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Correlation Analysis of Stock Markets Along the Belt and Road: A Generalised Complex Network Approach

Abstract. *This study investigates the correlations between stock market indices in representative countries or regions along the Belt and Road using a generalised complex network based on the maximum information coefficient. Also, the dynamic correlation characteristics of the focused stock market indices are analysed utilising the minimum spanning tree. Firstly, the results show that, since the introduction of the Belt and Road policy, the Chinese stock market has emerged as the center of the stock index networks, establishing stronger associations with the stock indices of other countries or regions. Secondly, throughout all sub-sample periods, especially before the policy was put forward, the stock index networks of the stock market indices of representative countries or regions along the Belt and Road generally exhibit aggregation patterns of regional geography in the mass. Thirdly, the correlation between these stock market indices is significantly strengthened during extreme shocks. Finally, since 2015, with the progressive deepening of investment and trade between China and other countries or regions along the Belt and Road, the degree of relationship between these stock market indices under discussion has been undergoing changes.*

Keywords: *complex networks, MIC, the Belt and Road.*

JEL Classification: C32, F39, G15.

1. Introduction

The past few decades have witnessed complex and profound changes worldwide and international financial integration, especially due to the recent outbreak of the COVID-19 pandemic and the ongoing Russia-Ukraine conflict. Emphasising the principle of global common development, Chinese President Xi Jinping, in 2013 after visiting Kazakhstan and Indonesia, proposed to jointly build the "New Silk Road Economic Belt" and the "21st Century Maritime Silk Road",

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hereinafter referred to as the Belt and Road or the “B & R”. The “B & R” policy serves as a vital framework for regional economic cooperation, aiming to facilitate the orderly and unrestricted circulation of economic elements and efficiently allocate market resources (Dai and Zhu, 2022). Numerous studies have highlighted China’s growing reputation and remarkable influence on global economics, as well as its increasingly close relationships with other countries (Cui and Song, 2019; Zhou and Li, 2020; Zhang and Mao, 2022). Concurrently, the economic links between the participating countries and regions have strengthened, resulting in accelerated capital flows between China and other countries along the “B & R” and the time-varying interconnections of their stock markets (Aibai et al., 2019; Yousaf et al., 2023). For example, Zhang et al. (2018) applied the MF-X-DMA method to investigate the cross-correlation between the Chinese stock index and three stock indices in the “B & R”, and found that compared to the pre-crisis period of 2004-2008, the cross-correlations between these markets are less persistent, while the multifractal characteristics are strengthened after the policy proposed. Lu et al. (2019) used the multiplicative error model to study the volatility spillover effects of the stock markets between China and the countries along the “B & R”, concluding the existence of bidirectional volatility spillover effects. However, according to the different research objects and research methods, mixed results have been obtained. In this regard, investigating the correlation between stock markets in participating countries within the context of the “B & R” policy is crucial to understanding the interaction mechanism and identifying the evolution trend of these stock markets. It is of great significance for China to further promote the “B & R” construction, strengthen trade cooperation with countries along the “B & R” and jointly maintain the stability of financial markets.

In particular, due to the complexity of the relationship of the stock markets, it has generally become a research hotspot for exploring the characteristics of the relationship between the stock markets from the perspective of complex network theory (You et al., 2015; Lu et al., 2023). Following Barbi and Prataviera (2019) and Huang et al. (2022), the minimum spanning tree method (MST) has been widely recognised as an effective tool to measure the correlation structure and evolution of stock market networks. Traditionally, when constructing the network edges, the Pearson correlation coefficient is the commonly used method by scholars. However, the coefficient is not robust and may be misleading if there are outliers. In addition, the coefficient is also misleading for series with nonstationary or non-Gaussian distribution. The stock market network itself is a complex nonlinear, nonnormal, and time-varying system (Wang et al., 2023; Zhou et al., 2023). Thus, the resulting MST based on the Pearson correlation coefficient is usually not robust. To overcome this shortcoming, Barbi and Prataviera (2019) constructed the novel MSTs of stock markets using the mutual information and found that the mutual information network matrix presents a higher degree of robustness and evidence of a power-law tail in the weighted degree distribution and is more effective in identifying the characteristics of financial markets due to nonlinear dependence. However, because the mutual information cannot be easily normalised and compared, Reshef et al. (2011) proposed the maximum information coefficient (MIC), a powerful statistical method for identifying the important potential relationship between variables in a large data set. Detecting the correlation between variables using MIC does not need to determine the type of correlations in advance. The computer will automatically capture a variety of underlying interesting associations without being limited to a specific function form. Moreover, MIC can identify the correlation characteristics between the same type of variables under different noise levels and can be used to detect complex patterns driven by multiple factors. Therefore, in the era of big data, MIC is widely applied in various fields, owing to its stronger applicability and unique advantages.

In this context, this paper estimates the pairwise nonlinear relationships between stock indices of representative countries or regions along the “B & R” using the MIC and further employs the generalised complex network approach to effectively capture the dynamics of the correlation features of stock market networks based on the MST method. The main contributions of this paper are twofold as follows: Firstly, the complex networks are generalised by replacing the linear Pearson correlation coefficient with the nonlinear MIC to construct the edges of stock index networks. The proposed method can more accurately identify (linear or nonlinear) relationships between stock indices and ensure relative fairness in assessing the correlations. Secondly, after analysing the stock index networks of representative countries or regions along the “B & R” before and after the introduction of “B & R” policy, the general properties of the network structure and the related statistics of each node measured by MST are explored. Our findings show that the policy has strengthened the connection between the stock markets of China and the countries along the “B & R”. Additionally, the COVID-19 pandemic exhibits a significant impact on the stock indices relationship between countries along the “B & R”. It has increased their correlations and the connection degree of each node of the MST. It can also be observed that the risk contagion between countries along the “B & R” accelerates with the tightening of MST. Consequently, identifying crucial intermediate hub nodes becomes crucial for effective monitoring, prevention, and control if necessary. To a certain extent, this approach can help mitigate stock market risks and effectively manage the impact of financial risks on the stock markets.

The remainder of this paper is organised as follows. Section 2 introduces the methods used in this study. The empirical results are provided and discussed in Section 3. Finally, the conclusions are given in Section 4.

2. Methodology

2.1 Maximal information coefficient

Intuitively, MIC is based on the idea that if a relationship exists between two variables, then a grid can be drawn on the scatter plot of the two variables that partitions the random variables dataset to form a grid G with X columns and Y rows. Thus, to calculate the MIC of a two-variable data set, we explore all grids up to a maximal grid resolution. For each pair of integers (x, y), we compute the largest possible mutual information achievable by any x-by-y grid applied to the data. Then, we normalise these mutual information values to ensure a fair comparison between grids of different dimensions and to obtain modified values between 0 and 1. We define the characteristic matrix $M = (m_{x,y})$, where $m_{x,y}$ is the highest normalised mutual information achieved by any x-by-y grid, and the statistic MIC to be the maximum value in M .

Let $G(X, Y)$ be a grid divided in the way of X and Y, then by changing the values of X and Y, according to the mutual information calculation method of discrete random variables, the mutual information values of different distributions of the data set D under different partition conditions are calculated. The maximum mutual information values are obtained under each partition condition, which are normalised respectively to form a mutual information matrix $M_{x,y}$:

$$
\begin{aligned}
M_{x,y} &= \frac{\max I(X, \mathrm{Y})}{\log\min(|\mathrm{X}|, |\mathrm{Y}|)} = \frac{\max\left[H(X)+H(Y)-H(X, Y)\right]}{\log\min(|\mathrm{X}|, |\mathrm{Y}|)} \\
&= \frac{\max\left[-\sum_{x\in\mathrm{X}} p(x)\log p(x) - \sum_{y\in\mathrm{Y}} p(y)\log p(y) + \sum_{x\in\mathrm{X}}\sum_{y\in\mathrm{Y}} p(x, y)\log p(x, y)\right]}{\log\min(|\mathrm{X}|, |\mathrm{Y}|)}
\end{aligned} \tag{1}
$$

where, $H(X)$, $H(Y)$ and $H(X, Y)$ are the entropies of X, Y and (X,Y), respectively. $I(X, Y)$ is the mutual information of (X,Y).

The maximum information coefficient (MIC) of the data set D can be obtained by calculating the maximum value in the matrix $M_{x,y}$. That is,

$$
MIC = \max_{|\mathrm{X}|\cdot|\mathrm{Y}|<\mathrm{B}(n)} \left\{M_{x,y}\right\} \tag{2}
$$

where $|\mathrm{X}|$, $|Y|$ respectively, indicate how many segments the data is divided in the x-axis direction and the y-axis direction. During the computation of MIC, allowing for the countless partition methods, the upper limit of search times, denoted as $B(n)$, is introduced to improve the efficiency of the calculation. The choice of $B(n)$ is crucial as an inaccurate selection can lead to unreliable results. Therefore, after many experiments, Reshef et al. (2011) determined that $B(n)$ is $n^{0.6}$ in general. Under the big data sample, the MIC approaches 1 for the noise-free correlation and 0 when the two variables are independent.

2.2 A generalised complex network

A complex network is usually defined as a network that has one or more properties such as self-organisation, self-similarity, attractor, small world and scale-free (Pastor-Satorras et al., 2003). It consists of several nodes and edges that connect these nodes. The node is the basic element of a complex network, often abstracting individuals in a real network. The edge represents the relationship between these individuals, which can be weighted according to the degree of relationship. Without loss of generality, we denote W_{ij} as the weight of an edge linking nodes i and j, where $i, j = 1, 2, \ldots, n$, n is the number of nodes in a network. For an undirected network:

$$W_{ij} = W_{ji} \tag{3}$$

When building complex networks to study problems in various fields, scholars use different nodes and edges depending on the specific context. Inspired by Reshef et al. (2011), this study employs the MIC to measure the correlation between the daily closing prices of the stock indices along the “B & R”. Then, the MICs are assigned as weights of the edges. Furthermore, we build a generalised complex network. Specifically,

$$MIC_{ij} = MIC_{ji} = W_{ij} \tag{4}$$

The MST is constructed using the Prim algorithm to further observe the statistical properties of each node. The process of Prim algorithm is shown in Figure 1 in Appendix 1. Following Memon and Yao (2019) and Nguyen et al. (2019), the MST selects the edge with the closest interaction among all edges to generate a visual representation of the relationship with edges in the tree. Notably, less significant edges are discarded, resulting in a simplified network where there is only one path between any two nodes. This construction of the complex network using the MST based on the Prim algorithm can offer a more concise and clearer depiction of the stock market relationship between countries along the “B & R”. In addition, it is easier to identify the key markets for stock price fluctuations in the complex network. In order to construct the MST, the first step is to convert the edges into distances. The generalised distance formula is usually used to measure the opposite relationship between the nodes in the stock index network; that is, the stronger the correlation between the two nodes, the shorter the distance in the network. The transformation function of the distance can be expressed as:

$$d_{ij} = e^{-MIC_{ij}} \tag{5}$$

2.3 Topology structure of complex network

2.3.1 Degree and the degree distribution

In a network, the degree of the *i*th node is the number of edges of other nodes connected by the node, e.g., $k_i = \sum_{j=1}^{N} a_{ij} = \sum_{j=1}^{N} a_{ji}$ with N nodes. In the stock index network, if the degree of a stock index node is greater, it means that the stock index is more closely related to other stock indices, and is in a central position in the network. The degree distribution of the nodes in the network is called a degree distribution. In real networks, the degree distribution is usually in the form of a power exponent.

$$p(k) \propto k^{-\gamma} \tag{6}$$

where γ is a constant greater than 0.

2.3.2 Average path length

The distance d_{ij} represents the number of edges on the shortest path between node i and node j. The average path length L is the average distance between node i and node j, and N is the number of nodes in the network, so:

$$L = \frac{1}{\frac{1}{2}N(N+1)} \sum_{i \geq j} d_{ij} \tag{7}$$

It is found that the average path length of many practical complex networks is, much smaller, that is a small world effect, although the number of nodes is huge. L can be used to estimate the connection degree between the average path length of stock index network along the "B & R". The larger the average path length of the network is, the looser the network connection is. On the contrary, if the average path length of the network is smaller, the network connection is closer.

2.3.3 Clustering coefficient

In a complex network, other nodes connected to one node are not independent, and there are some connections between them, which is the clustering feature of the network. If C_m represents the clustering coefficient of node m and K_m represents the actual number of edges between node m connected to N nodes, the relationship between them can be expressed as:

$$C_m = \frac{2K_m}{n(n-1)} \tag{8}$$

The average clustering coefficient C is to measure the average value of the clustering coefficients of each node in the network, with values ranging from 0 to

1. When C is equal to 0, all nodes in the network are isolated. Conversely, a clustering coefficient of 1 indicates that all nodes in the network are directly connected to each other. A lower C suggests a looser connection and less clustering within the network as a whole. If the average clustering coefficient is closer to 1, the closer the connection of the whole network will be.

2.3.4 Betweenness centrality

The betweenness centrality focuses on measuring the ability of a stock to play a mediating role in the stock index network by relating other stocks that are not adjacent to it. The greater the betweenness centrality is, the more important the stock i is, the expression being:

$$BC_i = \frac{2B_i}{(N-1)(N-2)} \tag{9}$$

where B_i is the betweenness of stock index i.

3. Empirical Results

3.1 Research data

Due to various limitations such as the lack of enough data from certain countries and the recent addition of some countries as members of the "B & R" policy, this study selects the stock indices of 20 representative countries according to the geographical distribution to ensure the consistency of financial information, covering main financial markets. The details of these countries and their corresponding stock indices can be found in Table 1 in Appendix 2. Because the "B & R" policy was presented in 2013, the closing prices from August 31, 2012 to May 21, 2021 are selected. In terms of the adjustment of the data window, September 2013 is divided into an important cut-off point, and after 2013. Subsequently, fixed windows of two years are used to examine the network correlation trends of the stock indices along the "B & R" in each period. The data used for the analysis is obtained from the Wind database.

Table 2 in Appendix 2 provides the descriptive statistics of the full sample data for the 20 selected countries. The table reveals that the standard deviation of daily closing prices in each country is large in the whole sample, indicating that the overall data is highly dispersed and fluctuating. These descriptive statistics also display the stylised features associated with stock prices, namely a fat-tailed and left-skewed distribution. These characteristics provide evidence that the daily closing prices in each country do not belong to a normal distribution, which is further supported by the P-values obtained from the Jarque-Bera (JB) statistics test.

3.2 Complex network diagrams based on the MIC

As mentioned above, September 1, 2013 is the cut-off point. Thus, we define August 31, 2012 to August 31, 2013 as the early stage of the "B & R" policy.

Additionally, since the policy was put forward after a period of trial implementation, it was officially set as the starting time on March 28, 2015. Considering the lag effect in the process of policy implementation, the later stage of the policy is defined as September 1, 2013 to September 1, 2015. Then, the MICs between the countries' stock indices along the "B & R" for each period can be calculated according to Equation 2. Furthermore, the distance between two nodes in the networks can be obtained according to Equation 5. Allowing for the fact that the correlations between some important nodes usually represent the main features of interdependence across stock markets, the top five MICs for each node are selected to shrink the high-dimensionality networks and further estimate the complex networks of stock indices of the countries along the "B & R". This selection process can help to get a clearer and more concise network topology structure and to overcome the curse of dimensionality in the complex networks. The resulting complex networks are shown in Figures 2 and 3.

Figures 2 and 3 provide a visual representation of the correlations between the stock indices of the representative countries or regions along the "B & R" in the early and later stage of the policy. The edges connecting the nodes represent the relationships between the stock indices of any two countries, while the different sizes of the nodes measure the strength of their relationships. Larger nodes indicate that a country's stock index is more closely correlated with other countries, placing it in a central position within the network. The colours of nodes are classified by modularisation, allowing us to perceive the communities to which the countries belong. A group of nodes with tight internal connections and sparse external connections in the network are defined as communities, which usually have the same attributes or similar functions. The networks reveal the high correlation between the stock index networks of countries or regions along the "B & R".

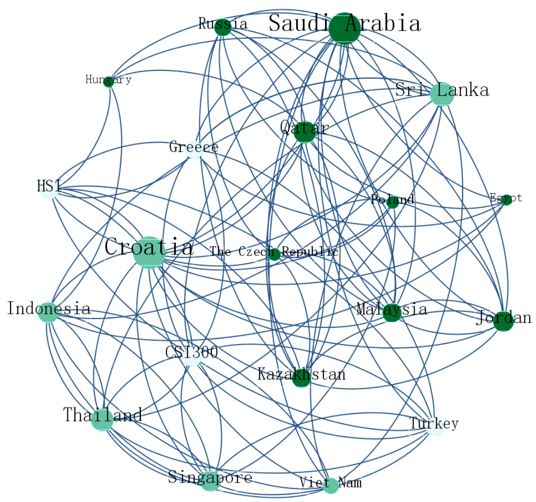

Figure 2. The stock index network before the "B & R" policy
Source: Authors' work.

Specifically, the two figures reveal that the CSI300 index has the strongest relationships, with 15 edges, after the introduction of the "B & R" policy, followed by the stock indices of Egypt, Indonesia, Kazakhstan, and Russia, with 14 edges. While, before the policy, the stock indices of Saudi Arabia and Croatia ranked the first, with 18 edges. The results indicate that the policy effect has made China occupy a central position in the countries along the "B & R" and made the Chinese stock market establish deeper links and stronger relevance with more countries. Before the policy, the degree of the stock indices of Singapore, Indonesia, Thailand, Jordan, Saudi Arabia, Turkey, Sri Lanka, and other countries is greater than 10. After the policy, the degree of the stock indices of China, Singapore, Indonesia, Thailand, Greece, Egypt, Kazakhstan, Russia, and other countries is greater than 10. It means that these countries or regions are closely related to the stock indices of other countries and have a great impact on other indices in the networks. Moreover, the countries at the center of the networks have also transferred from Jordan, Saudi Arabia, Turkey, and Sri Lanka to China, Greece, Egypt, Kazakhstan, and Russia, while Singapore, Indonesia, and Thailand, the three countries still have an important impact on the stock indices of other countries.

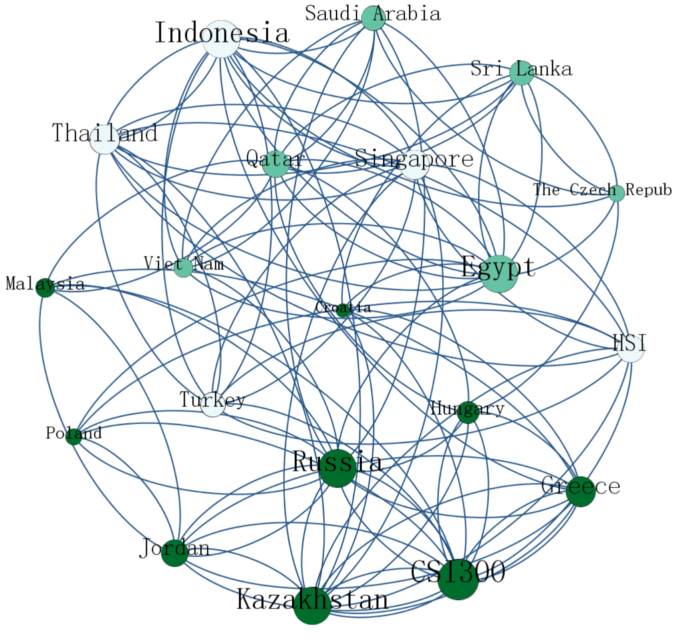

Figure 3. The stock index network after the "B & R" policy
Source: Authors' work.

The overall characteristics of the stock indices are calculated from the networks before and after the policy, as shown in Table 3. Before the "B & R" policy was proposed, the average degree of the stock network of countries along the “B & R” is 9.6, while it increases to 10 after the policy, indicating that the correlation between the countries’ stock markets along the “B & R” has been significantly enhanced. The average path length becomes larger after the policy from 1.684 to 1.695, which manifests that the transmission of stock price fluctuations in the network is not as easy as the previous year, and the price fluctuations of any two stocks are less likely to affect each other as the previous year, and the network becomes looser. In addition, before the policy, the average clustering coefficient of the network is 0.497, indicating that the stock market networks under discussion have the small-world feature. The small-world feature means that the information transmission of the stock market networks is easily affected by the core nodes, and the stock price fluctuations of a few countries in the core position are easy to cause complex changes in the whole network. After the policy, the average clustering coefficient of the network decreases to 0.482, showing that the small-world feature of the network is weakening. It also confirms that the trend of co-movements of stock indices along the “B & R” decreases.

Table 3. Characteristics of the networks before and after the “B & R” policy

Time	Average degree	Average path length	Average clustering coefficient
Before the policy	9.6	1.684	0.497
After the policy	10	1.695	0.482

Source: Authors’ work.

3.3 Minimum spanning tree

To fully grasp the essence of the markets and further analyse the structural changes of the network, multiple MST networks are constructed. In addition to the two phases before and after the policy (referred to as “Phase 1” and “Phase 2”), three additional two-year time windows are considered. That is, “Phase 3” is from September 2, 2015 to September 2, 2017, “Phase 4” is from September 3, 2017 to September 3, 2019, and “Phase 5” is from September 4, 2019 to May 20, 2021 (the last day of data collection). Their MSTs are depicted in Figures 4-8 in Appendix 3.

Figures 4 and 5 show that the CSI300 index has transitioned from a peripheral position to the central connection point in the MSTs, confirming the findings from Figures 2 and 3. Figure 4 illustrates that other countries are dispersed due to their geographical location, and the connection nodes are also connected by neighbouring countries. For example, China, Thailand, Singapore, and Indonesia in Asia and Oceania, Saudi Arabia, Qatar, and Jordan in West Asia, and Hassan Arabia in Central Asia are also adjacent to Jordan in West Asia. Before the policy, China, Singapore, Vietnam, Saudi Arabia, Qatar, and other countries became the central nodes of the “B & R” stock index network. After the policy, Russia, China, Singapore, and Egypt became the central nodes of the countries. This shift may be attributed to the “B & R” policy that opens up opportunities for these countries to become key hubs along the maritime Silk Road, thereby assuming significant roles in the network.

Figure 6 illustrates that Croatia, Poland, Indonesia, and Hungary emerged as the central nodes of the whole network from September 2, 2015 to September 2, 2017. In particular, Hungary exhibited a significant number of connections, highlighting its prominent role. Central and Eastern Europe is one of the most competitive and prosperous regions in global economic growth. Positioned in Central Europe, Hungary benefits from its advantageous geographical location, enabling it to extend its influence to more than 500 million consumers in the European Union and more than 200 million consumers in Eastern Europe. Since China introduced the “B & R” policy in 2013, Hungary has sought synergies and methods to better fit in with the Chinese initiative. In 2015, Hungary became the first European country to sign a cooperation document of jointly building the “B & R” with China. The years that followed witnessed frequent high-level exchanges, strengthening of political relations, and the establishment of a historically fruitful bilateral relationship between Hungary and China.

Figures 5 to 8 state that the evolution of representative countries or regions along the “B & R” is gradually polymorphic. From Phase 3 to Phase 4 (shown in Figures 6 and 7), the overall central country has gradually changed from Hungary, Indonesia, Poland and Croatia to Sri Lanka, Jordan, Singapore, and Saudi Arabia. Subsequently, from Phase 4 to Phase 5 (shown in Figures 6 and 7), the central countries became Croatia, China, Poland, the Czech Republic, Hungary, and Singapore. In addition, from Figures 5 to 6, and from Figures 7 to 8, the overall trend of the MST is more closely related to the previous stages. It can be associated with significant market events such as the stock market crash in 2015 and the outbreak of COVID-19 in early 2020. During such periods of extreme shocks, the central nodes in the MST networks experience an increase in their degree, indicating that the aggregation effect of MST networks is strengthened in a small scope, and the connection in a local range is closer. Similar to the financial crisis in 2008, during the period of market uncertainty or fluctuation, the performance of the stock market is always paid more attention by investors, who will increase trading operations or change investment objectives. Their increased trading activities contribute to an increased dependence between the stock markets, thereby facilitating a faster spread of risks (Goldstein and Pauzner, 2004).

The average path length is the average distance between the nodes in the network, while the network diameter corresponds to the longest path length between any two nodes. The shorter the network diameter, the closer the relationship between the nodes. Table 4 presents that the average shortest path decreased from 5.263 in Phase 1 to 4.242 in Phase 2, and the network diameter decreased from 12 to 9. These findings indicate that the “B & R” policy has deepened the relationship between their stock markets, consistent with the overall network analysis results. The average path length and network diameter of Phase 3, Phase 4, and Phase 5 are also smaller than those of Phase 2, showing that the long-term effects of the “B & R” policy have been positive. In addition, focusing on the stock market crash in 2015, from Phase 2 to Phase 3, the average shortest path decreased from 4.242 to 2.632, and the network diameter also decreased from 9 to

5. These changes indicate that the financial risks caused by the stock market crash led to the overall shrinkage of the MST networks, accelerating the speed of risk transmission. After the stock market crash (Phase 4), the average shortest path increased to 3.121, and the MST network gradually stretched. Similar trends can be observed during the COVID-19 pandemic in 2020. The average shortest path of Phase 5 showed an upward trend compared to Phase 4, but the magnitude of the change was smaller.

Table 4. The index of all the MST networks

Period	Average path length	Network diameter
Phase 1	5.263	12
Phase 2	4.242	9
Phase 3	2.632	5
Phase 4	3.121	6
Phase 5	3.795	8

Source: Authors' work.

Kuzubaş et al. (2014) highlighted the effectiveness of network centrality in identifying systemic risks and promoting financial supervision. Centrality metrics reflect the relative importance of nodes in the network. In complex network theory, the betweenness centrality and other indicators are usually used to measure the importance of nodes (shown in Table 5). There are a few important nodes in the scale-free network, which are called "hub nodes". The designation of a node as a "hub node" is closely related to its centrality in the network. Typically, the top 10 nodes of each indicator are selected as "hub nodes".

Table 5. The betweenness centrality of every state

Country	Phase 1	Rank	Phase2	Rank	Phase3	Rank	Phase 4	Rank	Phase5	Rank
China (CSI300)	65	9	98	2	0	6	0	8	35	6
China (HSI)	18	11	0	10	0	6	0	8	0	9
Singapore	70	8	105	1	0	6	51	4	90	3
Malaysia	18	11	0	10	0	6	0	8	0	9
Indonesia	84	5	83	5	35	4	0	8	0	9
Thailand	78	6	0	10	0	6	0	8	18	8
Viet Nam	90	2	0	10	18	5	0	8	0	9
Turkey	0	13	90	3	0	6	0	8	0	9
Jordan	35	10	0	10	0	6	76	2	48	5
Saudi Arabia	90	2	0	10	0	6	66	3	0	9
Qatar	76	7	0	10	0	6	0	8	18	8
Greece	0	13	88	4	0	6	18	6	0	9
Egypt	0	13	65	6	0	6	18	6	0	9
Sri Lanka	98	1	18	8	0	6	140	1	0	9

Country	Phase 1	Rank	Phase2	Rank	Phase3	Rank	Phase 4	Rank	Phase5	Rank
Kazakhstan	0	13	18	8	0	6	34	5	0	9
Russia	0	13	51	7	0	6	0	8	0	9
Poland	0	13	0	10	51	2	0	8	65	4
The Czech Republic	0	13	0	10	0	6	0	8	113	1
Hungary	0	13	0	10	156	1	0	8	35	6
Croatia	88	4	0	10	50	3	0	8	109	2

Source: Authors' work.

Table 5 shows the betweenness centrality and ranking of countries along the "B & R". A higher betweenness centrality indicates a stronger intermediary role, indicating that the stock index can be more affected and can experience spillover effects on other stock indices in terms of share price movements. The core stock indices of the five stages correspond to Sri Lanka, Singapore, Hungary, Sri Lanka, and the Czech Republic. It can be seen from the ranking in the table that the CSI300 index is the "hub node" in all stages, and the HIS index has also assumed this role four times. It follows that China's intermediary role in the "B & R" policy can make the stock index more impressive and have a certain impact on other stock indexes. Sri Lanka secures the top ranking twice in all stages. Due to its strategic geographical location near the main Eurasian international freight route and its position in the middle of the silk road, Sri Lanka enjoys natural advantages in transshipment, transit, and supply chain activities. As a result, it has emerged as one of the most attractive investment destinations in the Asia Pacific region. With the continuous improvement in economic and trade cooperation between China and Sri Lanka and the rapid growth of Chinese investment in Sri Lanka, Sri Lanka has become a very important node in the overall project in South Asia.

4. Conclusions

The stock indices of 20 countries or regions along the "B & R" are selected as the research object in this paper to study the correlation characteristics and evolution of their stock markets using the generalised complex network approach. On the one hand, the network structure diagrams of stock indices under discussion before and after the policy are depicted based on the generalised complex network. Instead of using the linear Pearson correlation coefficient, the nonlinear MIC is employed as a measure of the correlation between stock indices to construct the edges of the stock index networks. This allows for a more accurate representation of the correlation patterns among the stock indices. On the other hand, the MST method is utilised to analyse the evolutionary features of the stock index networks along the "B & R" in each sample period; the topological indicators are also introduced to measure the dynamic correlations between these stock indices before and after the policy is released.

The empirical results deliver the following four broad impacts.

Firstly, the generalised complex network can effectively measure the correlation features between the stock markets of interest. After the policy has been presented, China has assumed a central position in the stock network of representative countries or regions along "B & R". This centrality is reflected in its stronger relationships with the stock indices of other countries or regions, resulting in a more pronounced impact on their respective stock markets. In the following sample period, the influence of the Chinese stock market on other stock markets has shown periodic fluctuations. These fluctuations follow a trend of rising, falling, and then rising again. Such patterns can be attributed to various factors, including evolving economic conditions, policy shifts, and external events. They underscore the dynamic nature of financial interactions and the changing relationships between economies.

Secondly, during all sub-sample periods, especially before the policy is proposed, the stock index networks of the "B & R" representative countries or regions generally have the aggregation characteristics of regional geography in the mass. In addition, the introduction of the "B & R" policy has contributed to the deepening of the connections between these stock markets, a trend that persists even in subsequent sub-sample periods. Through trade liberalisation and market integration, the "B & R" strategy enables countries along the route to leverage their respective comparative advantages in resources. This, in turn, facilitates their integration into the global economic market and creates opportunities for a more extensive development.

Thirdly, during the periods of extreme shocks, the correlation between the Chinese stock market and the stock market along the "B & R" has been strengthened. For example, the degree of the nodes of the stock index networks of the "B & R" representative countries or regions increased in the stock market crash in 2015 and the COVID-19 in 2020, and the corresponding MST networks of stock market indices shrunk. The findings suggest that the spread and contagion speed of risks will accelerate when the stock markets under consideration plunge. In addition, as the fluctuations of the stock markets decline, the economy tends to remain stable, and the MST networks of the stock market indices gradually extend. To effectively manage systemic risks from a macro-perspective, regulatory authorities should proactively identify risk transmission channels within the stock markets. They should pay particular attention to countries that serve as mediation hubs in the network and take preemptive measures to mitigate and control risks. By reducing the speed and intensity of financial risk transmission, regulators can prevent the further spread of financial risks and ensure the stability and orderly functioning of the stock markets.

Fourthly, since 2015, the continuous deepening development of investment and trade between China and other countries or regions along the "B & R", coupled with the higher level opening of the financial market on the Chinese mainland, the degree of relationship between countries or regions along the "B & R" is constantly changing. However, the overall correlation among these countries or regions tends to remain stable. China, Singapore, Sri Lanka, Hungary, and other countries have always been the central nodes of the network and have played a certain intermediary hub role in the trade exchanges between other countries. During periods of extreme shocks, regulatory authorities should closely focus on the changes in stock market trends in these countries to prepare for the accelerated spread of risks.

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Appendix 1

Let the vertex set of the graph G be V. Firstly, arbitrarily select a point in graph G as the starting point a, add the point to the set U, and then find another point b from the set $U-V$, which minimises the weight W_{ab} from point b to point a. At this time, a point b is also added to the set U, and the current $U=\{a,\ b\}$. By analogy, find another point c from the set $U-V$ to minimise the weight from point c to any point of a or b. Then, add a point c to the set U until all vertices are added to U. At the same time, an MST is constructed. Because there are N vertices, the MST has $N-1$ edges. Each time a point is added to the set U, it means that an edge of the MST is found.

The Prim algorithm is as follows:

(1) $U = \{V1\}$, $V = \{V1,\ V2,\ V3,\ V4,\ V5,\ V6\}$

(2) while ($U <> V$):

$$(u,\ v) = \min\{W_{uv};\ u\ belongs\ to\ U, v\ belongs\ to\ V\};$$

$$U = U + \{(u,v)\};$$

$$V = V - v.$$

(3) End

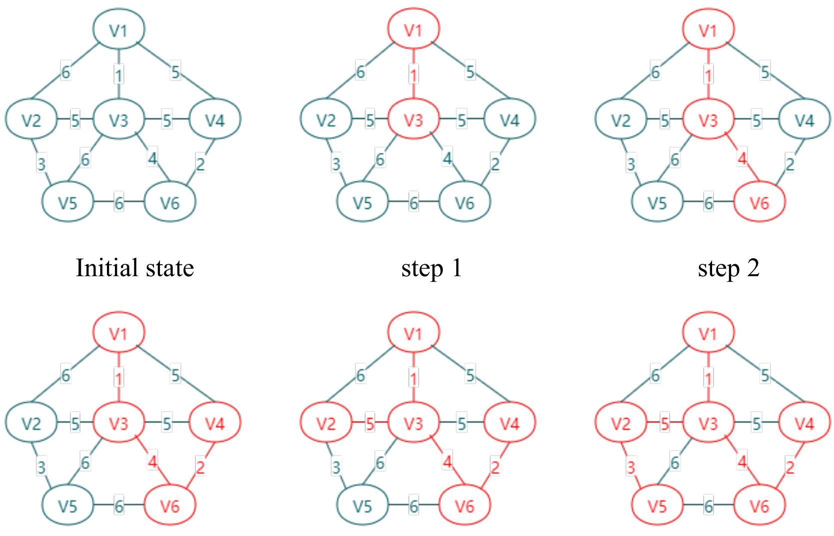
Step 1: initial $U = \{V1\}$, $V = \{V2,\ V3,\ V4,\ V5,\ V6\}$, select the edge with the smallest weight $< V1,\ V3 >$, and add $V3$ to the U set;

Step 2: $U = \{V1,\ V3\}$, $V = \{V2,\ V4,\ V5,\ V6\}$, select the edge with the smallest weight $< V3,\ V6 >$, and add $V6$ to the U set;

Step 3: $U = \{V1,\ V3,\ V6\}$, $V = \{V2,\ V4,\ V5\}$, select the edge with the smallest weight $< V6,\ V4 >$, and add $V3$ to the U set;

Step 4: $U = \{V1,\ V3,\ V6,\ V4\}$, $V = \{V2,\ V5\}$, select the edge with the smallest weight $< V3,\ V2 >$, and add $V2$ to the U set;

Step 5: $U = \{V1,\ V3,\ V6,\ V4,\ V2\}$, $V = \{V5\}$, select the edge with the smallest weight $< V2,\ V5 >$, and add $V5$ to the U set; At this point, we get an MST of G.



Initial state　　step 1　　step 2

step 3　　step 4　　step 5

Figure 1. The process diagram of Prim algorithm

Source: Authors' work.

Appendix 2

Table 1. Complex network region and country selection

Region	Country	Stock index code	Number
Asia Pacific	China	CSI300	1
	China	HSI	2
	Singapore	STI	3
	Malaysia	KLSE	4
	Indonesia	JKSE	5
	Thailand	SETI	6
	Viet Nam	VNINDEX	7
Western Asia	Turkey	XU100	8
	Jordan	MSCI Jordan	9
	Saudi Arabia	MSCI Saudi Arabia	10
	Qatar	MSCI Qatar	11
Africa	Egypt	HER	13
South Asia	Sri Lanka	MSCI Sri Lanka	14
Central Asia	Kazakhstan	MSCI Kazakhstan	15
Central and Eastern Europe	Greece	ASE	12
	Russia	RTS	16
	Poland	WIG	17
	The Czech Republic	PX	18
	Hungary	BUX	19
	Croatia	CRO	20

Source: Authors' work.

Table 2. The descriptive statistics of all countries

Country	Mean	Std	Skewness	Kurtosis	JB stat	P-value
China (CSI300)	3,467.94	838.01	0.2471	-0.4287	37.7871	6.23e-09
China (HSI)	2,4460.1	2,976.1	0.3070	-0.7244	80.6086	0.0000
Singapore	3,180.81	255.51	-0.7466	0.02158	203.2533	0.0000
Malaysia	1,691.31	110.23	-0.5703	0.6662	155.294	0.0000
Indonesia	5,260.33	691.94	0.0733	-1.2089	130.6917	0.0000
Thailand	1,524.11	147.02	-0.1624	-0.3972	23.32872	8.59e-06
Viet Nam	684.86	219.18	0.347	-0.9997	134.15788	0.0000
Turkey	874.78	881.78	43.325	1,972.24	355,462,352	0.0000
Jordan	82.225	15.476	-0.904	1.4765	513.76017	0.0000
Saudi Arabia	530.585	79.085	0.1492	-0.7420	60.23525	8.31e-14
Qatar	812.72	120.19	1.1210	0.83667	539.5547	0.0000
Greece	784.17	189.50	0.8599	0.2746	270.1221	0.0000
Egypt	1,023.24	321.72	0.0964	-1.1460	104.5593	0.0000
Sri Lanka	191.74	41.969	-0.0994	-0.6694	45.90859	0.0000
Kazakhstan	431.26	110.87	-0.2301	-0.7989	80.065586	0.0000
Russia	1,173.32	217.52	-0.1482	-0.6799	50.12180	1.30e-11
Poland	5,2995.9	5,973.3	0.0066	-0.9238	77.2251	0.0
The Czech Republic	998.84	75.671	-0.4040	-0.2543	65.15018	7.10e-15
Hungary	3,1876.2	9,498.1	0.0025	-1.5506	216.61238	0.0000
Croatia	1,804.51	124.48	0.2776	0.99854	117.9302	0.0000

Source: Authors' work.

Appendix 3

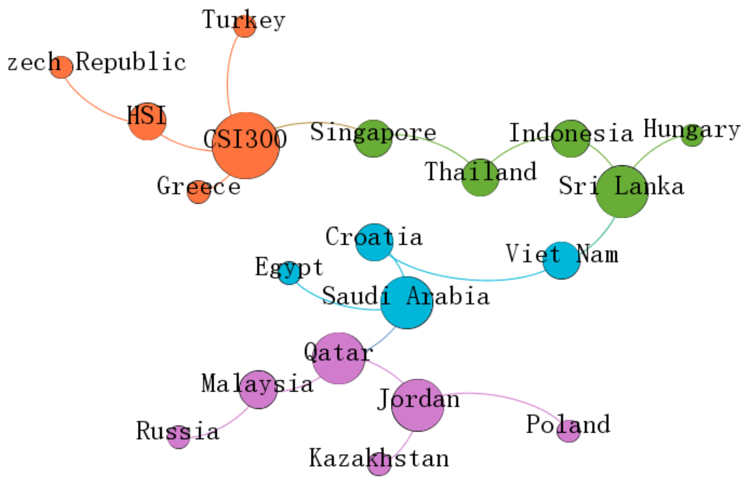


Figure 4. The MST network of the Phase 1
Source: Authors' work.

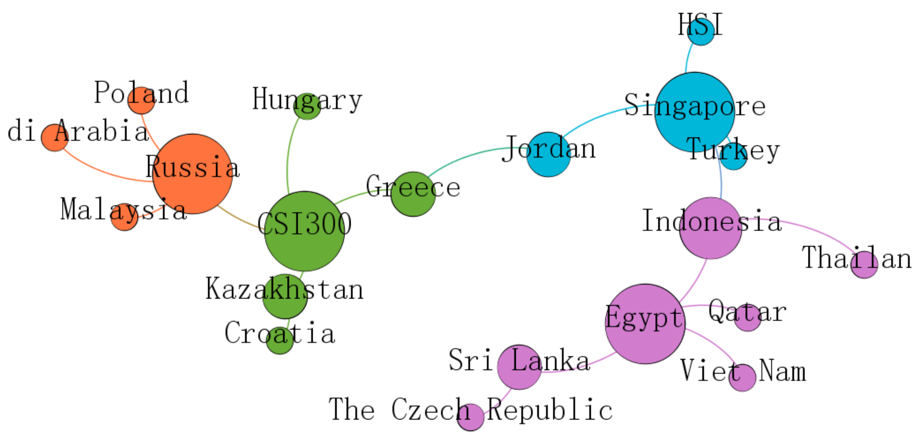


Figure 5. The MST network of the Phase 2
Source: Authors' work.

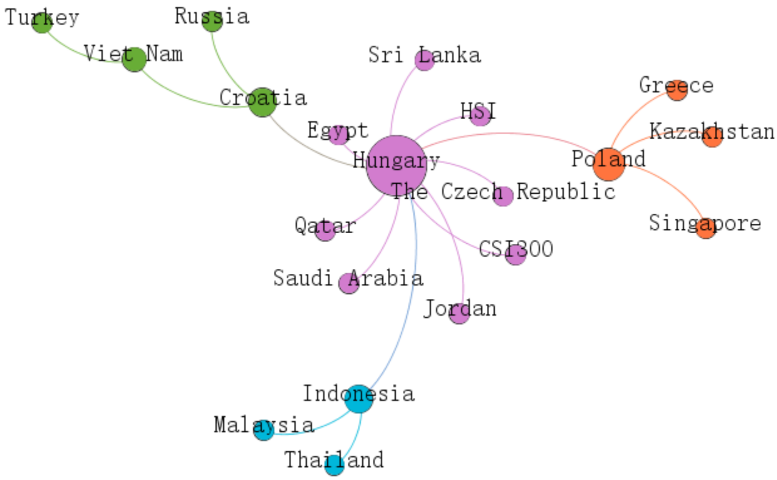


Figure 6. The MST network of the phase 3
Source: Authors' work.

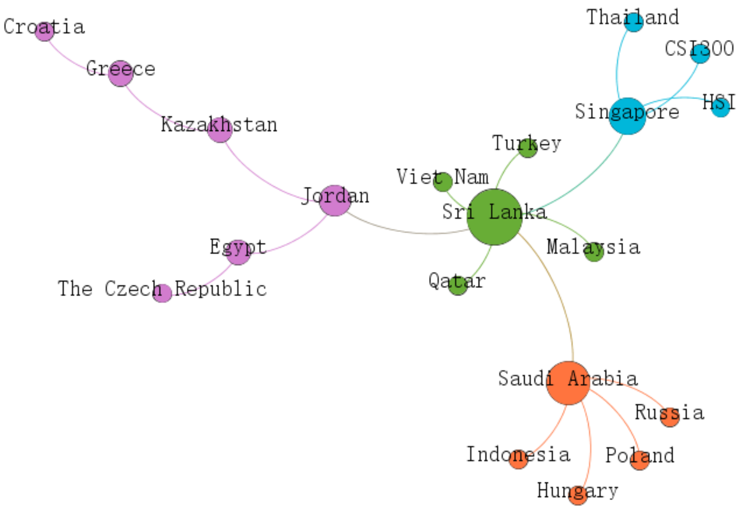


Figure 7. The MST network of the Phase 4
Source: Authors' work.

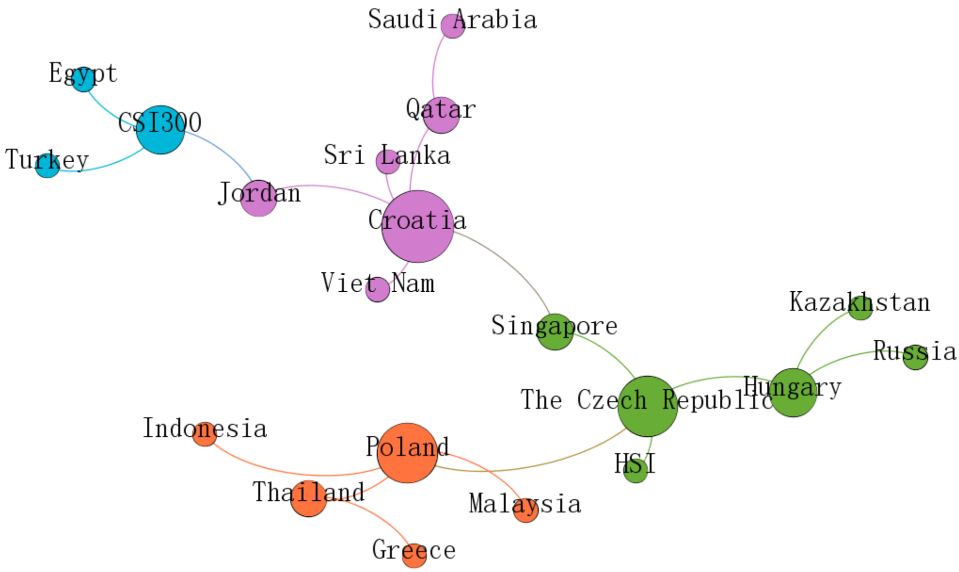


Figure 8. The MST network of the Phase 5
Source: Authors' work.