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Analysis On The Changes Of Network Topology Of Chinese Stock Market After COVID-19 Pandemic

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Abstract—Instability such as sudden public health events has the potential to affect the development of stock markets and possibly change the structure of it. Mature stock markets can effectively withstand external crises. In December 2019, COVID-19 outbreak occurred in Wuhan, Hubei Province, China. As a representative of emerging economies, how will the network structure of Chinese stock market change after the outbreak of COVID-19 or even during the pandemic? This study aims to analyze the impact of COVID-19 on *300* Chinese stock indices from December 1, 2018 to October 17, 2021 using a complex network approach. We used Pearson correlation coefficient to construct correlations between stocks and set up a network for the Chinese stock market in four periods (before the pandemic, during the pandemic, after the pandemic, and the overall period) through the threshold network for analysis. We found that COVID-19 has changed the topology of China's stock market network, making it more connected and more likely to cause systemic risk. This systemic risk has diminished significantly in the wake of the pandemic. The influence nodes and community structure of the stock market networks also changed under different thresholds in different periods. At the same time, we found that after more than thirty years of development, China's stock market has become more mature, and its ability to withstand external risks has also improved.

Keywords—Threshold network; Leiden algorithm; Improved k-shell algorithm; COVID-19; China stock market; Complex network.

I. INTRODUCTION

In December 2019, COVID-19 was reported in Wuhan during the Spring Festival. The special time and place caused the rapid spread of COVID-19 across the country, which had a negative impact on China's social development, especially in the economic field[1]. Evaluation of its impact on the economy and society has become a research hot spot.

The stock market is regarded as a barometer of the economy, and the impact of emergencies and crises is often reflected in the stock market at the first time[1]. The current COVID-19 pandemic is a major global public health emergency that is qualitatively very different from previous crises, such as the global financial crisis, with its particular urgency, uncertainty and repeatability creating significant challenges for markets both at home and abroad. Therefore, it is worth studying how the stock market has been affected by the epidemic. Unlike previous public health emergencies too, such as SARS, this outbreak was more widespread and lasted longer, and there has been a rebound that is still going on in several places[1]. The complexity of interaction on the share market space informs the suitability of the use of complex network analytical tools to study the structure change, liquidity risk and interdependence of the stock market. The stock market is in constant change too. By comparing the network topology of China's stock market before and after the COVID-19 pandemic, it can provide better help for the defense and response of public health emergencies in the future.

Li and Pi[2] studied the impact of the global financial crisis from 2005 to 2010 on major global stock indexes by using minimum spanning tree and threshold method, and found that regional clustering existed in all networks. For large thresholds, networks before and after the crisis had significant community structure, while networks during the crisis had the opposite. Memon and Yao[3] chose the stock market of Pakistan for their study. By using threshold method, they found that there were different core nodes in different periods, which were crucial to the stability of the entire stock market and required the attention of the government and other regulatory departments. In addition, Guo[4] explored the connection of global stock markets during financial crises or risks since 1995, focusing on the situation under COVID-19, and the results showed that when COVID-19 spread globally, markets were more closely linked than any other risk. So[5] studied the impact of the COVID-19 pandemic on the connectivity of Hong Kong's financial market. Both network density and clustering in partially-correlated networks were higher during the COVID-19 outbreak.

After comparison, it is found that few articles study the impact of COVID-19 on the topological structure of China's stock market, especially the changes in the topological structure of China's stock market before and after the pandemic. Therefore, this paper studies the topological evolution of China's stock market before, during and after COVID-19 and analyzes the entire time line too. With a relatively complete timeline, we can understand the full picture of the impact of COVID-19 on China's stock market. When similar public health emergencies occur in the future, the impact and harm can be minimized, which is of great significance for in-depth understanding of the characteristics and rules of the impact of public health emergencies on the stock market.

The innovation of this paper:

（i）COVID-19 on China's economy has a certain influence and causes a series of fluctuation of the industry, so it is of great significance to study the topological structure of Chinese stock market at this time, which can reduce the liquidity risk of the stock market. At present, there are few papers that use complex networks to study current topics, especially to analyze the changes of topological structure of Chinese stock market in different periods after COVID-19 pandemic.

（ii）Leiden algorithm is used to detect the community and improved k-shell algorithm(new algorithm) is used to identify the influence nodes, and the results are more accurate and convincing. For the influential nodes and core companies in the stock market, relevant government regulatory departments can focus on and supervise them to maintain the stability of these companies, which is conducive to the sustained stability and development of China's stock market.

The rest of the article is structured as follows. The second section introduces the literature review about network and the innovation of this paper. Section *3* describes the data and methods. Section *4* discusses the results of topology evolution. Finally, in section *5*, the conclusion is put forward.

II. Literature Review

Along with the information network to the depth of the field, the study of complex network[6] has increasingly shown its great practical value, and many complex network structures have emerged, such as social network, cooperative network and so on[7]. For the stock market, network method has become a useful means to analyze its static and dynamic characteristics[8, 9, 10]. The spread of risk and the complexity of external and internal events on the stock market require a thorough study of stock correlation networks and their structural dynamics.

Complex network is generally represented by graph structure, nodes represent individuals in the network, and edges represent connections between individuals[11]. Introduced by Mantegna[12], correlation-based network is widely used in financial network literature to quantify the impact of various crisis events[13, 14, 15, 16]. In many previous studies, researchers regarded stocks as nodes of the network, and the relationship between stocks was realized by Pearson correlation coefficient as edges[17, 18, 19, 20, 21, 22]. Among the most popular methods of complex network are threshold method[3, 15, 17, 19, 22, 23, 24], minimum spanning tree[2, 3, 13, 17, 19,20,21,25,26,27], using entropy[28, 29, 30, 31]]and granger coefficients[32, 33, 34],and so on. These methods have been applied to stock markets in many parts of the world. Memon and Yao[3] applied threshold method and MST method to *181* stocks in Pakistan's stock market, and applied entropy to the whole sample to measure the volatility of individual stocks. It was found that the overall market structure was not stable due to the external and internal crisis events in Pakistan. Yao[19] used Pearson coefficient to construct correlation between stocks and analyzed the network establishment of China's stock market in three periods (pre-trade, trade war and the whole period) through threshold network. The study found that the US-China trade war has changed the topology of China's stock market network, making it more dense and more likely to go into crisis.

Threshold method is one of the most basic methods used in stock market network analysis. How to determine the threshold is a crucial problem. Xu[35] proposed the concept of the dynamic consistency between the threshold network and the stock market, and estimated the optimal threshold through the maximum consistency function. Li[36] determined the optimal threshold according to the 3σ principle by using the relationship between threshold and the maximum number of connected subgraph nodes. After applying threshold method to stock market, many researchers find that degree distribution follows power law degree model[15, 37]. Gao[38] found by studying the dynamic threshold network and static threshold network of the US stock market that the small world of financial network was robust. When the big financial collapse occurs, the topology of the financial network changes greatly. Qiu[39] also used dynamic threshold network and static threshold network to study the stock markets in US and China, and compared the different dynamic behaviors of dynamic threshold network and static threshold network. At the same time, through the large average clustering coefficient and average degree, it can be found that there was a strong interaction between stocks in the financial market. Huang[37] conducted structural and topological analysis of the threshold network of *1080* stocks listed in Shanghai and Shenzhen stock markets of China from 2003 to 2007, and found that the stock related network was robust to the failure of random nodes in topology,but also vulnerable to deliberate attacks.

By analyzing previous research results, we pay more attention to the use of Pearson correlation coefficient to build a threshold network to study the impact of COVID-19 and its impact on the structural changes of China's stock market.

Community structure in complex networks is usually characterized by tight connections within communities and sparse connections between communities. Community detection[40] is one of the key technologies to study complex network structure. At present, the research results of community detection can be applied to network public opinion monitoring, risk dissemination prediction and many other fields. In order to explore the community structure of complex networks, many people have carried out in-depth research on it in recent years. Traditional community detection algorithms include spectrum method[41], clip-based method[42], edge clustering[43], label propagation[44] and so on. Modularity has been used to compare the quality of partitions obtained by different methods, but has also been used as an objective function of optimization. One of the most popular algorithms for optimizing modularity is Louvain algorithm[45], named after the location of its author, which is one of the fastest and best performing algorithms in community detection[46, 47] and one of the most cited literatures in community testing. But Louvain algorithm can produce any poorly connected community. In the worst case, the community may even be disconnected, especially when iteratively running the algorithm. Therefore, Leiden algorithm[48] is used for community detection of the constructed threshold network of China's stock market. The community guarantees generated by Leiden algorithm are connected. Furthermore, when Leiden algorithm is applied iteratively, it converges to a partition in which all subsets of all communities are locally optimally allocated. In practice, Leiden algorithm is superior to Louvain algorithm in speed and quality of results.

Identifying influential nodes in complex networks is a basic network project. With the rise of complex network research, identification of influential nodes in the network is crucial for global information dissemination and effective dissemination of all kinds of news[49]. This research has been used in many fields, such as disease transmission control[50], information dissemination[51]. Of course, the stock market network is no exception. Identifying influential nodes in the stock market network can minimize risk transmission and prevent network attacks, which has important reference value for the regulatory authorities to carry out targeted supervision. A basic problem is how to identify influential nodes in complex networks. Classic centrality indicators have Degree Centrality[52], Betweenness Centrality[53], Closeness Centrality[54], K-shell index[55] and so on. Among them, K-shell method proposed by Kitsak[55] is the most widely used[56], indicating that node location is one of the most basic factors to evaluate the most influential node. However, K-shell ignores the topological location information of nodes and is a coarse-grained node importance classification method. Wang[57] proposed an improved k-shell algorithm (IKS) based on k-shell and node information entropy. Nodes belonging to lower shells may sometimes be more powerful than those belonging to higher shells[58]. In addition, this method can more accurately rank influential nodes and can be extended to large-scale networks. Therefore, IKS is used to identify influential nodes in the constructed threshold network of Chinese stock market.

III. DATA DESCRIPTION AND METHODS

A. Data Description

After more than three decades of development, China's stock market continues to grow, and the number of A-shares has exceeded *4,500*. The CSI *300* Index (China Securities Index 300) represents the full picture of the A-share market, accounting for about *60* percent of the market's total value. In this study, we selected all stocks in the CSI *300* Index and used data covering *695* stock trading days from December 1, 2018 to October 17, 2021 in order to build the network of Chinese stock market. Among them, some companies in the CSI *300* Index were not listed or suspended during this period, and finally *208* stocks were selected, and *92* stocks were added from the SSE Index (Shanghai Stock Exchange) and the ShenZhen Component Index. These *300* representative stocks are used as network nodes to construct the Chinese stock market network. To explore the impact of COVID-19 on China's stock market and the changes in the network topology before and after the pandemic, we divide the entire sample period into four periods.

The first period is *242* trading days before the COVID-19 pandemic (December 1, 2018 to November 30, 2019); The second period is *242* trading days during the COVID-19 pandemic (December 1, 2019 to November 30, 2020); The third period is *211* trading days after the COVID-19 pandemic (December 1, 2020 to October 17, 2021); The fourth period is *695* trading days from December 1, 2018 to October 17, 2021. By constructing the network of these four periods, the impact of COVID-19 on China's stock market was analyzed. Table I shows *15* industries of *300* stocks (according to the new industry classification standards issued by China Securities Regulatory Commission).

TABLE I. TOTAL NUMBER OF STOCKS CLASSIFIED ACCORDING TO THEIR RESPECTIVE INDUSTRY SECTOR

No.	***Industries***	***Number of companies***
1(A)	farming,forestry,animal husbandry and fishery	2
2(B)	mining industry	13
3(C)	manufacturing industry	158
4(D)	production and supply of electricity,heat,gas and water	8
5(E)	construction industry	10
6(F)	wholesale and retail	12
7(G)	transportation,warehousing and postal services	18
8(I)	information transmission,software and information technology services	18
9(J)	financial industry	38
10(K)	real estate industry	14
11(L)	leasing and business services	2
12(M)	scientific research and technology services	1
13(P)	education	1
14(Q)	health and social work	3
15(R)	culture,sports and entertainment	2

B. Methods

1) Construction of threshold network of Chinese stock market

We used the stock as the network node and Pearson correlation coefficient as the connecting edge to construct the threshold network of China's stock market, in which Leiden algorithm was used for community detection and IKS algorithm was used for influential node identification. We built twelve threshold networks and evaluated the topological properties of them.

A group of *N* stocks is represented by $S=\{i \mid i=0,1,\ldots,n\}$, where a single stock corresponds to the numeric label *i* in *S*. $\{P_i(t)\}$ is defined as the closing price of stock *i* on day *t*, and the logarithmic return rate $r_i(t)$ of the stock can be calculated as:

$$r_i(t)=In(p_i(t))-In(p_i(t-1)) \quad (1)$$

Nodes in the network represent stocks, and edges represent correlations between stocks. Then, Pearson correlation coefficients[12] of any two stocks *i* and *j* in *S* are calculated as follows:

$$C_{ij}=\frac{\langle r_i r_j\rangle-\langle r_i\rangle\langle r_j\rangle}{\sqrt{\left(\langle r_i^2\rangle-\langle r_i\rangle^2\right)\left(\langle r_j^2\rangle-\langle r_j\rangle^2\right)}} \quad (2)$$

r_i and r_j are the logarithmic return rates of stock *i* and stock *j*, and $\langle\square\rangle$ represents the average of these stocks over the period. In this way, it is possible to construct a *300×300* cross-related, single-diagonal, symmetric matrix *C* with ranging from -1 (negative correlation) to 1 (positive correlation) for all nodes[12].

$C_{ij}=1$: represents the complete positive correlation between node *i* and node *j*.

$C_{ij}=0$: indicates there is no correlation between node *i* and node *j*.

$C_{ij}=-1$: represents the complete negative correlation between node *i* and node *j*.

Next, threshold method[23, 24] is used to construct the network. Firstly, a threshold value $\theta(-1\le\theta\le1)$ is selected. When two nodes satisfy $|C_{ij}|\ge\theta$, it is considered that there is a connected edge between nodes *i* and *j*. In this way, we will build a threshold network for the Chinese stock market. That is:

$$C_{ij}=\begin{cases}1, |C_{ij}|\ge\theta\\ 0, |C_{ij}|\le\theta\end{cases} \quad (3)$$

In this way, the networks constructed on the basis of different thresholds are different. They have the same number of nodes and different numbers of edges, and the topological properties of the networks are different.

After using different threshold network tests, it is decided to focus on the networks generated by three thresholds, namely, threshold *θ=0.3, θ=0.6* and *θ=0.8* in this paper (when *θ* is *0.8*, the actual situation is a small probability event; in order to simulate extreme situations and compare with other fixed thresholds, the threshold *0.8* is selected.).

2) Community discovery

Modularity[59] is a standard to measure the quality of community division, commonly defined as:

$$Q=\frac{1}{2m}\sum_{ij}\left(a_{ij}-\frac{k_i k_j}{2m}\right)\delta(C_i,C_j), A=(a_{ij}) \quad (4)$$

Where, *m* is the number of edges of the entire network, and *A* is the adjacency matrix of the actual network (if there are edges between node *i* and node *j*, then $a_{ij}=1$, otherwise $a_{ij}=0$.), k_i is the degree of node *i*, C_i and C_j indicate the community to which node *i* and *j* belong in the network. If the two nodes belong to the same community, the value δ is 1; otherwise, the value δ is 0.

If the network is weighted, modularity is defined as:

$$Q_w=\frac{1}{2W}\sum_{ij}\left(w_{ij}-\frac{s_i s_j}{2W}\right)\delta(C_i,C_j) \quad (5)$$

Where, *W* is the sum of weights of all edges in the network, s_i is the strength of node *i*, that is, the sum of weights of all edges connected to node *i*, and w_{ij} is the weight of connected edges between node *i* and node *j* in the network.

Leiden algorithm[48] can be regarded as an improvement of Louvain algorithm (based on the optimized quality function; the modularization degree is taken as the quality function, and the Constant Potts Model is commonly used too.), integrating several early improvements, including the combination of intelligent local movement algorithm, fast local movement algorithm and random neighbor movement. The algorithm runs iteratively and uses partitions determined in one iteration as the starting point for the next. In this paper, the resolution of modularity is 1.0, the number of iterations is 10, and the number of restarts is 1. Leiden algorithm consists of three stages : (1) local movement of nodes; (2) refinement of partition; (3) Network aggregation based on refined partition, using non-refined partition to create an initial partition for the aggregation network.

3) Node centrality index

Degree[59] is one of the simplest and most important concepts to describe the attributes of a single node, representing the number of connections to other nodes. For directed network, it can be divided into out-degree and in-degree. Intuitively, if the degree value of a node is larger, the node is more important in the network in a certain sense.

Using an improved K-Shell algorithm (IKS) [57] can effectively sort and measure influential nodes in complex networks. IKS method combines k-shell function and node information entropy, considers the influence of node shell position and node's nearest neighbor nodes, optimizes the use of available resources, and enables information to spread effectively.

Node information[57] describes the global structure of the network, and the greater the entropy, the greater the influence of the node. The importance of node (node *i*) is defined as:

$$I_i = \frac{k_i}{\sum_{j=1}^{N} k_j} \tag{6}$$

Where, k_i is the degree of node *i* and *N* is the number of nodes in the network.

Node information entropy is defined as:

$$e_i = -\sum_{j \in \Gamma(i)} I_j \cdot \ln I_j \tag{7}$$

Where, $j \in \Gamma(i)$ is the set of neighbor nodes of node *i*.

Considering the propagation effect of neighbor nodes, the larger the information entropy of nodes is, the easier the influence is to be transmitted to neighbor nodes, therefore, the greater the influence of nodes is. The node importance of each node is different, and the distribution of node information entropy is uneven. Therefore, the more important the node, the greater the node information entropy. The process of IKS algorithm is as follows[57]:

Step 1: Decompose the network into k-shells according to the k-shell decomposition algorithm;

Step 2: Calculate the node information entropy of each node according to Equation (7);

Step 3: Rank nodes in each shell from large to small according to node information entropy;

Step 4: In the shell with the largest k-shell value, select the node with the largest node information entropy. Then choose the node with the maximum node information entropy in the second largest shell. This process continues until the node with the highest entropy of node information is selected in the 1-shell. At this point, the first iteration is complete;

Step 5: Repeat Step 4 to select the remaining nodes until all nodes are selected. The shells of all nodes are ignored. When the information entropy of nodes is equal in a specific shell, nodes are randomly selected.

The data and methods of this paper are summarized as Fig. 1.

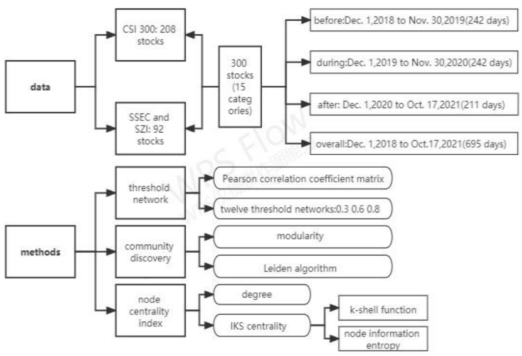


Fig. 1. *Block diagrams of data and methods*

IV. Results and Discussion

A. Results of Pearson Correlation Coefficient

Before analyzing the threshold network, we analyze the probability density functions (PDFs) of Pearson correlation coefficient matrix C (symmetric and main diagonal elements are 1.) with 300×300 elements. Fig. 2 shows the probability density functions for the three periods. Table II shows the descriptive statistics of Pearson correlation coefficient matrix in four periods (the main diagonal elements are removed when the maximum value is counted.).

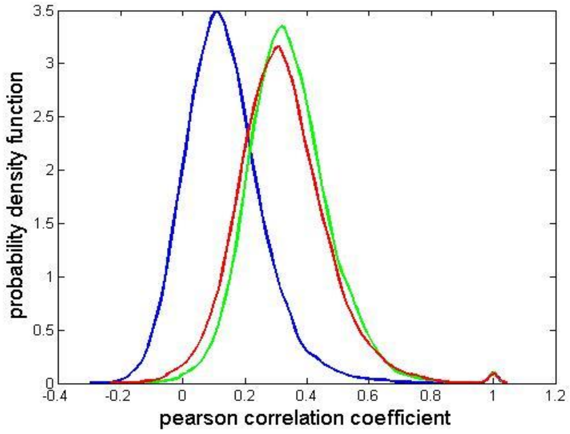


Fig. 2. *PDFs of correlation coefficient of Chinese stock market (Green: before COVID-19; Red: during COVID-19; Blue: after COVID-19).*

TABLE II. Descriptive Statistics of Pearson Correlation Coefficients

Data sample period	***Before COVID-19***	***During COVID-19***	***After COVID-19***	***Overall***
Mean correlation	0.3409	0.3187	0.1351	0.2584
Standard deviation	0.3653	0.3794	0.3689	0.338
Skewness	0.6485	0.5987	1.3636	1.5881
Kurtosis	4.9098	4.7114	8.7309	9.5165
Maximum	0.9317	0.9315	0.8755	0.9095
Minimum	-0.1137	-0.1905	-0.2623	-0.0395

As can be seen from Fig. 2, the probability density function during the COVID-19 pandemic is wider and has a lower peak before the pandemic, and moves to the left as a whole, indicating that although the overall correlation between stocks is reduced during the pandemic, there is still a broad and highly correlated relationship. After the pandemic, the probability density function becomes narrower and the peak value becomes higher, and the overall probability density function shifts to the left significantly, indicating that the correlation between stocks is significantly reduced, and most of them are concentrated between 0 and 0.2. This shows that the COVID-19 epidemic has a great impact on China's stock market, leading to a general increase in the correlation between stocks. Since then, a series of emergency policies adopted by the Chinese government and companies, such as home quarantines, traffic restrictions and store closures, has reduced the correlation between stocks[1]. At the same time, it can be seen from Table II that the average correlation during the COVID-19 pandemic is 0.3187, which increases compared with the whole sample period and then decreases significantly. Analysis of the data shows that the COVID-19 epidemic has had a negative impact on China's stock market, which increases the probability of a crisis in China's stock market, as the market tends to act as a whole in a crisis event.

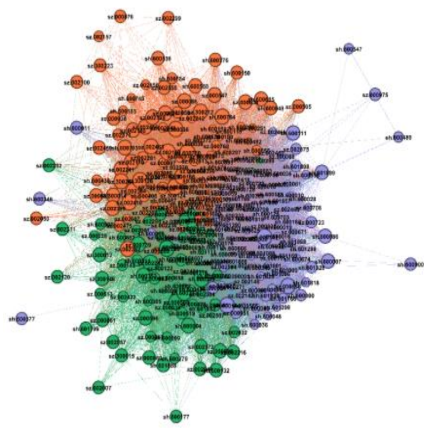
B. Threshold Networks and Topological Structure Change Analysis

Next, the stock correlation networks under different threshold levels are analyzed. We give the critical thresholds 0.3, 0.6 and 0.8. There are three sub-periods and the entire sample period to analyze the changes in topological properties and structure of China's stock market networks before and after the COVID-19 pandemic. In the following graphs, the node color represents the community in which it is located, and the node size represents the size of the central measure based on IKS centrality.

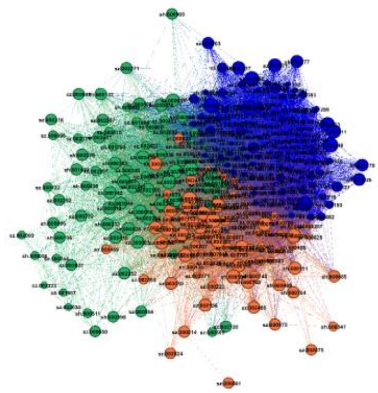
1) Threshold θ=0.3

In Fig. 3, we present three networks for Chinese stock market before, during, and after the COVID-19 pandemic. It can be seen from Fig. 3(a) that, the most important nodes are Avic Shenyang Aircraft (manufacturing), Wanhua Chemical (manufacturing) and GF (Guangfa) Securities (finance), and these three companies are in three different industries. In Fig. 3(b), important nodes have changed and have been replaced by Meijin Energy (manufacturing), Oriental Pearl (information transmission, software and information technology services), and CITIC Securities (finance). In Fig. 3(c), important nodes become China Merchants Bank (finance), Conch Cement (manufacturing) and GF Securities (finance). At the same time, contrast Fig. 3, we can see that compared with before the COVID-19 pandemic, the number of edge connections in the stock market network during the pandemic does not increase, but slightly reduces, this is because time of sub-sample period during the pandemic is taken to November 30, 2020. According to the actual situation, since the outbreak of the COVID-19 pandemic, the Chinese government took a series of measures to control the spread of the epidemic, such as home quarantine, traffic control and store closure. By May 2020, the epidemic had been preliminarily controlled[1], so the network density only decreases from 0.604 before the pandemic in Fig. 3(a) to 0.534 during the pandemic in Fig. 3(b), without a significant decrease. For the short-term impact during the COVID-19 pandemic, please refer to literature[5]. After the pandemic, the number of network connections and network density decrease significantly, with the density only 0.094, and the correlation between nodes also weakens, indicating that the crisis brought by COVID-19 has decreased significantly.

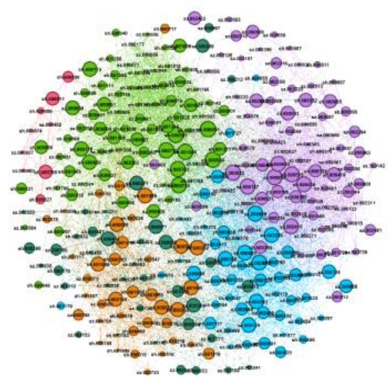
There are three communities in Fig. 3(a), Fig. 3(b) and Fig. 3(c) is six communities, indicating that after the COVID-19 pandemic, the connection between nodes in stock market network has weakened, the phenomenon of clustering has decreased, and the risk of contagion and liquidity caused by the epidemic has greatly reduced. This situation is promoted by China's understanding and control of the COVID-19 epidemic as well as the research and development of vaccines.



(a)



(b)



(c)

Fig. 3. *Threshold network of Chinese stock market in three periods based on IKS centrality and θ>0.3. (a) before the COVID-19 pandemic; (b) during the COVID-19 pandemic; (c) after the COVID-19 pandemic.*

Table III and Table IV show the influential nodes in different periods and communities when the threshold is 0.3. Among them, during the pandemic, a large community formed by Oriental Pearl, IFlytek and Hypergraph Software is formed. This is because the epidemic restricts people's travel. For example, students have to go to class online, kill time by electronic devices, and shop online,etc. In addition, Xinhecheng (medical manufacturing) appears in the table as an important node of the third association, and influences many industry companies from this point. During the epidemic, the medical manufacturing industry is positively affected by the large demand for medical supplies and masks. In the wake of the pandemic, the influence of these industries has been significantly reduced. According to its third-quarter financial statement, Xinhecheng's net profit rose from *1.71* billion yuan in 2019 to *2.945* billion yuan in 2020, up *77.22* percent year on year, and to *3.380* billion yuan in 2021, up *14.81* percent year on year. These industries are more connected and influential than usual during the COVID-19 pandemic.

TABLE III. THE TOP TEN INFLUENTIAL NODES IN DIFFERENT PERIODS WHEN $\Theta>0.3$

Influence node	before-COVID-19	during-COVID-19	after-COVID-19
1	Avic Shenyang Aircraft C	Meijin Energy C	China Merchants Bank J
2	Wanhua Chemical C	Oriental Pearl I	Conch Cement C
3	GF Securities J	CITIC Securities J	GF Securities J
4	Huayu Automobile C	IFlytek I	Huatai Securities J
5	Oriental Guoxin I	Sinoma C	CITIC Securities J
6	Diving Medical C	Hypergraph Software I	Guoyuan Securities J
7	Groundmass Information I	Sichuan Investment Energy D	Changjiang Securities J
8	Baiyunshan C	China Happiness K	Flush J
9	Daan Gene C	Huayu Automobile C	Oriental Wealth J
10	Luzhou Laojiao C	Ganfeng Lithium C	Zoomlion C

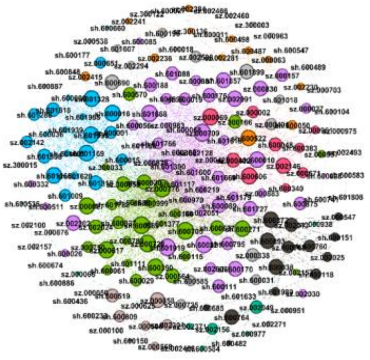
TABLE IV. THE TOP THREE INFLUENTIAL NODES OF THE TOP THREE ASSOCIATIONS IN DIFFERENT PERIODS WHEN $\Theta>0.3$

Community	before-COVID-19	during-COVID-19	after-COVID-19
1	Huayu Automobile C	Meijin Energy C	Flush J
	Saic C	Sichuan Investment Energy D	Zoomlion C
	Jinke Shares K	China Happiness K	Wuliangye C
2	Avic Shenyang Aircraft C	Oriental Pearl I	China Merchants Bank J
	Oriental Guoxin I	IFlytek I	Conch Cement C
	Groundmass Information I	Hypergraph Software I	GF Securities J
3	Wanhua Chemical C	CITIC Securities J	Oriental Wealth J
	GF Securities J	Sinoma C	Large Laser C
	Diving Medical C	Xinhecheng C	IFlytek I

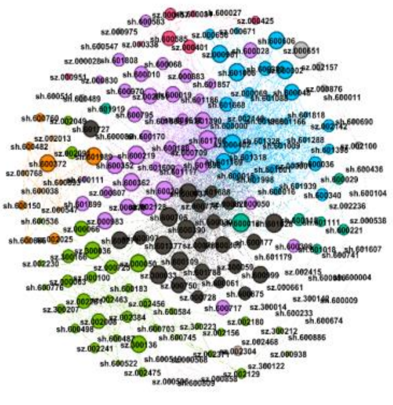
2) Threshold θ=0.6

When the threshold is raised to *0.6* and influence nodes are identified according to IKS centrality, we find that the density of the stock market network is greatly reduced in all three periods. As can be seen from Fig. 4(a), the most important nodes with higher IKS ranking are GF Securities (finance), Hesteel (manufacturing) and Avic Capital (finance). Avic Capital is still the center of the network and an important node. According to Fig. 4(b), it can be seen that influence nodes have changed during the pandemic, namely, Financial Street (real estate), CRRC (manufacturing) and Haitong Securities (finance). After the COVID-19 pandemic, the nodes of influence are Guoyuan Securities (finance), Haitong Securities (finance), and Wuliangye (manufacturing), as shown in Fig. 4(c). In addition, when the threshold is *0.6*, both the number of network edges and network density are higher during the pandemic than before the outbreak, and decrease significantly after the pandemic. This shows that for the above medium threshold, even if the sub-sample period is long, the correlation between nodes is still strengthened during the pandemic, and the systemic risk increases. Liquidity risks are prone to occur between node companies with high correlation. Therefore, supervision should be strengthened on influential nodes at this time.

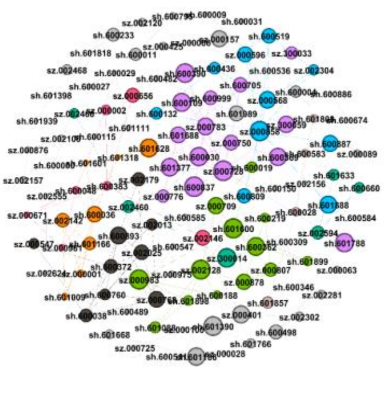
The number of communities increases significantly with the threshold increasing, but at the moment, the number of communities after the COVID-19 pandemic remains higher than before and during the pandemic, from *23* to *28*. This indicates that after the pandemic, the number of small clusters in China's stock market network increases, the clustering phenomenon decreases, and the risk of contagion and liquidity caused by the epidemic has been greatly reduced. At this time, the local outbreak of the epidemic will only affect a small number of node companies, and the risk is not easy to spread, only spread in a small area, easy to control.



(a)



(b)



(c)

Fig. 4. *Threshold network of Chinese stock market in three periods based on IKS centrality and θ>0.6. (a) before the COVID-19 pandemic; (b) during the COVID-19 pandemic; (c) after the COVID-19 pandemic.*

Table V and Table VI show the influential nodes in different periods and communities when the threshold is *0.6*. After comparison, it is found that the influential industries before the COVID-19 pandemic are mainly financial industry and transportation industry, while during the pandemic, the influential industries become more diversified, including manufacturing, real estate, financial industry, etc. After the COVID-19 pandemic, coal mining and washing industry have been added to the list of influential sectors, while transportation industry has not been in the top ten influential nodes, as the pandemic has limited the growth of all transport sectors since the outbreak. To prevent the spread of the disease, China has introduced a series of policies, including the suspension of flights, the reduction of import and export trade, and restrictions on the movement of people between regions, which naturally affects transportation industry. The influential industries and nodes in the community in different periods are also different.

TABLE V. THE TOP TEN INFLUENTIAL NODES IN DIFFERENT PERIODS WHEN *Θ>0.6*

Influence node	***before-COVID-19***	***during-COVID-19***	***after-COVID-19***
1	GF Securities J	Financial Street K	Guoyuan Securities J
2	Hesteel C	CRRC C	Haitong Securities J
3	Avic Capital J	Haitong Securities J	Wuliangye C
4	Southwest Securities J	Xinhu Zhongbao K	Aluminum Corporation of China C
5	Guoyuan Securities J	Avic Capital J	Shanxi Coking Coal B
6	Hainan Airlines G	Minmetals Capital J	Open-pit Coal Industry B
7	Zhongyuan Sea Control G	SIPG Group G	CRCC E
8	Minmetals Capital J	Nanshan Aluminum C	Minmetals Capital J
9	Petrochina Capital J	China Life J	Ev Lithium Energy C
10	Chinese Architecture E	Industrial Securities J	Everbright Securities J

TABLE VI. THE TOP THREE INFLUENTIAL NODES OF THE TOP THREE ASSOCIATIONS IN DIFFERENT PERIODS WHEN *θ>0.6*

Community	***before-COVID-19***	***during-COVID-19***	***after-COVID-19***
1	Hesteel C	CRRC C	Guoyuan Securities J
	Hainan Airlines G	Xinhu Zhongbao K	Haitong Securities J
	Zhongyuan Sea Control G	Nanshan Aluminum C	Minmetals Capital J
2	GF Securities J	Deep Pegasus A C	Aluminum Corporation of China C
	Avic Capital J	Telecommunication C	Shanxi Coking Coal B
	Southwest Securities J	Hypergraph Software I	Open-pit Coal Industry B
3	CMBC J	Financial Street K	Wuliangye C
	Citic Bank J	Vanke K	China Zhongmian L
	Bank of Communications J	Daqin Railway G	Luzhou Laojiao C

3) Threshold θ=0.8

Next, we continue to increase the threshold to *0.8*, resulting in visible and less dense networks, as shown in Fig. 5. At this point, we find that the number of nodes and edges is greatly reduced again, indicating that it is a low-probability event for a large threshold value, and the correlation between nodes in the network is relatively strong. Before the outbreak of COVID-19, the number of network connected edges is *67*, while during the pandemic, the number of network connected edges is slightly higher at *71*, indicating that the probability of systemic liquidity risk in the stock market network increases at this time. After the pandemic, the number of network connected edges is just *15*, so the risk is reduced. In addition, through the comparison of influence nodes, we find an interesting phenomenon that before and during the epidemic, most of the industries of influence nodes is financial industry, such as CITIC Securities and Huaxia Bank, as shown in Table VII. In this case, China's government supervision departments should focus on improving the attention to the financial industry. However, after the pandemic, the influence nodes have changed, and there are important nodes in manufacturing and transportation industry.

As can be seen from Fig. 5(a), Chinese stock market network is healthy and there are low interconnection clusters. By contrast, Fig. 5(b) shows an increase in cluster connectivity in the network at this time. After the pandemic, clustering disappears and the maximum number of nodes in a cluster is *3*. As can be seen from Table VIII, most of the influence nodes in the same cluster belong to the same industry, but the companies of the influence nodes in the industry change in different periods.

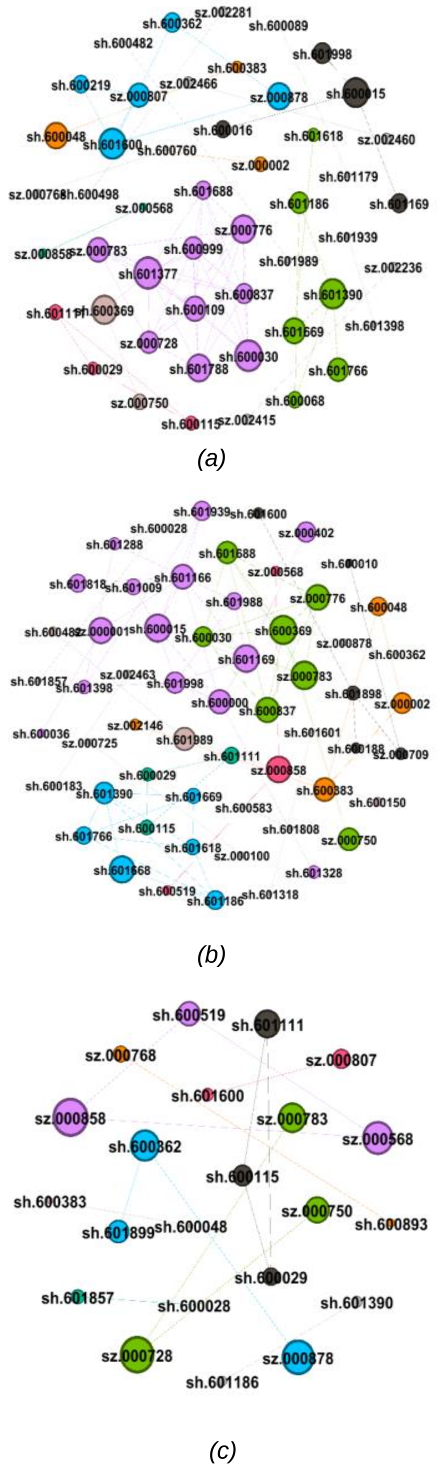


Fig. 5. *Threshold network of Chinese stock market in three periods based on IKS centrality and θ>0.8. (a) before the COVID-19 pandemic; (b) during the COVID-19 pandemic; (c) after the COVID-19 pandemic.*

TABLE VII. THE TOP FIVE INFLUENTIAL NODES IN DIFFERENT PERIODS WHEN *Θ>0.8*

Influence node	***before-COVID-19***	***during-COVID-19***	***after-COVID-19***
1	Industrial Securities J	Southwest Securities J	Air China G
2	CITIC Securities J	Haitong Securities J	Yunnan Copper C
3	Aluminum Corporation of China C	Huaxia Bank J	Guoyuan Securities J
4	China Railway E	Bank of Beijing J	Luzhou Laojiao C
5	Huaxia Bank J	Chinese Architecture E	Changjiang Securities J

TABLE VIII. THE TOP THREE INFLUENTIAL NODES OF THE TOP TWO ASSOCIATIONS IN DIFFERENT PERIODS WHEN *Θ>0.8*

Community	***before-COVID-19***	***during-COVID-19***	***after-COVID-19***
1	Industrial Securities J	Huaxia Bank J	Wuliangye C
	CITIC Securities J	Bank of Beijing J	Luzhou Laojiao C
	GF Securities J	Pingan Bank J	Kweichow Moutai C
2	China Railway E	Southwest Securities J	Guoyuan Securities J
	Power Construction of China E	Changjiang Securities J	Changjiang Securities J
	CRRC C	GF Securities J	Sealand Securities J

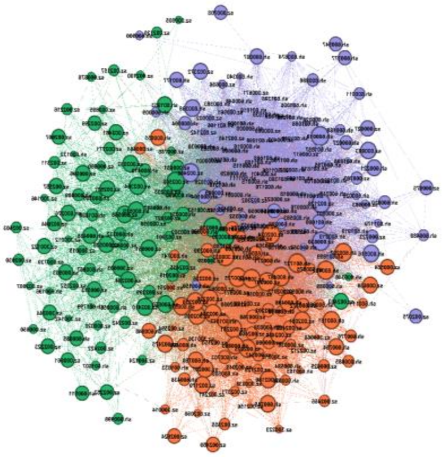
4) Threshold networks of the whole sample period

Fig. 6 shows the threshold network structure of China's stock market at *θ>0.3, θ>0.6* and *θ>0.8* in the whole sample period. Fig. 6(a) shows that the most important influence nodes when *θ>0.3* are CITIC Securities (finance), Open-pit Coal Industry (mining), and Weichai Power (manufacturing). According to the financial statement of Eastmoney.com in the third quarter, the net profit of Weichai Power fell from *9.329* billion yuan in 2019 to *8.702* billion yuan in 2020, down *6.73%* year on year, but by 2021, the net profit increased to *10.19* billion yuan, up *17.12%* year on year. Except for Weichai Power, the net profit of the other two companies continued to grow. CITIC Securities' net profit rose *20.82%* and *39.53%* year-on-year respectively. Open-pit Coal Industry's net profit rose *20.49%* and *55.25%* year-on-year respectively. It can be seen that although China's stock market is not yet a mature stock market, it has made great progress in more than thirty years of development and needs to be gradually improved.

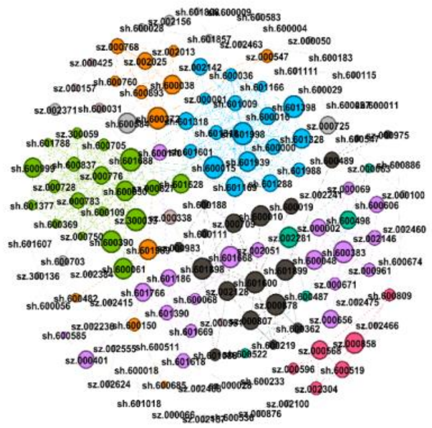
It can be seen from Fig. 6(b) that the important influence nodes of *θ>0.6* are Huatai Securities, Citic Bank, and Huaxia Bank, so we should pay attention to the importance of finance for China's economic development. According to the financial statements of the third quarter, the net profit of Huatai Securities increased from *6.488* billion yuan in 2019 to *8.942* billion yuan in 2020 and then to *11.25* billion yuan in 2021, with a continuous growth. The net profit of the other two companies declined during the pandemic and then recovered. Thus, the impact of COVID-19 on China's stock market is significant, as reflected directly in the company's net assets.

In Fig. 6(c), Huatai Securities, Haitong Securities and Poly Development (real estate) rank high in IKS centrality. We can see the important role of these three companies in China's economic development. The net profit of Huatai Securities increased from *6.488* billion yuan in 2019 to *8.942* billion yuan in 2020, and then to *11.25* billion yuan in 2021, with continuous growth; Haitong Securities' net profit increased *14.59%* and *37.94%* year-on-year respectively. Poly Development also continued to increase its net profit. As can be seen, the three most important nodes in the network still increased their net profits over the entire sample period, especially during the COVID-19 pandemic.

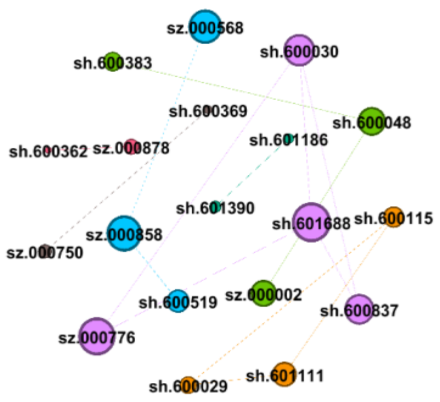
When *θ* is *0.3*, the stock market network has three big communities, and the connection between the nodes within the associations is close, but the connection between the associations is sparse. In this case, the influence nodes are crucial to the stability of the stock market. The fluctuation of a node company, such as CITIC Securities, will drive the fluctuation of node companies in the whole community, causing systemic risks. When *θ* is *0.8*, the nodes and edges in the stock market network are greatly reduced, mainly including the financial industry, manufacturing and real estate industry, which are highly correlated with each other and have a mutually beneficial relationship.



(a)



(b)



(c)

Fig. 6. *Threshold network of Chinese stock market in different thresholds based on IKS centrality and the entire sample period. (a) θ>0.3; (b) θ>0.6; (c) θ>0.8.*

Table IX and Table X show the influential nodes in different thresholds and in different communities with different thresholds in the whole sample period. After comparison, it is found that when θ is *0.3*, the influential industry is mainly manufacturing. When θ is *0.6*, the influence industry is mainly financial industry. The influential industries are mainly financial industry and manufacturing industry when θ is *0.8*. At this time, there are only four nodes at most in the community structure, and all nodes within the community belong to the same industry, indicating that the situation with strong correlation occurs within the industry.

TABLE IX. THE TOP TEN INFLUENCE NODES UNDER DIFFERENT THRESHOLDS THROUGHOUT THE ENTIRE SAMPLE PERIOD

Influence node	***θ> 0.3***	***θ> 0.6***	***θ> 0.8***
1	CITIC Securities J	Huatai Securities J	Huatai Securities J
2	Open-pit Coal Industry B	Citic Bank J	Haitong Securities J
3	Weichai Power C	Huaxia Bank J	Poly Developme nt K
4	Baosteel C	Flush J	Luzhou Laojiao C
5	Flush J	ICBC J	CITIC Securities J
6	Suning Shopping F	Minmetals Capital J	GF Securities J
7	Boss Electrical C	AVIC C	Wuliangye C
8	Shanghai Electric C	Gemdale K	Kweichow Moutai C
9	Boe C	Chinese Architecture E	China Eastern Airlines G
10	Hengtong Photoelectri c C	Aluminum Corporation of China C	Vanke K

TABLE X. THE TOP THREE INFLUENCE NODES OF THE TOP THREE ASSOCIATIONS UNDER DIFFERENT THRESHOLDS THROUGHOUT THE ENTIRE SAMPLE PERIOD

Comm unity	***θ> 0.3***	***θ> 0.6***	***θ> 0.8***
1	Open-pit Coal Industry B	Gemdale K	Huatai Securities J
	Baosteel C	Chinese Architecture E	CITIC Securities J
	Luxi Chemical C	Poly Development K	GF Securities J
2	Flush J	Huatai Securities J	Poly Development K
	Suning Shopping F	Flush J	Vanke K
	Shanghai Electric C	Minmetals Capital J	Gemdale K
3	CITIC Securities J	Citic Bank J	Luzhou Laojiao C
	Weichai Power C	Huaxia Bank J	Wuliangye C
	Boss Electrical C	ICBC J	Kweichow Moutai C

V. CONCLUSION

Overall, we studied the structural changes and network evolution of China's stock market over *695* trading days from December 1, 2018 to October 17, 2021, using a representative sample of *300* stocks. When we use the threshold method to build a network for Chinese stock market and compare the four periods, we found that COVID-19 has a dramatic impact on the stock market network. This made Chinese stocks more correlated with each other during the pandemic, so that when one stock was affected, it spread to a large number of stocks, leading to a large decline in the stock market, which was not good for the health of the stock market. After the pandemic, mean correlation was significantly reduced. This may be thanks to the concerted efforts of all departments and people in China and a series of effective measures taken to bring the epidemic under control. We also found that when threshold reached 0.8, the most influential nodes were in the financial sector before and during the pandemic. This means that in order to ensure the safety of the stock market and avoid a financial crisis, the government and regulators should focus on China's financial industry and strengthen supervision of key enterprises among them. In the wake of the COVID-19 pandemic, transportation and manufacturing industries have emerged as nodes of influence. In addition, when comparing three sub-periods, we can see that when threshold was *0.3*, manufacturing, software and information technology services were a larger proportion of the influence nodes before and during the pandemic, and mainly in the financial sector after the pandemic. When threshold was *0.6*, these sectors were still important, along with important sectors such as transport and mining. In analyzing the *300* stock nodes, we also found that manufacturing companies accounted for a large proportion of Chinese stock market. COVID-19 has had a big impact on China's manufacturing sector. Manufacturing enterprises need to improve competitiveness, expand sales channels. Relevant supportive policies from the government are also needed to help these enterprises develop more healthily and stably.

Finally, we also conclude that after more than thirty years of development, Chinese stock market is maturing and the ability of enterprises to withstand external risks is increasing. After analyzing the influence nodes of stock market network throughout the whole sample period, we found that the net profits of three influence node companies increased in 2020 and 2021 when threshold reached *0.8*. We also observed that although some of the net profits of the major nodes of influence in the network declined during the pandemic, they all increased after the pandemic, suggesting that the impact of COVID-19 on the profitability of Chinese companies is short-lived. The paper will help regulators and investors study the current topology of Chinese stock market. It is of great significance to deeply understand the characteristics and rules of the impact of public health emergencies on China's stock market. At the same time, it will also provide a basis for investors and policy makers to make decisions when dealing with emergencies.

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