Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 8 Issue 7, July - 2021

Comparison Of Network Structure Between Local Stock Disaster And COVID-19 In Chinese Stock Market

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Abstract— This study considers the impact of the 2015 stock disaster and the COVID-19 on threshold network of China's local financial market. Prices of each stocks belonging to CSI300 (China Securities Index 300) are considered into three periods: the stock market disaster in 2015, common period and the COVID-19 period. We find that the probability distribution of the cross-correlations of the stocks during the stock market disaster is wider than that of two others. Besides, threshold networks are constructed through fully connected cross-correlation networks, and thresholds of cross-correlation coefficients are assigned to obtain threshold networks, and we find that the degree distribution of these networks have power-law characteristic in a limited range of threshold values. The networks during the stock market disaster also show that they have bigger mean degree and modularity, which means these stock prices have strong correlations.

Keywords—Threshold network; Modularity; Degree distribution; China stock market; Complex network.

I. INTRODUCTION

Complex network is a complex system, which describes various complex systems in nature and societies, such as the Internet[1], biological neural networks[2], the transportation network[3], financial networks[4]and so on. These networks can be naturally divided into communities or modules[5]. In recent years, a lot of researchers have devoted themselves to the research of complex networks and found that many complex network systems show amazing fault tolerance[6]. In particular, many scholars paying their attention on topological structures and the community characteristics of the complex network, such as entropy[7], closeness centrality[8], clustering coefficient[9], and so on. Financial market is a highly complex and constantly evolving system[10], which is the reason why more and more scholars put their attention to the financial market. Scholars around the whole world have already done corresponding researches on financial markets, such as Hu, Sunyang et al.[11] use the complex network method to analyze the clustering effect of China stock price jumps, Q. Nguyen a et al.[12] analyze the impact of the Vietnamese financial crisis during 2011 2012 into the stock market, JG Brida et al.[13] by constructing minimal spanning trees (MST) and hierarchical trees (HT) to analyze the German stock market, M Qiu et al.[14] apply an artificial neural network (ANN) to study the Japanese stock market, Michele Guida a et al.[15] analyze the structure of the Italian Airport Network (IAN) looking at it as a mathematical graph and investigate its topological properties, BM Tabak et al.[16] investigate the topological properties of the Brazilian stock market networks, Nobi, A., et al.[17] analyze the effects of the 2008 global financial crisis on threshold networks of a local Korean financial market around the time of the crisis, and so on.

There are many research methods for complex networks, and the commonly used methods for studying financial networks are as follows: threshold method[18], minimum spanning tree method[19], PMFG method[20] and so on. Among them, the threshold method is an extremely common method. Chun-Xiao et al. [21] proposed a correlation-based network named PMFG-based threshold network (PTN) to study the community structure of the stock market during crisis. Ku, S. et al.[22] proposed an associated threshold network based on the minimum spanning tree and studied the fractal dimension of the threshold network, moreover, they proposed an appropriate fractal dimension measure. Xu, X. J. et al.[23] proposed the optimal threshold method on the basis of the threshold method, and analyzed the S&P 500 data during the optimal threshold value 0.28.

When certain major crises occur, we pay attention to whether the structure and stability of the financial market will change accordingly. Han, R. Q[24] analyzed the changes of China stock market before and after the global financial crisis in 2008 through a random matrix analysis of the high-frequency returns of 1228 stocks. They found that the average correlation and partial correlation of Chinese stocks in 2008 were both stronger than in 2007. Kumar, S. et al.[25] made a comparative analysis of the financial markets before and after the 2008 financial crisis of the United States, Europe and the Asia-Pacific region. Lisi Xia et al.[26] compared the impact of two different crises, namely the 2008 financial crisis and the 2015 local stock market disaster, on China stock market through the threshold method. Heiberger, R. H.[27] proved the effectiveness of the May-Wigner theorem as an indicator of the stability of the US stock market by comparing the US financial market with a complex ecosystem. They found that during the financial turmoil period, the stock network has changed its composition. However, the difference from the ecosystem is that the non-coordinated structure is transformed into a more concentrated topology structure.

Our study mainly focus on the impact of different crises on China stock market. Due to CSI300 is a really representative stock data of China, we select 228 stocks which belong to CSI300 from January 23, 2014 to March 31, 2021. We divide them into three periods for our research as: the stock market disaster period, the common period and the COVID-19 period. A complex network is established based on the closing price of stocks and the cross-correlation relationship between them, and a threshold network is established by setting different thresholds. When the value of cross-correlation coefficient between stocks is greater than or equal to a given threshold, then a connected edge is formed. Through the threshold method, the topological characteristics, degree distribution and community characteristics of the network in different periods are analyzed. In some previous papers, they used the absolute value of some independent cross-correlation coefficients as the threshold[28, 29].In this study, we consider the average and standard deviation of the cross-correlation coefficient as the threshold.

The rest of the paper is organized as follows: The second part will introduce the data description and the statistical properties of stock indices; The third part introduces the construction of threshold network; we will introduce the threshold network and it’s topology characteristics in the forth part. We conclude the paper and make some suggestions in the last part.

II. DATA DESCRIPTION AND THE STATISTICAL PROPERTIES OF STOCK INDICES

A. Data description

Due to the CSI300 stock data is the most representative index in China's stock market, we selected the data from January 23, 2014 to March 31, 2021 which belongs to CSI300. During this period, the stock market disaster of 2015 happened and the same year from June to August China's stock market fell after two rounds of precipice type, which is widely concerned and worried by the society. The outbreak of COVID-19 has also had a certain impact on China stock market. In order to analyze the COVID-19, as well as compare it to the stock disaster of 2015. we selected 228 stocks which belonging to CSI300(Due to the suspension of the stock market or other influences, we get less than 300 stocks.). The time series are chosen from January 23, 2014 to March 31, 2021, which including 1750 trading days. We divide the sample data into three periods: period 1(the stock disaster of 2015 period): from January 23, 2014 to April 26, 2016, which consists of 550 trading days; Period 2(Common period): from April 27, 2016 to October 23, 2019, which consists of 850 trading days; Period 3(COVID-19 period): from October 24, 2019 to March 31, 2021, which consists of 350 trading days. The 228 stocks which belongs to CSI300 are classified into 11 industries according to the industry classification standards of China Securities Regulatory Commission, as shown in Table I.

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

No.	***Sectors***	***Number of companies***
1	manufacturing industry	87
2	financial industry	38
3	Information transmission, software and information technology services	27
4	Transportation, warehousing and postal services	23
5	mining industry	17
6	real estate	12
7	construction industry	8
8	Production and supply of electricity, heat, gas and water	5
9	wholesales and retail trade	4
10	Agriculture, forestry, animal husbandry and fishery	4
11	Culture, sports and entertainment	3

B. The statistical properties of stock indices

We determine the three periods by volatility, the average volatility of each time window are calculated as follows:

$$v(t) = \frac{\sum_{i=1}^{N} |R_i(t)|}{N} \tag{1}$$

Where $R_i = \frac{P_i(t+1) - P_i(t)}{P_i(t)}$ represents the return of stock i on day t, and N represents the number of all stocks. $P_i(t)$ represents the closing price of stock i at the time t. In other words, v(t) represents the volatility index of the whole stock market. The stock market disaster of China's stock market happened in June 2015, during this period, stock market volatility increased significantly and continued to fluctuate for a period of time. While the stock market disaster happened, the Chinese government took corresponding measures to maintain the relative stability of the China stock market. The global pandemic (COVID-19) has been initially detected in a major city of Wuhan China during the month of December 2019. Then explode in the world caused, the COVID-19 has caused China and even the global stock market a bad influence. In this paper, we mainly focus on these two periods of China's stock market and it's topological characteristics. The average volatility of whole time period is shown in Fig.1.

As can be seen from Fig.1, the average volatility is relatively high in the stock market disaster of 2015, as well as the COVID-19 period. Specifically, the average volatility of three period are 0.02264, 0.01519 and 0.01861. Obviously, it can be found that the volatility of stock market disaster is much larger than that in the period of COVID-19. This indicates that the COVID-19 has a certain impact on China stock market, but not as large as that in the period of stock market disaster.

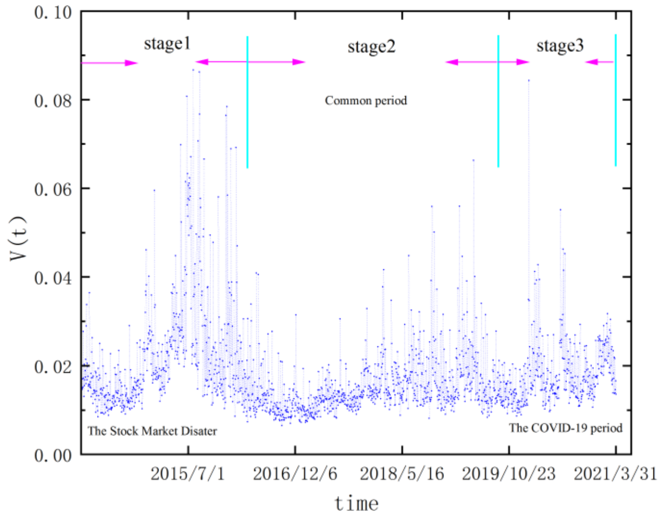


Fig. 1. *The Average volatility of stocks from January 23, 2014 to March 31, 2021. In the panel, we divide the whole period into three periods: the stock market disaster, the common period and the COVID-19 period.*

III. THE CONSTRUCTION OF THRESHOLD NETWORK

A group of n stocks is represented by $S=\{i \mid i=0,1,...,n\}$, where a single stock corresponds to a numerical tag i in S. We define the return of stock i at time t as $r_i(t)$, where $P_i(t)$ represents the closing price of stock i at time t. For each time window, the normalized return can be calculated as:

$$r_i(t) = \ln P_i(t) - \ln P_i(t-1) \quad (2)$$

Thereafter, the Pearson correlation coefficient of stock i and stock j in S can be calculated as follows:

$$C_{ij} = \frac{<r_i r_j> - <r_i><r_j>}{\sqrt{(<r_i^2> - <r_i>^2)(<r_j^2> - <r_j>^2}} \quad (3)$$

Where <·> represents the statistical mean, r_i is the logarithmic return of stock i. With this method, a (228×228) cross-correlation symmetric matrices for all nodes will be constructed. The range of C_{ij} is $[-1,1]$,where $C_{ij}=1$ represents a completely positive correlation between stock i and stock j; $C_{ij}=-1$ means a completely negative correlation between stock i and stock j; $C_{ij}=0$ indicates that stock i and stock j are completely unrelated. Then the probability distribution of the correlation coefficients is shown in Fig.2. It is obvious to find that the stock market disaster has a broader probability distribution and lower peaks than the common period and the COVID-19 period.

We use Gaussian distribution to better understand the probability distribution. Interestingly, we find that the fit lines of Gaussian distribution appear to have a high accuracy with the probability distribution. The Gaussian distribution can be calculated as:

$$f(x) = ae^{-\frac{(x-b)^2}{c^2}} \quad (4)$$

Where a, b and c are parameters. Specifically, The Gaussian distribution equations of the three periods is shown as below:

$$f_1(x) = 0.3146 \cdot e^{-(\frac{x-0.3301}{0.0482})^2}$$

$$f_2(x) = 0.1966 \cdot e^{-(\frac{x-0.2343}{0.0192})^2}$$

$$f_3(x) = 0.1643 \cdot e^{-(\frac{x-0.2684}{0.0264})^2} \quad (5)$$

In addition, we also summarize the statistical characteristics of three periods as shown in table II. Kurtosis is used to describe the value distribution of steep degree, while Skewness is used to describe the symmetry of the distribution. If the value of Kurtosis is positive, it indicates that the distribution is steeper than Gaussian distribution. However, a positive value of Skewness means a right-skewed distribution. We found that the stock market disaster period is a left-skewed distribution, while the common period and the COVID-19 period are both right-skewed distributions. The value of Kurtosis of three periods both indicate that they are steeper than Gaussian distribution. The mean correlation coefficients of the stock market disaster period and the COVID-19 period are higher than the common period, indicating that when crisis happen, the stocks in financial system will have higher correlations.

TABLE II. THE STATISTICAL CHARACTERISTICS OF THREE PERIODS

Parameter	***mean cross correlation***	***standard deviation***	***Skewness***	***Kurtosis***	***Mean volatility***
stage1	0.3361	0.1448	-0.1183	0.3100	0.02264
stage2	0.2431	0.1108	2.4557	0.9150	0.01519
stage3	0.2827	0.1297	1.0331	0.6965	0.01861

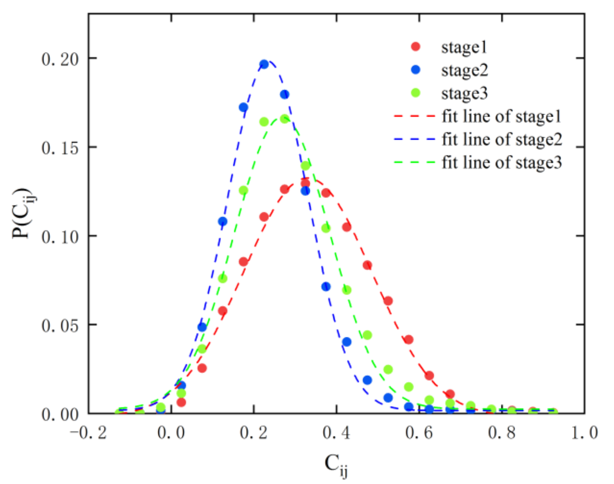


Fig. 2. *The probability distribution function of cross-correlation of 228 stocks.The red, blue and green coded circles mean the distribution of stage 1 (the stock market disaster), stage 2 (common period) and stage 3(COVID-19 period), respectively. Besides, the three dotted lines are the fitting results by means of Gaussian distribution. Specifically, the red, blue and green lines correspond to stage 1, stage 2 and stage 3, respectively.*

IV. THRESHOLD NETWORK AND TOPOLOGY CHARACTERISTIC ANALYSIS

We construct the stock correlation network $G = (V, E)$ by edges and vertices , where the vertices (V) represent the different stock companies, and the edges (E) are what we need to establish by the threshold method. The θ of the cross-correlation coefficient where $\theta \in [-1,1]$ is specified for a certain threshold. If the cross-correlation coefficient $C_{ij} \geq \theta$, then there is an undirected edge between node i and node j is added, otherwise there is no edge. Therefore, different values of θ define networks with the same group of vertices but different groups of edges.

In previous studies, an absolute value of cross-correlation coefficient was selected as the threshold value for researches[30]. However, the distribution of cross-correlation coefficients are wide as shown in Fig2, it's better for us to choose the threshold value according to the distribution of cross-correlation coefficients. Therefore, we set the threshold as $\overline{C_{ij}} + \sigma$, $\overline{C_{ij}} + 2\sigma$ and $\overline{C_{ij}} + 3\sigma$, where $\overline{C_{ij}}$ and σ represent the average cross-correlation coefficient and standard deviation of each period respectively.

A. Modularity

Since the financial market is a complex system which contains many different company sectors, it is of great essential to study the complex system (community characteristic) of the built networks. Modularization is the number of edges in a group minus the expected number in an equivalent network with randomly placed edges. Suppose we divide the network into two groups. If s_i belongs to group 1, then let $s_i = 1$; if s_i belongs to group 2, let $s_i = -1$, then the definition of modularity is shown as follows[5]:

$$Q = \frac{1}{4m}\sum_{ij}(A_{ij} - \frac{k_i k_j}{2m})(s_i s_j + 1) = \frac{1}{4m}\sum_{ij}(A_{ij} - \frac{k_i k_j}{2m})s_i s_j \qquad (6)$$

If there is an edge between node i and node j, then $A_{ij} = 1$; otherwise, $A_{ij} = 0$. In addition, $m = \frac{1}{2}\sum_i k_i$ represents the total number of all connected edges. k_i,k_j represent the degree of node i and node j respectively. For the expansion of more than two communities, we only need to repeat the division into two parts, and so on.

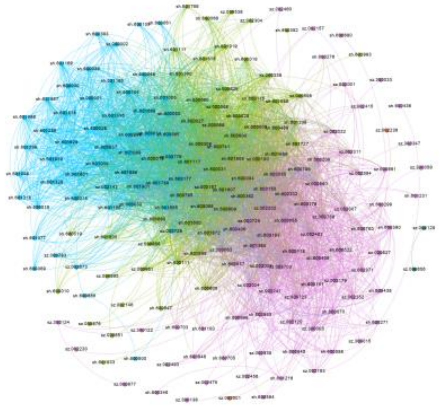
In the past researches, many researchers' results have shown that the maximization of modularization is an appropriate method for community detection. Therefore, in this paper, we also adopt the modularization method to study the Chinese stock market threshold network in three different periods, as shown in Fig. 3 and Fig. 4 and Fig. 5. The companies represented by these different codes are all belong to the CSI 300. The network we draw is undirected and unweighted, because $C_{ij}=C_{ji}$, we draw all the edges between any two nodes and give the value index of modularity index of three periods in Table III.

As shown in Figures 3-5, we find that these networks are quite different from each other in terms of the number or the structure of communities. To put it simply, when $\theta=\overline{C_{ij}}+\sigma$ (the threshold values of the three periods are 0.4809, 0.3539, 0.4125, respectively), we find that communities are clearly divided. Three communities are mainly composed in stock market disaster period and the COVID-19 period, while four communities are mainly composed in common period. During the stock market disaster period, the communities are mainly divided into three communities based on the industry classification of stocks and the region where the companies are located (such as Shanghai, Beijing, Guangzhou, Shenzhen, and so on.). During the common period and the COVID-19 period, communities are mainly divided according to the industry classification standards of stocks.

When $\theta=\overline{C_{ij}}+2\sigma$ (The threshold values of three periods are 0.6257, 0.4647, 0.5422, respectively) , an obvious phenomenon we can observed is that the community numbers of stocks become sparse and the division of communities is not obvious. As for the division of communities, sh.600031(Sany Heavy Industry), sh.601006(Daqin Railway), sh.600809(Shanxi Fenjiu) and sz.000568(Luzhou Laojiao) belong to the same community. According to the industry classification standard, sh.600031, sh.600809 and sz.000568 belong to the manufacturing industry, while sh.601006 belongs to the transportation, storage and post industry, they both fluctuate synchronarily with the economy, so the stock prices also show good consistency. This shows that the modularity division of stocks through the threshold method can fully represent the inherent relationships among companies. In addition, some small companies also form a community with some large companies, but the community structure which we have drawn only shows the community for more than three companies. The stock prices of these smaller companies have moved roughly in line with those of larger companies, which reflecting their liquidity characteristics in line with the overall stock market.

When $\theta=\overline{C_{ij}}+3\sigma$ (Threshold values of three periods are 0.7704, 0.5754, 0.6719, respectively), compared with $\theta=\overline{C_{ij}}+2\sigma$, Community division of networks is not obvious, and network structure is sparse. For example, during the COVID-19 period, six companies constitute a small community, which consist of sz.000858(Wuliangye), sz.000568(Luzhou Laojiao), sz.002304(Yanghe Joint Stock), sz.000596(Gujing Gongjiu), sh.600809(Shanxi Fenjiu) and sh.600519(Guizhou Maotai). These companies both belong to the manufacturing industry and the division of the community is satisfied with the industry standard of the company. While $\theta=\overline{C_{ij}}+2\sigma$, sz.000858 and sz.000568 belong to a large community consists of 17 companies. When $\theta=\overline{C_{ij}}+\sigma$, sz.000858 and sz.000568 belong to a large community composed of 85 companies, indicating that with the increase of threshold value, the structure and number of communities are gradually decreasing.

From the modularization index point of view, the larger the threshold value is, the bigger the modularization index is. Since the edges of the stock network are only established when $C_{ij}\geq\theta$, the bigger the threshold value is, the stronger the connection between the companies are. Besides, for a fixed value of threshold, no matter threshold value $\theta=\overline{C_{ij}}+\sigma$, $\theta=\overline{C_{ij}}+2\sigma$ or $\theta=\overline{C_{ij}}+3\sigma$, the lowest modularity value is at common period and the highest modularity value is during the stock market disaster. The modularity value is middle in the COVID-19 period, illustrating the stock market disaster's influence is greater than the COVID-19 period. We also find that the market displays extremely high correlations in the stock market disaster period. In addition, we also find that the stock market disaster is due to liquidity difficulties in the stock market, because the stock market cannot bear sell too much at once.



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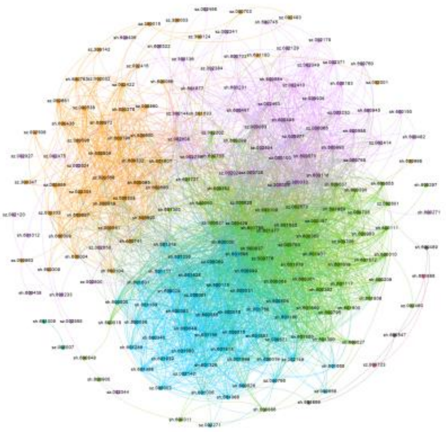

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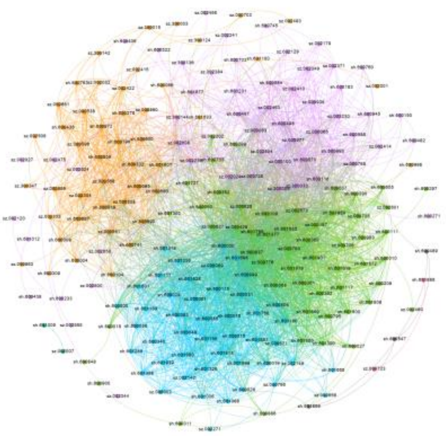
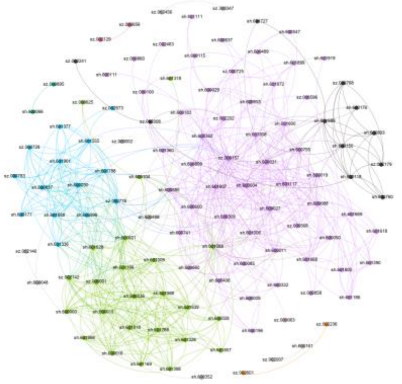


(c)

Fig.3 *The community structure of threshold network of China stock market in three periods. The threshold parameters $\overline{C_{ij}}+\sigma$ are set as follows :(a) the threshold value of the stock market disaster is 0.4809; (b) the threshold value of the common period is 0.3539; (c) the threshold value of the COVID-19 period is 0.4125. Nodes with the same color belong to the same community. The stock network is mainly composed of three communities in the stock market disaster period and the COVID-19 period, while the stock network in the common period is mainly composed of four communities.*



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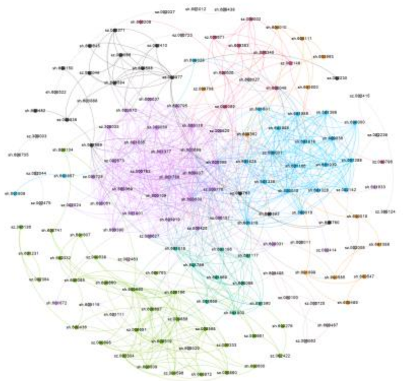

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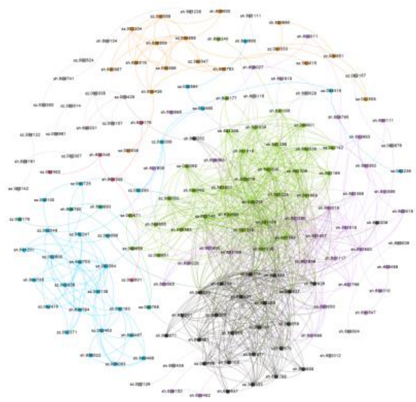

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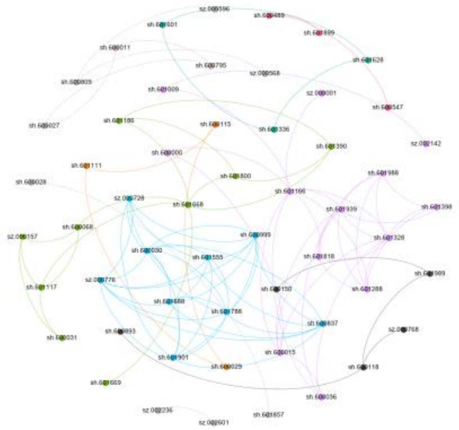
Fig.4 *The community structure of threshold network of China* *stock market in three periods. The threshold parameters* $\overline{C_{ij}}+2\sigma$ *are set as follows :(a) the threshold value of the stock market disaster is 0.6257; (b) the threshold value of common period is 0.4647; (c) the threshold value of the COVID-19 period is 0.5422. Nodes of the same color indicate that they belong to the same community.*



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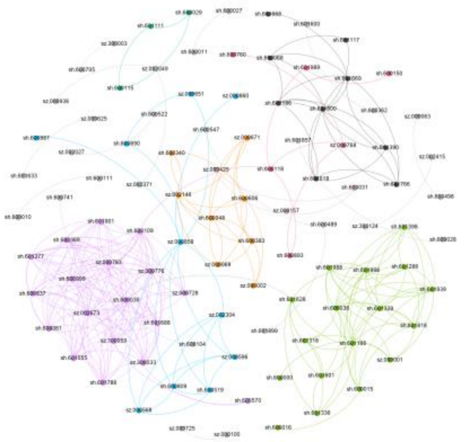

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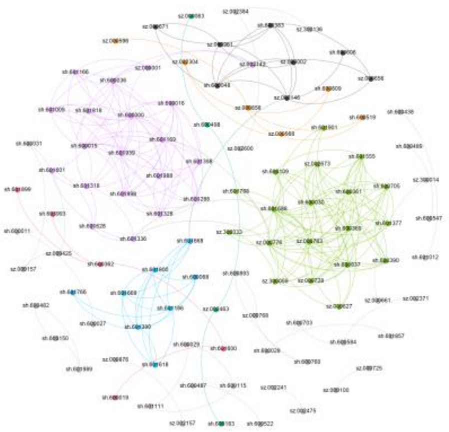

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Fig.5 *Community structure of threshold network of China stock market in three periods. Threshold parameters* $\overline{C_{ij}}+3\sigma$ *are set as follows :(a) the threshold value of the stock market disaster is 0.7704; (b) the threshold value of the common period is 0.5754; (c) the threshold value of the COVID-19 period is 0.6719. Nodes of the same color indicate that they belong to the same community.*

TABLE III. THE VALUES OF MODULARITY INDEX IN THREE PERIODS

threshold value	***the stock market disaster***	***common period***	***COVID-19 period***
$\overline{C_{ij}}+\sigma$	0.4809	0.3539	0.4125
$\overline{C_{ij}}+2\sigma$	0.6257	0.4647	0.5422
$\overline{C_{ij}}+3\sigma$	0.7704	0.5754	0.6719

B. *Mean degree and degree distribution*

In a complex network, degree is a basic property to describe the characteristics of the network. Therefore, we study the mean degree and degree distribution of stock market network in this study. We make the mean degree of the network of different thresholds of three periods as shown in Fig.6. Obviously, we can find that as the threshold increases, the mean degree of the network gradually decreases regardless of the period. In Figure 6, we can also observe that no matter what the threshold value is, the mean degree curves of the common period and the COVID-19 period are always below the average degree curve of the stock market disaster period, which indicates that the correlation between companies in the stock market disaster period is stronger than others, which is also consistent with the results of the analysis of modularization. Through the above analysis, we can conclude that the occurrence of crisis events (such as the stock market disaster) can increase the connectivity between companies. Different crises have different influences on the stock market, for example, the average degree of the stock market in the COVID-19 period and the stock market disaster period are quite different. The average *degree curve of the stock market in the stock market disaster period is higher than that in the COVID-19 period, which indicating that the connection between different nodes during the stock market disaster period is closer.*

Many studies have shown that the the power-law distribution of the network also adapted to the degree. Previously, some scholars have already done corresponding researches in other fields, such as the Internet network, the actor cooperation network, and the biological cell network and so on. In this study, we also pay our attention on the degree distribution of the China stock network. During the stock market disaster period, when the threshold value θ is in [0.65, 0.78], it conforms to the power-law distribution; for the common period, when the threshold θ is in [0.52,0.65], it conforms to the power-law distribution; as for the COVID-19 period, when the threshold θ is [0.56,0.68], it conforms to the power-law distribution. However, for other thresholds θ (too large or too small), the network does not have the scale-free characteristics. Therefore, we study the degree distribution under some fixed values and slopes, as shown in Figure 7.

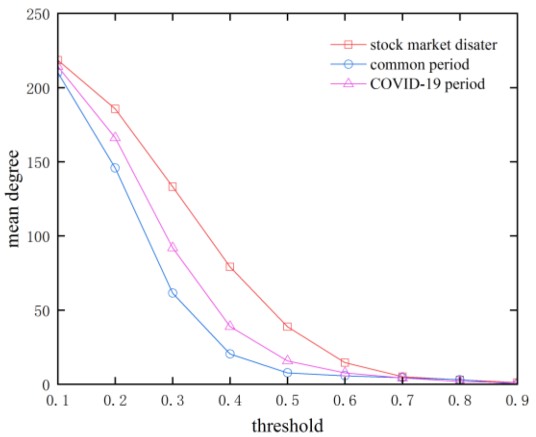
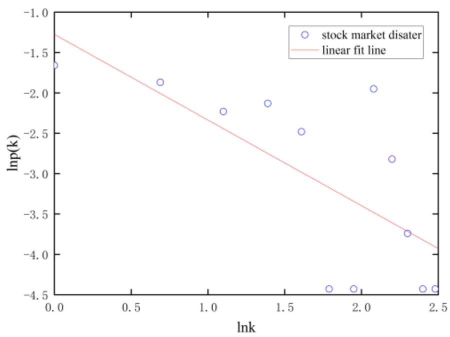


Fig. 6 *The average degree of threshold networks of three periods as a function of the parameter θ. The red line (common period) and the green line (COVID-19 period) are below the blue line (the stock market disaster period). The higher the average degree value is, the stronger the correlation between these companies is.*



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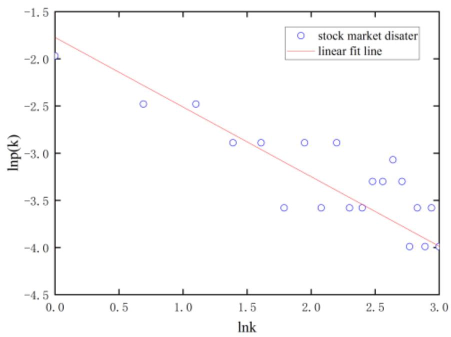

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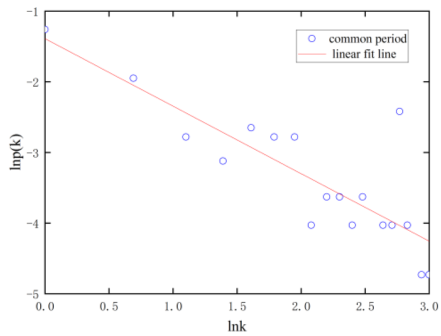

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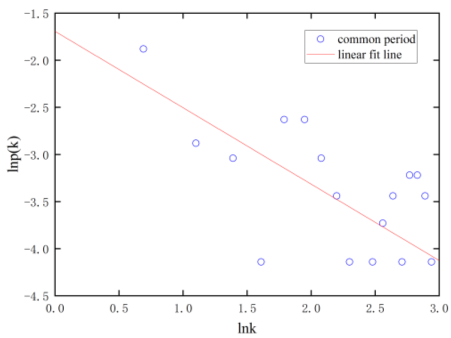

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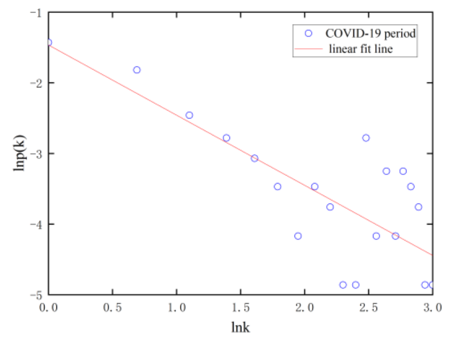

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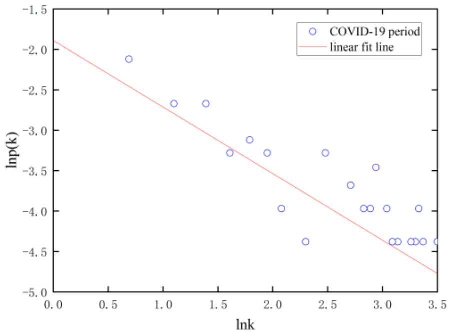

(f)

Fig.7 *Log-log plots of degree distribution and the linear fitting lines of them. The threshold value θ and the slope γ of stock market disaster period (a,b), common period (c,d) and COVID-19 period (e,f) are set as follows :(a) θ=0.7, γ=1.06; (b) θ=0.65, γ=0.74; (c) θ=0.55, γ=0.96; (d) θ=0.52, γ=0.81; (e) θ=0.62, γ=0.99; (f) θ=0.56, γ=0.82.*

V. CONCLUSION

In this study, we analyzed the closing prices of 228 stocks which belong to Shanghai and Shenzhen 300 for three periods, namely the stock market disaster period, the common period and the COVID-19 period. We establish the threshold networks through the cross-correlation between stocks, and establish the threshold networks of different periods with different thresholds. We find that no matter what the period is, the probability distributions of the cross-correlations of stock prices all can be fitted with the Gaussian distribution with high accuracy. We also find that the connectivity of nodes of networks for crisis period is closer, especially during the stock market disaster period and the COVID-19 period. As for the modularity of networks, we find that the modularity value of the common period is the lowest, while the stock market disaster period has the highest modularity value, which indicates that the influence of the stock market disaster is much greater than that of the common period. We also find that the stock market's connectivity is very strong during the stock market disaster period. Moreover, we find that the degree distributions conform to the power-law distribution within a certain threshold range. Our study will be helpful for the regulatory authorities to research effectively monitor the stability of the stock market. However, our study is still very limited, as we have not studied the financial market of other counties during the same period. In general, the study of this paper has some implications for the understanding of the complex financial systems.

ACKNOWLEDGEMENT

All authors contributed equally to the conception and design of the study.This work was supported by the National Natural Science Foundation of China no. 71701082.

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