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IMPACT OF US-CHINA TRADE WAR ON THE NETWORK TOPOLOGY STRUCTURE OF CHINESE STOCK MARKET

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ABSTRACT

Sustainable environment is needed for a progressive stock market. Simultaneously, international events of crisis exert chaos among investors and affect progress of the stock market. It is observed that a mature stock market can resist external crisis effectively. On March 23 2018, a trade war broke out between China and the United States. As a representative of emerging economies, how will the network structure of China's stock market change when China and the United States fueled a trade war? We use Pearson's coefficient to construct the correlation between stocks, and set up a network for the Chinese stock market in three periods (before trade war, during trade war, and the overall period) through the threshold network for analysis. We find that recent trade war between China and US changes the topological structure of China's stock market network, making it denser and more likely heading towards a crisis. At the same time, we find that after 30 years of development, China's stock market has become more mature and its ability to resist external risks has improved. This study will be of a great significance for the government to regulate the stock market and for others to study the stock market of an emerging economy.

Contribution/ Originality: To the best of our knowledge, this is first paper that examines China stock market network structure from the perspective of US-China trade war. Additionally, this study performs comparative approach by dividing the overall 10 years long data period into two subperiods of before, and during trade war.

1. INTRODUCTION

As the world's two largest economies, trade between China and the United States is crucial to the global economy. US President Donald trump has signed a Presidential memorandum to impose tariffs on Chinese imports and restrict Chinese companies from investing in the United States, marking the start of a new round of trade wars between the two countries. The reason for the trade war between China and the United States is that the United States believes that China's long-term trade surplus with the United States is increasing. Figure 1 shows trade data between China and the US from March 2017 to March 2019, that shows an increasing order and dominance of china`s exports over imports to US.

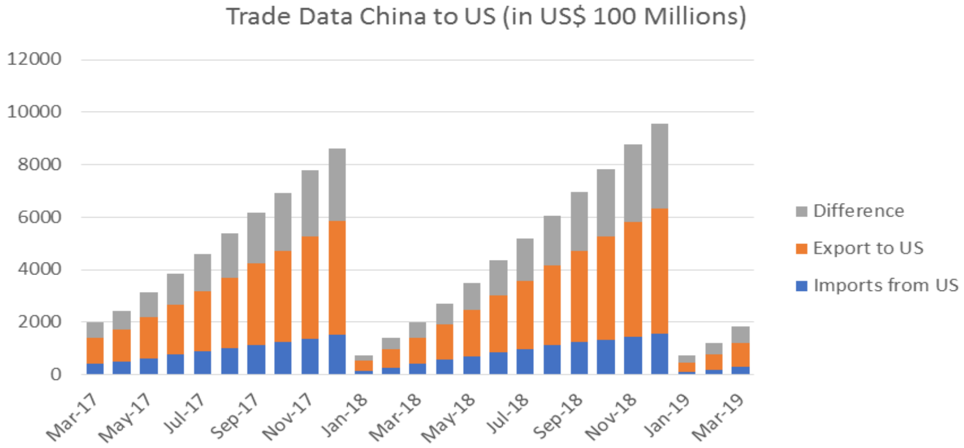

Figure-1. Trade data between US and China.

However, after the start of the trade war, different tariff measures by the two sides has been introduced, while further escalation will increase the difficulty of import and export, and is bound to have a huge impact on the stock markets of both China and the United States. We will study the impact of this trade war on the network structure of the Chinese stock market to understand the spread of risks. In previous studies, researchers used stocks as the nodes of network and relationship among stocks achieved through Pearson correlation coefficient acting as edges (see, e.g., (Lee & Nobi, 2018; Memon & Yao, 2019; Nobi, Maeng, Ha, & Lee, 2014; Wang., Xie, Chen, Yang, & Yang, 2013)). In addition, researchers define stock index value as node of the network (Long, Zhang, & Tang, 2017); (Namaki, Shirazi, Raei, & Jafari, 2011); (Nobi, Lee, Kim, & Lee, 2014); due to varied research focuses, where some scholars focus on the study of the interaction between different stocks in the stock market, while others focus on the study of the interaction between different industries. Among the most popular methods of complex network are threshold method (Namaki et al., 2011); (Yang, Li, & Zhang, 2014); (Gao, Wei, & Wang, 2013); (Huang, Zhuang, & Yao, 2009); (Memon & Yao, 2019); (Qiu, Zheng, & Chen, 2010); (Li & Pi, 2018); (Xia, You, Jiang, & Guo, 2018); (Xu, Wang, Zhu, & Zhang, 2018); (Ha, Lee, & Nobi, 2015); (Hu, Yang, Cai, & Yang, 2013) minimum spanning tree (Yao & Memon, 2019); (Tabak, Serra, & Cajueiro, 2010); (Majapa & Gossel, 2016); (Bonanno, Caldarelli, Lillo, & Mantegna, 2003); (Bonanno et al., 2004); (Nguyen, Nguyen, & Nguyen, 2019); (Coletti, 2016); (G.-J. Wang, Xie, & Stanley, 2018); (Birch, Pantelous, & Soramäki, 2016); (Patwary, Lee, Nobi, Kim, & Lee, 2017); (Song, Ko, & Chang, 2018) Using entropy(Lv, Han, Wan, & Yin, 2018); (X. Wang & Hui, 2018); (Hou, Liu, Gao, Cheng, & Song, 2017); (Bekiros, Nguyen, Junior, & Uddin, 2017); (Teng & Shang, 2017) and granger coefficient (Výrost, Lyócsa, & Baumöhl, 2015); (G.-J. Wang, Xie, He, & Stanley, 2017); (Sun, Gao, Wen, Chen, & Hao, 2018); (Papana, Kyrtsou, Kugiumtzis, & Diks, 2017) These methods are applied on many local stock markets of the world. Nobi, Maeng, et al. (2014) used the minimum spanning tree to study the impact of the global financial crisis in 2008 on the threshold network of the local financial market in South Korea before and after the financial crisis. Raddant and Kenett (2017) analyzed the dependencies among nearly 4,000 stocks in 15 countries and estimated relationships between stocks from different markets using the GARCH model and the robust regression process. Tabak et al. (2010) studied the Brazilian stock market with the minimum spanning tree method. Bonanno et al. (2004) compared the topological properties of a minimum spanning tree derived from a large number of stocks over a 12 year trading cycle at the New York stock exchange with those derived from alternative data simulated using a simple market model. Oh (2014) studied the grouping coefficient of the industrial sector in the stock network with the minimum spanning tree method based on the stock data of the US and South Korean stock markets. Nguyen et al. (2019) studied the impact of the financial crisis in Vietnam from 2011 to 2012 on the stock market by using the minimum spanning tree. Coletti (2016) used four different methods to establish the network of the top 100 Italian listed companies from 2001 to 2011, and compared the method with the minimum spanning tree of the industry sector. Recently, Memon and Yao (2019) applied threshold and MST methods on 181 stocks of Pakistan stock market and found a crisis-like less stable overall market structure due to the external and internal events of crisis for Pakistan. Zhao et al. (2018) analyzed the time evolution of the three major stock markets in the US, UK and China through the application of different network based methods.

Although, global financial crisis and major international events are found to have a serious impact globally, on almost all the stock markets of the world. From the perspective of Chinese stock market, Xia et al. (2018) established threshold network for China's stock market network and compared the impact of different crises, such as the global financial crisis of 2008 and the stock market disaster of 2015 for china. Han, Xie, Xiong, Zhang, and Zhou (2017) made a comparative analysis of the Chinese stock market before and after the crisis in 2008.The partial correlation matrix between the original correlation matrix and the market index over two time periods of one year is studied. Li and Pi (2018) propose a sophisticated network approach to analyze the impact of the 2008 global financial crisis on the world's major stock indexes from 2005 to 2010. Wang and Hui (2018). studied the information transfer before and after the Chinese stock market crash in 2015 by using effective transfer entropy, and analyzed the centrality and directed maximum spanning tree of network nodes. Zhang, Zhu, and Yang (2018) studied the multifractal characteristics of China stock index and "One Belt and One Road" three major stock indexes in global and local time by using multifractal method, and found the source of multifractal.

Comparing previous methods, we decided to use stocks as a node of the network, and Pearson correlation coefficient as the construction of China's A-share stock market network edges, adopted on January 4, 2010 to April 2, 2019, comprising 2247 trading session of 300 stocks. China`s CSI-300 index and CSI-500 index represents 70% of whole stock market. We have divided overall sample period into two periods of before the trade war (March 16, 2017 to March 22, 2018), and during trade war (March 23 to April 2, 2019), to evaluate the impact of recent trade war of US-China on the structural change of Chinese stock market. Additionally, we construct threshold network of overall data sample period (January 4, 2010 to April 2, 2019), and evaluate topological properties of nine threshold networks. To the best of our knowledge, this is first study that focuses on analyzing the impact of recent trade-war between US and China on the structural change and topological properties of the Chinese stock market.

The rest of this paper is organized as follows: In section 2, we present the literature review. In section 3, we describe empirical data and methodology. The results and detailed discussion are mentioned in section 4. Finally, in section 5 we present our concluding remarks.

2. LITERATURE REVIEW

The stock market is a complex network due to complexity of stocks and their interactions. It is due to this characteristic, the method of using complex network to build the network of the stock market can be used to study examine structural change, interdependency and dynamics of the stock market. Threshold method is one of the most basic methods used by predecessors for the threshold network, how to determine the threshold is a crucial issue. For example, Xu et al. (2018) 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. Many researchers after applying threshold method on stock markets found degree distribution following a power-law model Nobi, Maeng, et al. (2014); Huang et al. (2009); Xia et al. (2018); Xu et al. (2018). Gao et al. (2013) with dynamic threshold and static threshold networks on the US stock markets found that the small world of financial network has robust properties, and when the big financial collapse occurs, dramatic changes have taken place in financial network topology, thus for academic research provides a new perspective to the financial crisis. Qiu et al. (2010) also used dynamic threshold network and static threshold network to study the us and Chinese stock markets, and compared 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 is a strong interaction between stocks in the financial market. Huang et al. (2009)

found in their study of the Chinese stock market that the stock related network was topologically robust to the failure of random nodes, but also vulnerable to deliberate attacks.

The stock market is in constant change, and by comparing the network topology structure of the stock market before and after the financial crisis, it can provide better help for the prediction of the financial crisis in the future. The global financial crisis in 2008 had a serious impact on stock markets in different countries. Li and Pi (2018) studied the impact of the global financial crisis on major stock indexes from 2005 to 2010 and found that for the large threshold, the network before and after the crisis had a significant community structure, while the network during the crisis was on the contrary. Nobi, Maeng, et al. (2014) searched for the impact of the financial crisis on the south Korean stock market by analyzing the prices of 185 stocks in the Kospi 200 Index, and found that the degree of closeness between stocks was stronger after the financial crisis than before the financial crisis. Xia et al. (2018) waiting for Chinese stock market to study the two crises of 2008 and 2015, by the Shanghai and Shenzhen 300 Index selecting 121 stocks, the study found that when the crisis easy means of companies and investors institutions, investment institutions tend to adopt similar investment choices, will seriously affect the liquidity of the stock market, the extent of the deepening crisis. Memon and Yao (2019) selected the Pakistani stock market for research, and used threshold method, minimum spanning tree and other methods to find that there are core nodes in different periods, which are crucial to the stability of the whole stock market and need to be paid attention to by the government and other regulatory authorities. Through studying the research results of previous scholars, we have a stronger emphasis on applying threshold method to construct a network to study the impact of recent trade war between US and China, and its impact of the structural change of Chinese stock market.

3. DATA AND METHODOLOGY

After nearly 30 years of development, China's stock market keeps growing and the number of A-shares has exceeded 3,600. The CSI 300 Index reflects the whole picture of the A-share market. The market value of the CSI 300 Index accounts for about 60% of the total market value of the A-share market. In this study, we selected all the stocks belonging to CSI 300 Index, in order to construct the network of China's stock market, we have taken data from January 4, 2010 to April 6, 2019, comprising 2247 stock trading days. Among them, some companies in the CSI 300 Index are not listed or suspended from trading, finally filtering down to 202 stocks confirms to the situation, we added additional 98 stocks from CSI 500 Index, and construct Chinese stock markets among 300 Stocks acting as nodes of the network. In order to explore the impact of US and China war on China's stock market, we divide the whole time into three periods.

Table-1. Total number of stocks classified according to their respective industry sector.

No.	Sector	Number of companies
1	Comprehensive	6
2	manufacturing industry	142
3	Information technology industry	23
4	Social services industry	11
5	Wholesale and retail trade	11
6	Agricultural, forestry, animal, fishery industry	3
7	Finance, insurance	31
8	Transportation, warehousing	15
9	Construction industry	11
10	Real estate industry	17
11	Production and supply of electricity, gas and water	12
12	Communication and cultural industry	2
13	Extractive industry	16

The first period is of 250 trading days (before the trade war starting from March 16, 2017 and ending March 22, 2018); the second period also comprises 250 trading days (During trade war starting from March 23, 2018 until April 2, 2019). The third period comprising 2,247 trading days

(Overall sample period starting from January 4, 2010 and ending April 2, 2019). In the following text, we abbreviate the three periods BTW, DTW and Overall respectively for the convenience of writing. By constructing the network of these three periods, the impact of current trade war between US and China will be analyzed on the Chinese stock market. Table 1 shows the 13 industries of 300 stocks (divided according to the old version of industry classification standard issued by China securities regulatory commission).

A group of n stocks is represented by S = {i | i = 0, 1,.., n}, where a single stock corresponds to the number tag i in S. We define $\{P_i(t)\}$ as the closing price of stock i on day t, and the logarithmic return of stock $r_i(t)$ can be calculated as:

$$r_i(t) = \ln(P_i(t)) - \ln(P_i(t-1)) \tag{1}$$

Then we calculate the Pearson correlation coefficient of any two stocks i and j in S, using the following formula:

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

r_i and r_j are logarithmic returns for stocks i and j, while <···> Represents the average of these stocks over time. In this way, we construct a cross-correlation with dimensions 300×300, mono-diagonal and symmetric matrices for all nodes, where the values are from -1 (negative correlation) to 1 (positive correlation).

Next, we will use the threshold method to construct the network, and select a threshold θ ($-1 \leqq \theta \leqq +1$). As C_{ij} between two nodes is greater than threshold, an edge will be formed between nodes i and j. In this way, with different thresholds for the same number of nodes, the number of edges will be different. Through this method, we will construct a threshold network for the Chinese stock market. To assess topological properties of the Chinese stock market network, we use well-known network measures. Sabidussi (1966) is used to evaluate the power level associated with a specific node in the network, where the node with a higher value represents the key node that transmits information in different groups. This measure is used to determine the node (i.e., the company) that is closer to other companies or departments in the network. The formula is as follows:

$$\mathrm{Cc}\,(\mathrm{i}) = \frac{1}{\sum_{h \in G} d_G\,(i,j)} \tag{3}$$

Where $d_G(i,j)$ represents the minimum distance from node i to node j. Betweenness Centrality (Brandes, 2001) is used to evaluate the intermediary role that some nodes play in the transmission of information in the network. It calculates all the shortest paths of any two nodes in the network, if many of these shortest paths pass through a node, the Betweenness Centrality of that node is considered to be high, and calculated as follows:

$$C_B(k) = \sum_{s \neq k \neq t \epsilon V} \frac{\sigma_{st}(k)}{\sigma_{st}} \tag{4}$$

Where $\sigma_{st}(i)$ represents the number of shortest paths from s→t through node i, and σ_{st} represents the number of shortest paths from s→t. We also introduced the concept of modularity (Heiberger, 2014). The larger the modularity is, the better the division of community will be. The definition is as follows:

$$Q = \frac{1}{2m} \sum_{i,j} \left[\alpha_{ij} - \frac{k_i k_j}{2x}\right] f\,(c_i, c_j) \tag{5}$$

Here, m is the edge of the whole network, when i and j are directly connected, and α_{ij} is strength, such as: $\alpha_{ij} = 1$ (when two stock are connected); otherwise, $\alpha_{ij} = 0$. k_i is the degree of node i, when two nodes are in the same community. Additionally, $f = 1$ implies that $c_i = c_j$ and zero otherwise.

4. RESULTS AND DISCUSSION

4.1. PDFs and Statistics of Pearson Correlation Coefficients

Before analyzing the threshold network, we investigate the probability density functions (PDFs) of N (N − 1)/2 elements $\{C_{ij}\,; i < j\}$ in the Pearson correlation matrix C. Figure 2 shows a diagram of the PDF. Additionally, Table 2 provides the Pearson correlation coefficient $\{C_{ij}\,; i< j\}$

descriptive statistics. From Figure 2, we can see that the probability density function during trade war is wider and the peak value is lower than that of before trade war period, indicating that there is a wide and highly correlated relationship among stock during the trade war period. Therefore, it can be seen that a trade war has a bad impact on the Chinese stock market. At the same time, we can see from Table 2 that the average correlation during trade war rises sharply. Through this analysis of the data, it can be seen that trade war has a bad impact on the Chinese stock market, which increases the probability of crisis in the Chinese stock market, because markets tend to act as one during the events of extreme crisis (Wang et al., 2018).

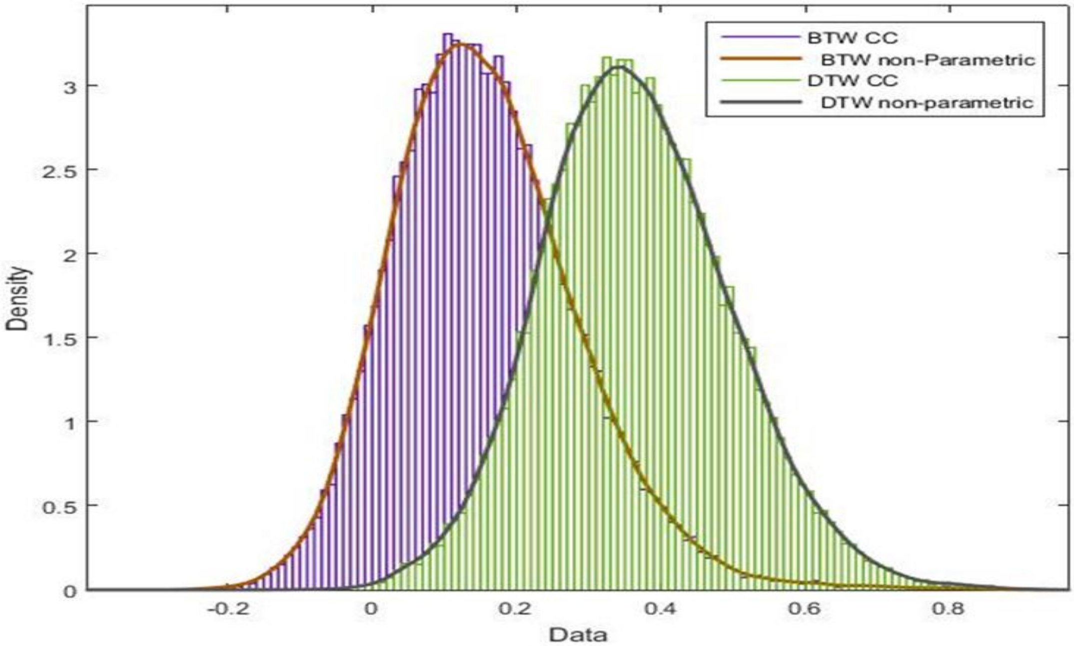

Figure-2. Probability density function (PDF) of correlation coefficients of chinese stock market (During and before trade war between US and China).

Table-2. Descriptive statistics of Pearson correlation coefficients.

Data sample period	Before trade war	During trade war	Overall
Mean correlation	0.157	0.366	0.291
Standard deviation	0.129	0.130	0.093
Skewness	0.630	0.258	0.675
Kurtosis	1.226	0.210	1.139

4.2. Results of Correlation Threshold Network

Next, we analyze the stock correlation network of different thresholds θ levels. We present the key thresholds $\theta > 0.2$, $\theta > 0.4$, and $\theta > 0.8$, for BTW (on March 17, 2017 to March 22, 2018), DTW (March 23, 2018 to April 2, 2019), and Overall sample period (January 5, 2010 to April 2, 2019) of China's stock market networks. The size of the node in the figure below indicates the size of the central metric value it processed, based on the selected network centrality measure.

In Figure 3 and Figure 4, we select the threshold value $\theta=0.2$ according to betweenness centrality, and present two threshold networks of Chinese stock market BTW and DTW. As can be seen from Figure 3, most important nodes according to betweenness centrality measure are GF Securities (belonging to finance, insurance sector), CIMC group (manufacturing), Fiberhome Telecommunication Technologies (information technology), three companies belonging to three different sectors. From Figure 4, important nodes have changed, and replaced by Shenzhen Salubris Pharmaceuticals, Lepu Medical Technology, Sanan Optoelectronics. At the same time, by comparing both Figures 3 & 4, we can see that the edge connection of the stock increases obviously, and the density of the network increases greatly during trade war, changing from density of 0.337 before trade war in Figure 3 to 0.909 during trade war in Figure 4.

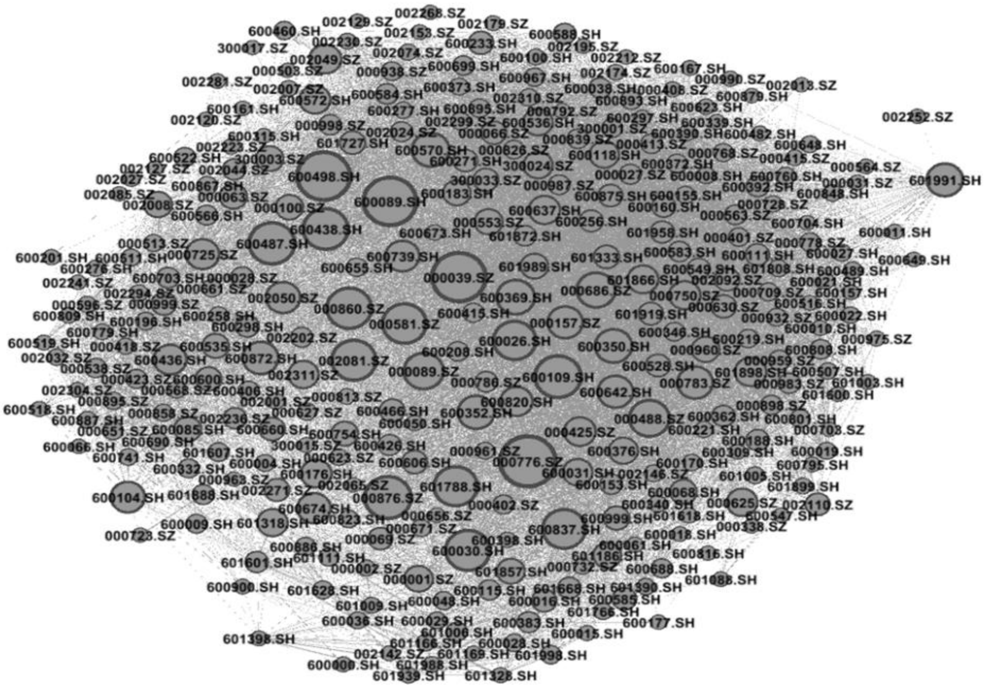

Figure-3. Before trade war (BTW) θ>0.2, betweenness centrality.

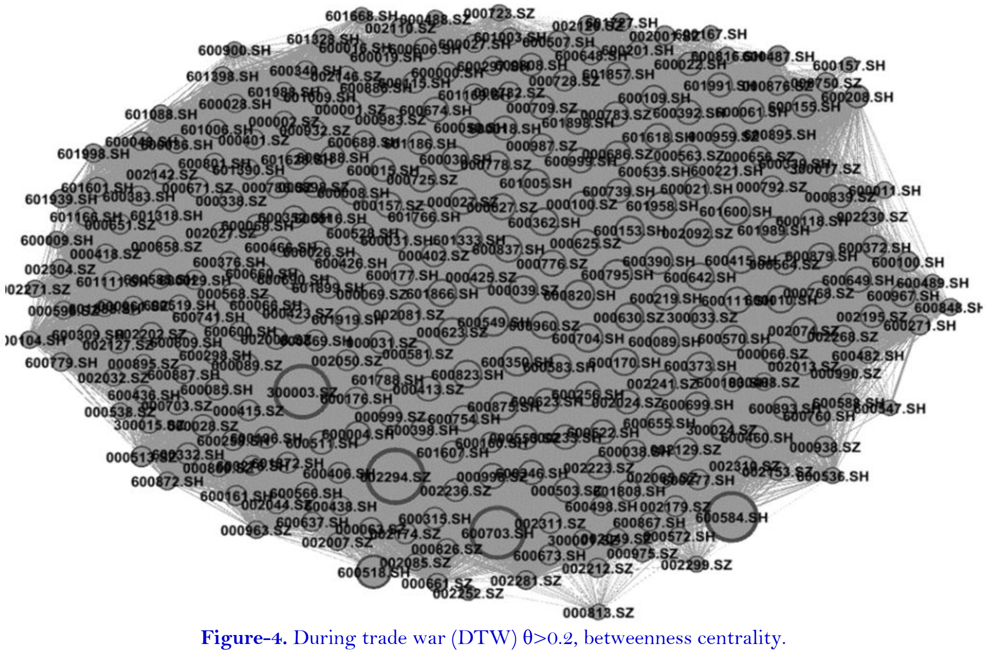

Figure-4. During trade war (DTW) θ>0.2, betweenness centrality.

When we increase the threshold value to 0.4, and classify according to the Betweenness Centrality measure, we found that the density for both periods of the stock market network is greatly reduced. From Figure 5, we can see most important nodes with high betweenness centrality score are Cosco Shipping Energy Transportation (belonging to transportation, warehousing sector), CIMC group (manufacturing), and Beijing Shunxin Agriculture (farming, forestry, animal husbandry, fisheries). CIMC remain central and most important node in the network. Figure 6 shows threshold network θ>0.4 of Chinese stock market for during trade war period. As can be seen, the central node during the trade war has changed compared with before the trade war, and except Jinduicheng Molybdenum for extractive industries, other central nodes of Jilin Aodong Pharmaceutical Group and Suzhou Gold Mantis Construction Decoration still belong to the manufacturing industry. Furthermore, the density of during trade war period at θ>0.4 is higher compared to before trade war period.

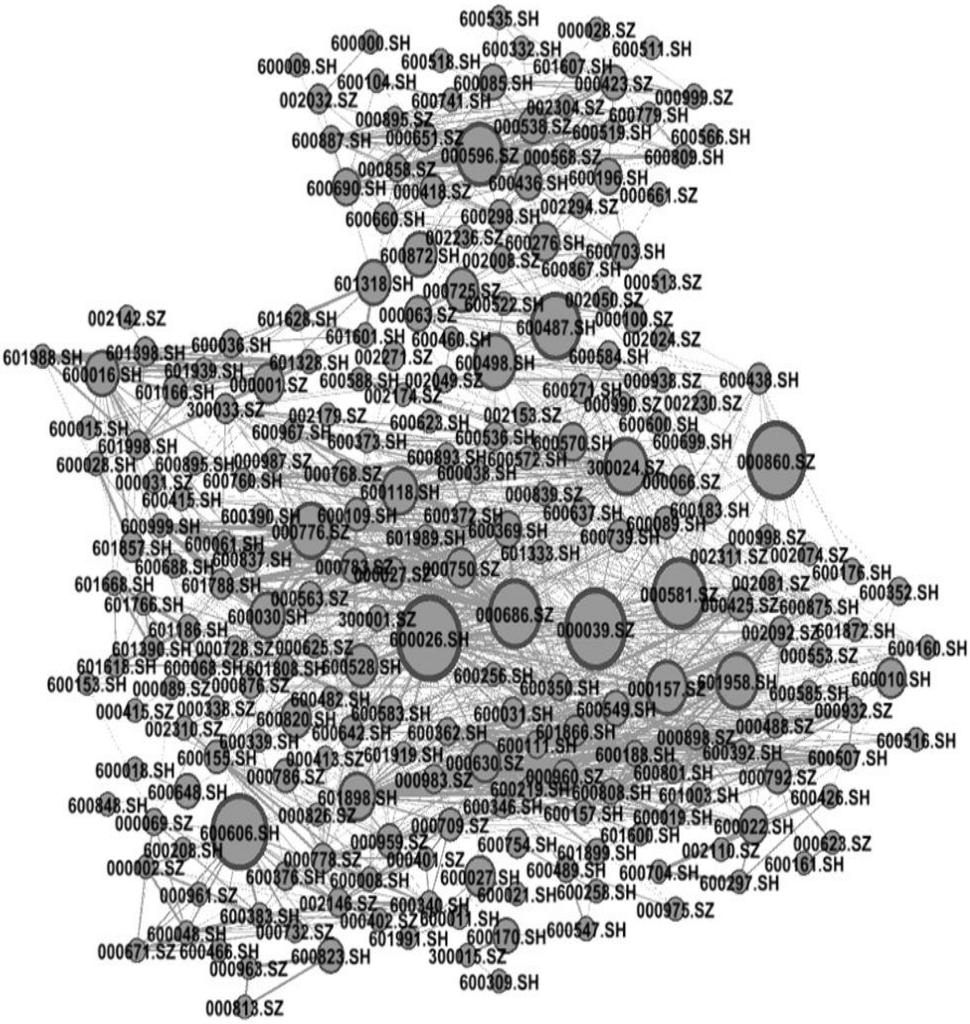

Figure-5. Before trade war (BTW) θ>0.4, betweenness centrality.

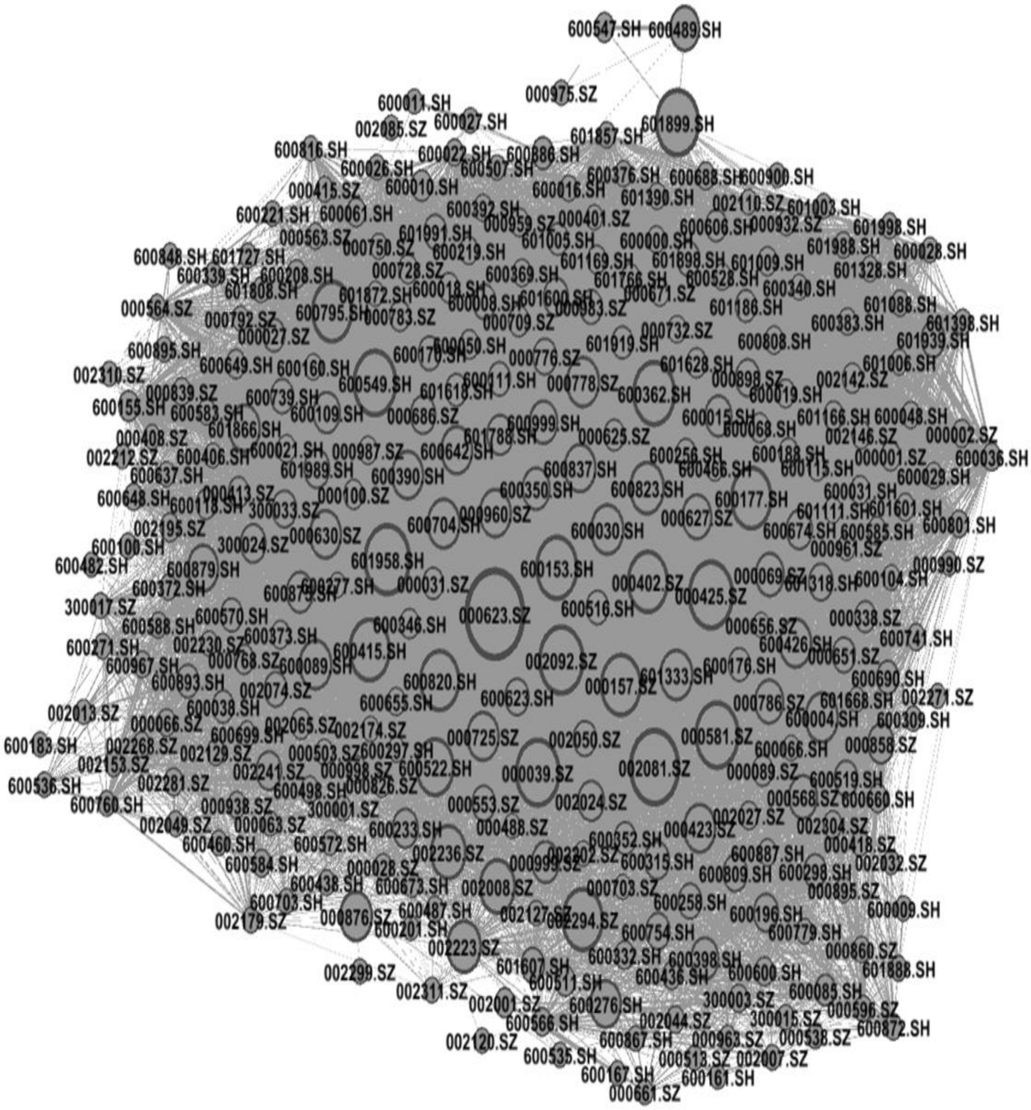

Figure-6. During trade war θ >0.4, betweenness centrality.

Next, we continue to increase the threshold to 0.8 to obtain a visible less dense network, and classified the threshold network according to degree of connections per node. At this time, we found the node and edge quantity are greatly reduced, and density of before trade war remain at 0.054, compared to slightly higher density of 0.056 during trade war. While comparing the central nodes, we find an interesting thing, that during both periods, sectors of the central nodes are finance and insurance industry. In this case, our government regulatory departments should focus on improving the attention of the financial industry. Chinese stock market network is healthy, as can be seen from in the Figure 7, at this point there are low interconnected clusters. In contrast Figure 8, show at this point in the network there still exist a large number of interconnected and big clusters. Thus, we can conclude that the trade war between China and the United States has a huge impact on the stability structure of China's stock market.

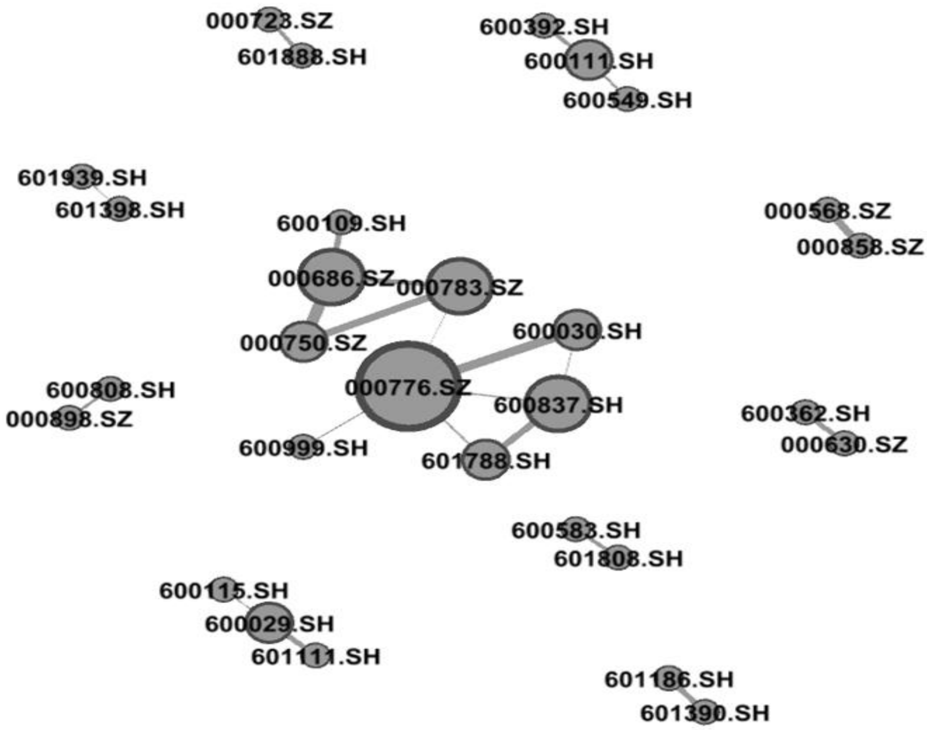

Figure-7. Before trade war θ >0.8, average degree of connections.

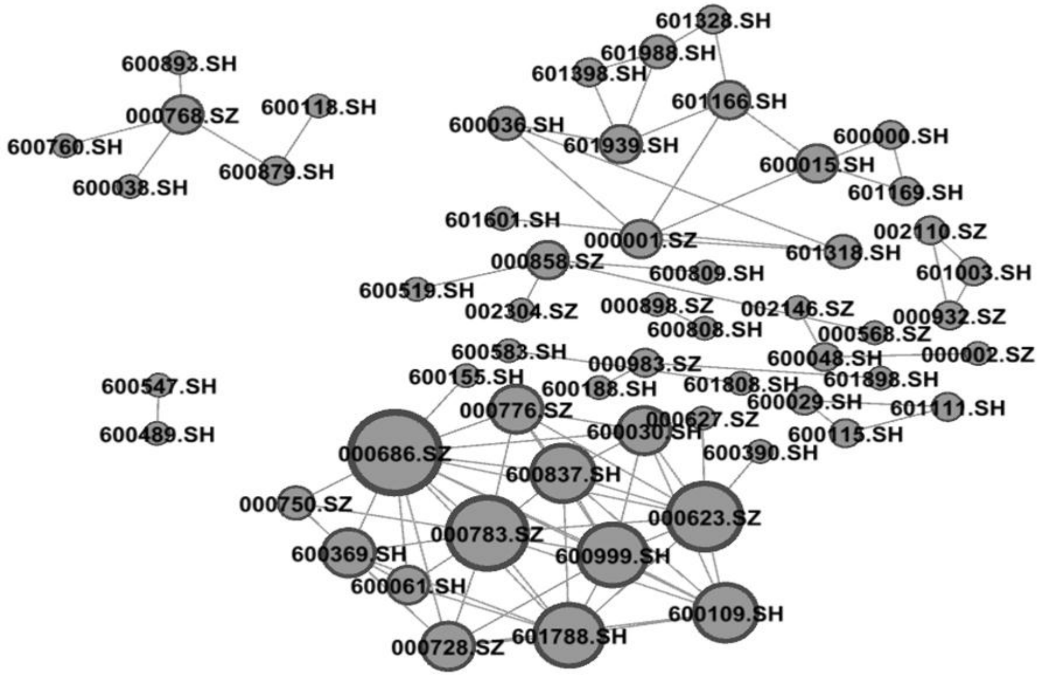

Figure-8. During trade war θ >0.8, average degree of connections.

Figure 9, Figure 10, and Figure 11 show threshold network structure of Chinese stock market during overall data sample for θ>0.2, θ>0.4, and θ>0.8. The stock market network in the Figure 11 for the overall period show important central nodes belonging to financial sectors, that confirms importance of financial sector industry for the development of Chinese economy. Figure 9 shows important nodes having high betweenness centrality scores are Shanghai Pharmaceuticals Holding (manufacturing sector), China Resources Sanjiu Medical & Pharmaceutical (manufacturing), and China National Medicines Corporation (wholesale and retail trade). The net profit of important node Shanghai Pharmaceuticals holding has increased from 3.521 billion yuan in the year 2017 to 3.881 billion yuan in the year 2018. The net profit of China Resources Sanjiu Medical & Pharmaceutical was 1.302 billion yuan in the year 2017, and increased to 1.432 billion yuan in the year 2018. Finally, the net profit of China National Medicines Corporation was 1.41 billion yuan in the year 2017, compared to 1.44 billion yuan in the year 2018. It can be seen that the three most important node companies in the network during the whole period (from January 5, 2010 to April 2, 2019) still achieved the growth of net profit specially during the US-China trade war.

Figure 10 shows that at θ>0.4 important nodes are Shenzhen Airport (transportation, storage industry), Jilin Aodong Pharmaceutical Group (manufacturing industry), and China Coal Energy Company Limited (extractive industry). Excluding Jilin Aodong Pharmaceutical Group that has witnessed a decline in the net profit from 18.63 billion yuan in 2017 to 9.35 billion yuan in 2018, the remaining two companies continue to maintain an increase in the net profit, 6.68 billion yuan (Shenzen airport), 34.35 billion yuan (China coal energy) for the year 2018 compared to 6.61 billion yuan, and 22.92 billion yuan net profit in 2017 respectively. Thus, it can be seen that in 30 years of development of China's stock market that has made great progress, though Chinese stock market is still not a mature stock market, and gradual improvement is required.

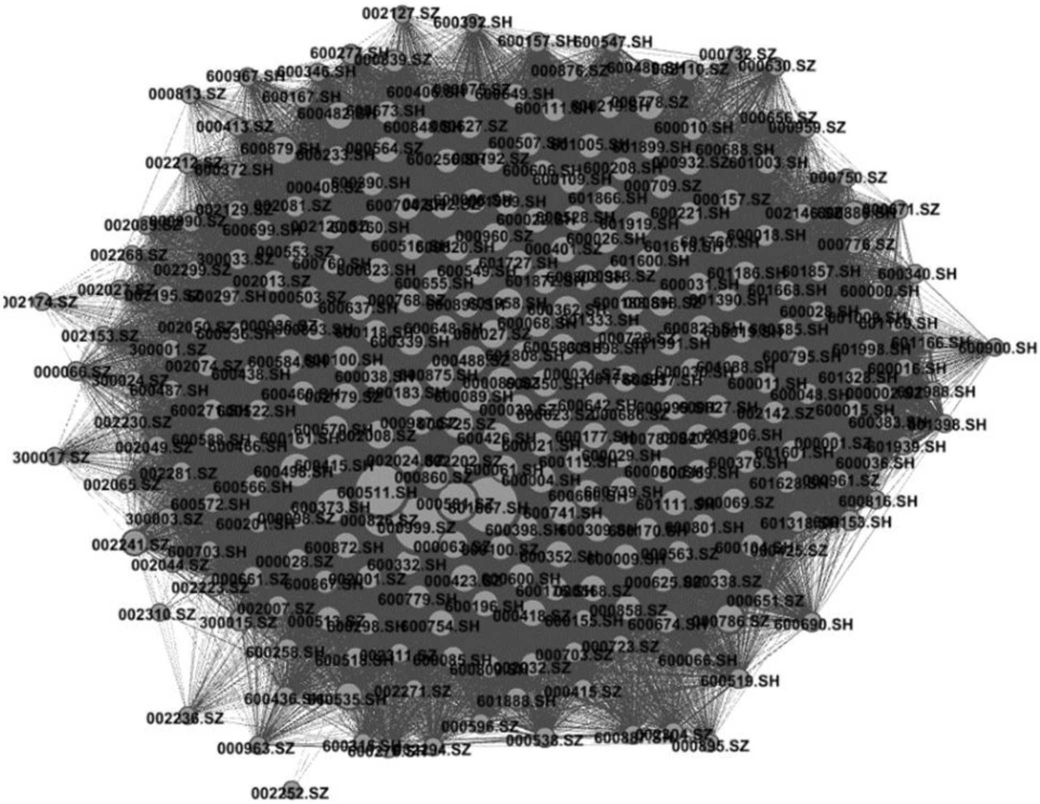

Figure-9. Overall sample period θ >0.2, betweenness centrality.

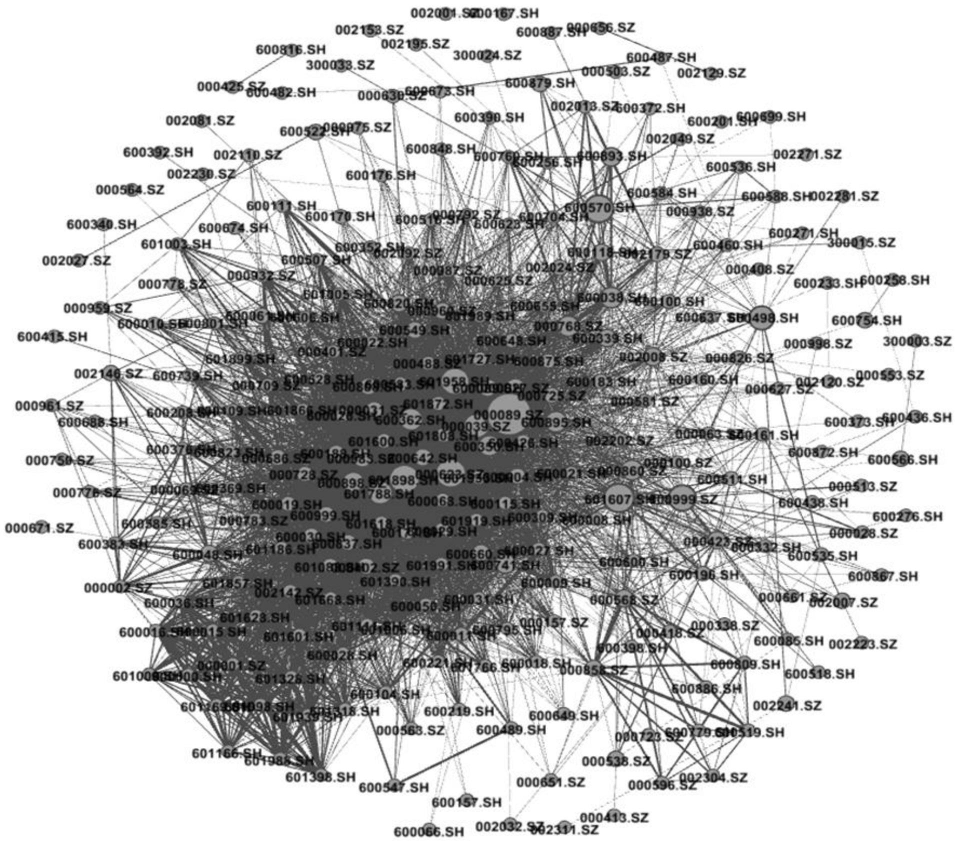

Figure-10. Overall θ >0.4, betweenness centrality.

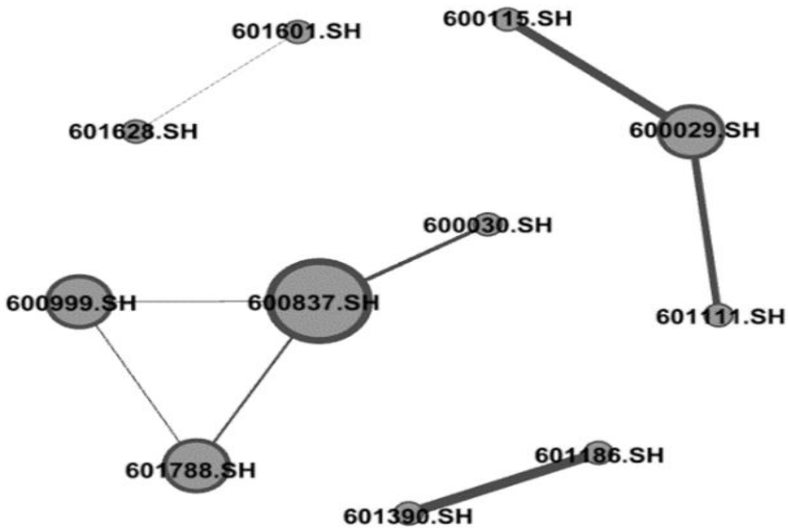

Figure-11. Overall θ >0.8, Average degree of connections.

Figure 11 shows threshold network of Chinese stock market at θ>0.8 for the entire sample under consideration. We can observe important nodes having high degree of connections are Haitong Securities Company, China Merchants Securities, China Southern Airlines, and Everbright Securities. We can observe important role of these four companies for the development of Chinese economy. However, due to US-China trade war the net profit of three companies including: Haitong Securities, China merchants, and china southern airlines has been affected, and witnessed a decline in the year 2018 compared to the net profit in the prior year 2017. Hence, substantial steps need to be taken to resolve this conflict that will further deteriorate the overall stability of the Chinese stock market. Following Table 3 shows synoptic topology chart of nine threshold networks of Chinese stock market.

Table-3. Topological properties of nine threshold networks of Chinese stock market.

Data sample period	Before trade war			During trade war			Overall		
Correlation	Θ>0.2	Θ>0.4	Θ>0.8	Θ>0.2	Θ>0.4	Θ>0.8	Θ>0.2	Θ>0.4	Θ>0.8
Nodes	300	250	29	300	295	57	300	258	11
Edges	15120	1772	22	40763	16912	90	37821	5425	8
Density	0.337	0.057	0.054	0.909	0.390	0.056	0.843	0.164	0.145
Diameter	5	8	4	3	5	4	3	6	2
Radius	3	1	1	2	3	1	2	1	1
Average path length	1.712	3.173	1.897	1.091	1.666	1.823	1.156	2.193	1.272
Modularity	0.230	0.520	0.796	0.055	0.168	0.635	0.067	0.216	0.659
Number of communities	4	14	11	3	5	11	3	7	4

5. CONCLUSION

In general, we studied the structural changes and network evolution of China's stock market from January 5, 2010 to April 2, 2019 by selecting 300 representative stocks. When we use the threshold method to establish a network for the Chinese stock market, and compare the three periods before trade war (BTW), during trade war (DTW), and Overall sample period. We find that the trade war between China and the United States has a huge impact on the Chinese stock market network. It made Chinese stocks more correlated with each other during the trade war period, so that when one stock was affected, it spread to a large number of stocks, causing a large decline in the stock market, which was not good for the health of the Chinese stock market. At the same time, we found that when the threshold value reached 0.8, the most central nodes were all those belonged to the financial industry. This means that in order to ensure the safety of the stock market and avoid financial crisis, the government and regulatory authorities should focus on China's financial industry, and the key enterprises among them should be taken under strengthened supervision. At the same time, when comparing two periods of before and during trade war between US and China, we can see that the proportion of manufacturing industry as the central node is larger when the threshold is 0.2 and 0.4. While analyzing 300 stock sectors, we also found that manufacturing companies accounted for a large proportion of Chinese stock market during sub-sample periods. Therefore, in such an environment, it can be found that the trade war between China and the United States has a great impact on China's manufacturing industry. Under such circumstances, manufacturing enterprises need to improve their competitiveness and expand their sales channels. At the same time, they also need relevant supporting policies from the government to help these enterprises grow more healthily and stably. On the other hand, it stabilizes the manufacturing sector and stabilizes most of the Chinese stock market, which is conducive to the stability of the stock market.

Finally, we can conclude that the Chinese stock market is becoming mature after 30 years of development, and the ability of enterprises to resist external risks is increasing. After analyzing the core nodes of China's stock market network in the overall period, we found and increase in the net profit of major companies of the network. But at the same time, we observed that for the Chinese stock market network in the Overall period, when the threshold value reaches 0.8, the net profit of the four central node companies in the year 2018 drop sharply, indicating a strong signal of the impact of US-China trade war on the overall profitability of the Chinese companies. Therefore, for china that is currently in the process of development, and still needs to create a fair-trading environment in the global context, needs to resolve this trade dispute. This study will assist government regulators and international investors in examining the current topological structure of China's stock market. Meanwhile, it is also hoped that China and the United States can conduct fair trade policies with each other, resolve trade war disputes at an early date, and jointly safeguard the stable and orderly development of the world trade.

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REFERENCES

Bekiros, S., Nguyen, D. K., Junior, L. S., & Uddin, G. S. (2017). Information diffusion, cluster formation and entropy-based network dynamics in equity and commodity markets. *European Journal of Operational Research*, *256*(3), 945-961.Available at: https://doi.org/10.1016/j.ejor.2016.06.052.

Birch, J., Pantelous, A. A., & Soramäki, K. (2016). Analysis of correlation based networks representing DAX 30 stock price returns. *Computational Economics*, *47*(4), 501-525.Available at: https://doi.org/10.1007/s10614-015-9481-z.

Bonanno, G., Caldarelli, G., Lillo, F., & Mantegna, R. N. (2003). Topology of correlation-based minimal spanning trees in real and model markets. *Physical Review E*, *68*(4), 046130.Available at: https://doi.org/10.1103/physreve.68.046130.

Bonanno, G., Caldarelli, G., Lillo, F., Micciche, S., Vandewalle, N., & Mantegna, R. N. (2004). Networks of equities in financial markets. *The European Physical Journal B*, *38*(2), 363-371.

Brandes, U. (2001). A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, *25*(2), 163-177.Available at: https://doi.org/10.1080/0022250x.2001.9990249.

Coletti, P. (2016). Comparing minimum spanning trees of the Italian stock market using returns and volumes. *Physica A: Statistical Mechanics and its Applications*, *463*, 246-261.Available at: https://doi.org/10.1016/j.physa.2016.07.029.

Gao, Y.-C., Wei, Z.-W., & Wang, B.-H. (2013). Dynamic evolution of financial network and its relation to economic crises. *International Journal of Modern Physics C*, *24*(02), 1350005.Available at: https://doi.org/10.1142/s0129183113500058.

Ha, G.-G., Lee, J. W., & Nobi, A. (2015). Threshold network of a financial market using the P-value of correlation coefficients. *Journal of the Korean Physical Society*, *66*(12), 1802-1808.Available at: https://doi.org/10.3938/jkps.66.1802.

Han, R.-Q., Xie, W.-J., Xiong, X., Zhang, W., & Zhou, W.-X. (2017). Market correlation structure changes around the great crash: A random matrix theory analysis of the chinese stock market. *Fluctuation and Noise Letters*, *16*(02), 1750018.Available at: https://doi.org/10.1142/s0219477517500183.

Heiberger, R. H. (2014). Stock network stability in times of crisis. *Physica A: Statistical Mechanics and its Applications*, *393*, 376-381.Available at: https://doi.org/10.1016/j.physa.2013.08.053.

Hou, Y., Liu, F., Gao, J., Cheng, C., & Song, C. (2017). Characterizing complexity changes in chinese stock markets by permutation entropy. *Entropy*, *19*(10), 1-10.Available at: https://doi.org/10.3390/e19100514.

Hu, S., Yang, H., Cai, B., & Yang, C. (2013). Research on spatial economic structure for different economic sectors from a perspective of a complex network. *Physica A: Statistical Mechanics and its Applications*, *392*(17), 3682-3697.Available at: https://doi.org/10.1016/j.physa.2013.04.010.

Huang, W.-Q., Zhuang, X.-T., & Yao, S. (2009). A network analysis of the Chinese stock market. *Physica A: Statistical Mechanics and its Applications*, *388*(14), 2956-2964.

Lee, J. W., & Nobi, A. (2018). State and network structures of stock markets around the global financial crisis. *Computational Economics*, *51*(2), 195-210.Available at: https://doi.org/10.1007/s10614-017-9672-x.

Li, B., & Pi, D. (2018). Analysis of global stock index data during crisis period via complex network approach. *PloS one*, *13*(7), e0200600.Available at: https://doi.org/10.1371/journal.pone.0200600.

Long, H., Zhang, J., & Tang, N. (2017). Does network topology influence systemic risk contribution? A perspective from the industry indices in Chinese stock market. *PloS One*, *12*(7), e0180382.Available at: https://doi.org/10.1371/journal.pone.0180382.

Lv, Q., Han, L., Wan, Y., & Yin, L. (2018). Stock net entropy: Evidence from the Chinese growth enterprise market. *Entropy*, *20*(10), 1-20.Available at: https://doi.org/10.3390/e20100805.

Majapa, M., & Gossel, S. J. (2016). Topology of the South African stock market network across the 2008 financial crisis. *Physica A: Statistical Mechanics and its Applications*, *445*, 35-47.Available at: https://doi.org/10.1016/j.physa.2015.10.108.

Memon, B. A., & Yao, H. (2019). Structural change and dynamics of Pakistan stock market during crisis: A complex network perspective. *Entropy, 21*(3), 1-20.Available at: https://doi.org/10.3390/e21030248.

Namaki, A., Shirazi, A., Raei, R., & Jafari, G. (2011). Network analysis of a financial market based on genuine correlation and threshold method. *Physica A: Statistical Mechanics and its Applications, 390*(21-22), 3835-3841.Available at: https://doi.org/10.1016/j.physa.2011.06.033.

Nguyen, Q., Nguyen, N., & Nguyen, L. (2019). Dynamic topology and allometric scaling behavior on the Vietnamese stock market. *Physica A: Statistical Mechanics and its Applications, 514*, 235-243.Available at: https://doi.org/10.1016/j.physa.2018.09.061.

Nobi, A., Lee, S., Kim, D. H., & Lee, J. W. (2014). Correlation and network topologies in global and local stock indices. *Physics Letters A, 378*(34), 2482-2489.Available at: https://doi.org/10.1016/j.physleta.2014.07.009.

Nobi, A., Maeng, S. E., Ha, G. G., & Lee, J. W. (2014). Effects of global financial crisis on network structure in a local stock market. *Physica A: Statistical Mechanics and its Applications, 407*, 135-143.Available at: https://doi.org/10.1016/j.physa.2014.03.083.

Oh, G. (2014). Grouping characteristics of industry sectors in financial markets. *Physica A: Statistical Mechanics and its Applications, 395*, 261-268.Available at: https://doi.org/10.1016/j.physa.2013.09.031.

Papana, A., Kyrtsou, C., Kugiumtzis, D., & Diks, C. (2017). Financial networks based on Granger causality: A case study. *Physica A: Statistical Mechanics and its Applications, 482*, 65-73.Available at: https://doi.org/10.1016/j.physa.2017.04.046.

Patwary, E. U., Lee, J. Y., Nobi, A., Kim, D. H., & Lee, J. W. (2017). Changes of hierarchical network in local and world stock market. *Journal of the Korean Physical Society, 71*(7), 444-451.Available at: https://doi.org/10.3938/jkps.71.444.

Qiu, T., Zheng, B., & Chen, G. (2010). Financial networks with static and dynamic thresholds. *New Journal of Physics, 12*(4), 043057.Available at: https://doi.org/10.1088/1367-2630/12/4/043057.

Raddant, M., & Kenett, D. Y. (2017). Interconnectedness in the global financial market. Kiel Working Papers No. 2076, Kiel Institute for the World Economy.

Sabidussi, G. (1966). The centrality index of a graph. *Psychometrika, 31*(4), 581-603.Available at: https://doi.org/10.1007/bf02289527.

Song, J. W., Ko, B., & Chang, W. (2018). Analyzing systemic risk using non-linear marginal expected shortfall and its minimum spanning tree. *Physica A: Statistical Mechanics and its Applications, 491*, 289-304.Available at: https://doi.org/10.1016/j.physa.2017.08.076.

Sun, Q., Gao, X., Wen, S., Chen, Z., & Hao, X. (2018). The transmission of fluctuation among price indices based on Granger causality network. *Physica A: Statistical Mechanics and its Applications, 506*, 36-49.Available at: https://doi.org/10.1016/j.physa.2018.04.055.

Tabak, B. M., Serra, T. R., & Cajueiro, D. O. (2010). Topological properties of stock market networks: The case of Brazil. *Physica A: Statistical Mechanics and its Applications, 389*(16), 3240-3249.Available at: https://doi.org/10.1016/j.physa.2010.04.002.

Teng, Y., & Shang, P. (2017). Transfer entropy coefficient: Quantifying level of information flow between financial time series. *Physica A: Statistical Mechanics and its Applications, 469*, 60-70.Available at: https://doi.org/10.1016/j.physa.2016.11.061.

Výrost, T., Lyócsa, Š., & Baumöhl, E. (2015). Granger causality stock market networks: Temporal proximity and preferential attachment. *Physica A: Statistical Mechanics and its Applications, 427*, 262-276.Available at: https://doi.org/10.1016/j.physa.2015.02.017.

Wang, G.-J., Xie, C., He, K., & Stanley, H. E. (2017). Extreme risk spillover network: application to financial institutions. *Quantitative Finance, 17*(9), 1417-1433.Available at: https://doi.org/10.1080/14697688.2016.1272762.

Wang, G.-J., Xie, C., & Stanley, H. E. (2018). Correlation structure and evolution of world stock markets: Evidence from Pearson and partial correlation-based networks. *Computational Economics, 51*(3), 607-635.Available at: https://doi.org/10.1007/s10614-016-9627-7.

Wang, X., & Hui, X. (2018). Cross-sectoral information transfer in the Chinese stock market around its crash in 2015. *Entropy, 20*(9), 1-14.Available at: https://doi.org/10.3390/e20090663.

Wang., G.-J., Xie, C., Chen, S., Yang, J.-J., & Yang, M.-Y. (2013). Random matrix theory analysis of cross-correlations in the US stock market: Evidence from Pearson's correlation coefficient and detrended cross-correlation coefficient. *Physica A: Statistical Mechanics and its Applications, 392*(17), 3715-3730.Available at: https://doi.org/10.1016/j.physa.2013.04.027.

Xia, L., You, D., Jiang, X., & Guo, Q. (2018). Comparison between global financial crisis and local stock disaster on top of Chinese stock network. *Physica A: Statistical Mechanics and its Applications, 490*, 222-230.Available at: https://doi.org/10.1016/j.physa.2017.08.005.

Xu, X.-J., Wang, K., Zhu, L., & Zhang, L.-J. (2018). Efficient construction of threshold networks of stock markets. *Physica A: Statistical Mechanics and its Applications, 509*, 1080-1086.Available at: https://doi.org/10.1016/j.physa.2018.06.083.

Yang, R., Li, X., & Zhang, T. (2014). Analysis of linkage effects among industry sectors in China's stock market before and after the financial crisis. *Physica A: Statistical Mechanics and its Applications, 411*, 12-20.Available at: https://doi.org/10.1016/j.physa.2014.05.072.

Yao, H., & Memon, B. A. (2019). Network topology of FTSE 100 Index companies: From the perspective of Brexit. *Physica A: Statistical Mechanics and its Applications, 523*, 1248-1262.Available at: https://doi.org/10.1016/j.physa.2019.04.106.

Zhang, X., Zhu, Y., & Yang, L. (2018). Multifractal detrended cross-correlations between Chinese stock market and three stock markets in The Belt and Road Initiative. *Physica A: Statistical Mechanics and its Applications, 503*, 105-115.Available at: https://doi.org/10.1016/j.physa.2018.02.195.

Zhao, L., Wang, G.-J., Wang, M., Bao, W., Li, W., & Stanley, H. E. (2018). Stock market as temporal network. *Physica A: Statistical Mechanics and its Applications, 506*, 1104-1112.Available at: https://doi.org/10.1016/j.physa.2018.05.039.