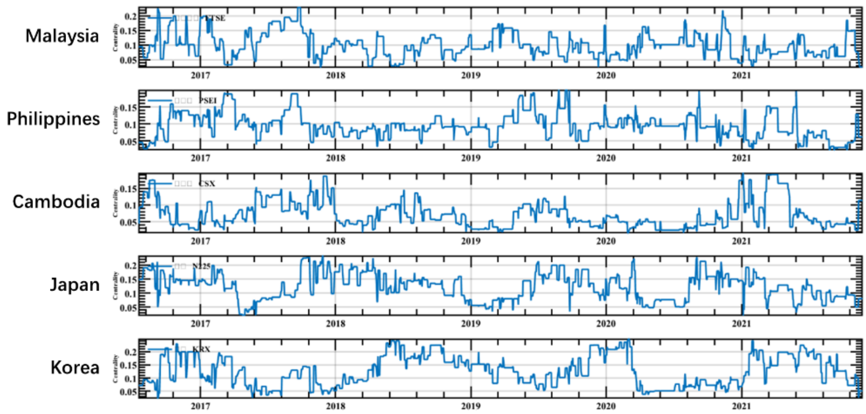

Figure 6. Dynamic structure of eigenvector centrality in major countries (Jan 2006 to Mar 2021)

6. CONCLUSION

This paper constructs a volatility network of stock market indexes in China and ASEAN-9, takes the COVID-2019 as an example to investigate the impact of major sudden emergencies on the volatility network of share indexes, and analyses the mechanism of cross-border transmission of market risk and the characteristic of key nodes. The research conclusions are as follows:

First, the volatility network better depicts the link characteristics and tightness in share index volatility of various countries. The COVID-2019 led to a significant increase in convergence of behaviour patterns of major country stock indexes, and significant differences in node changes and topological features of the volatility network. The share index volatility network of major countries reflects clustering and homogeneity based on geographical distribution. Singapore and Thailand's share indexes are key nodes and sources of market risk in cross-border stock markets. The risk spreads through the key nodes. The most centrality key node is the first to be impacted by the sudden shock, which is the source of market risk and transmits the fluctuation information to the directly related share index. Recognizing the highest centrality fluctuates node of share indexes which can warn the other share indexes associate with it to prevent. The above conclusions are helpful for market regulators to grasp key objects of the financial market to monitor the high centrality nodes and the nodes connected of them. Deploying risk prevention measures that combinates with the law of network centrality, intervening in advance or even designing the "firewall" mechanism transmission path to prevent violent market shocks.

Secondly, the evolution of the share index volatility network reflects the overall risk of the volatility network change over time. The sharp rise and decline driven by "major events" is a typical feature. For example, the COVID-2019, the Sino US trade frictions in 2018 and the Brexit, both of them led a significant increase in the correlation level of share index volatility. Besides, the information link structure of the market changes over time. Major emergencies broke the original structure and triggered information connection in the market. As major external shocks are easy to spread and pass on, the systematic risks of the stock market cannot be ignored. It is suggested that market regulators should always pay attention to the market dynamics, do an early warning and prepare a response plan as soon as possible to prevent risks spreading to other markets. Under the impact of emergencies, targeted risk management and risk management measures should be formulated.

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