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Sudden shock and stock market network structure characteristics: A comparison of past crisis events

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ABSTRACT

Studying the correlation structure of the stock market is crucial for systemic risk and portfolio optimization. We construct the price volatility network of the Shanghai and Shenzhen 300 index components in China's stock market in the period 2007–2020. We select three representative major emergencies: the global financial crisis in 2008, the stock disaster in 2015, and the COVID-19 epidemic in 2020. First, we find that when the stock market is impacted by the major events, the network shows a cluster phenomenon. The cluster effect of the financial crisis events is smallest, while that of the epidemic events occurs most rapidly. Second, the key nodes in the stock market network have greater risk transmission ability. The manufacturing plays a crucial role during the later stages of events, while the financial industry plays an important role during the epidemic's recovery period. Third, the network structure of the stock market has an indicator effect on the systemic risk contributions. Generally, the greater a stock's eigenvector centrality, the greater its systemic risk contribution, while its closeness centrality and clustering coefficient have opposite effects. The study has important enlightenment significance for market regulators to prevent risk diffusion and reduce portfolio risk for market participants.

1. Introduction

The outbreak of COVID-19 in late 2019 has attracted worldwide attention. The impacts of this event on the global economy are severe and still unfolding. In addition to a decline in GDP and increased unemployment, the economic fallouts include increased family poverty and a loss of thousands of enterprises (Aslam et al., 2020a; Martin et al., 2020; Hunjra et al., 2021). These economic consequences led to violent turbulence in oil prices on the stock market (Akhtaruzzaman et al., 2021; Zaremba et al., 2020). The three major U.S. stock indexes plummeted and experienced four circuit breakers in less than two weeks (March 9–18), triggering worldwide capital market turmoil. During this period, the stock markets of 10 countries, including Thailand, the Philippines, South Korea, Pakistan, Indonesia, Brazil, Canada, Mexico, Colombia and Sri Lanka, experienced circuit breakers. On March 12, the European Stoxx 600 index, which is regarded as an indicator of market panic, expanded its decline to 10%, the largest one-day decline in history. Germany's DAX index and France's CAC40 index fell more than 10%, while Britain's FTSE 100 index fell nearly 10%. The earliest outbreak of the epidemic occurred in China; the sudden major event significantly impacted all aspects of China's economy, including the stock market, which is an important part of China's financial market (Ren et al., 2021). On the first trading day after the Chinese New Year in 2020, the stock market reacted strongly. The Shanghai and Shenzhen 300 Index, Shanghai Stock Exchange Index, and Shenzhen Composite Index fell by 9.09%, 8.73%, and 8.99%, respectively, while more than 3000 stocks in the A-share market fell by the limit. This major public health emergency has the typical attribute of the "black swan" theory (Yarovaya et al., 2022), which describes an event that is outside the normal expected range, has an extreme impact, and is often inappropriately rationalized after the fact with the benefit of hindsight (Taleb, 2007).

In addition, China's stock market has experienced two serious stock disasters in recent years: the global financial crisis (GFC) in 2008 and the sharp domestic stock index decline following the promulgation of the deleveraging policy of the domestic regulatory authorities in 2015. Both show the characteristics of typical "black swan" events (Albonico and Tirelli, 2020; Rizvi and Itani, 2021). When the subprime crisis broke out

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in the U.S. in 2008, the S&P 500 index fell by 30%, while other countries' indexes performed worse. Affected by the decline in U.S. stocks and the panic due to the global crisis, the China Securities Index 300 (CSI 300) experienced its largest decline of 71%. During the stock disaster in 2015, the liquidity crisis caused by capital leverage triggered a stock market stampede, with 16 limit falls for 1000 shares in half a year. These major emergencies have brought great strife to investors and regulators.

When the market is impacted by major risks, the correlations among stock markets are enhanced, and the market risks are continuously transmitted among the stock markets, resulting in a "contagion effect" (Huang and Chen, 2020). The sharp change in financial market volatility that is caused by an increase in stock return variance due to major emergencies may also lead to a rapid selling of stocks due to panic and risk aversion. Such a sell-off increases short-term liquidity pressure in the stock market, or leads to market systemic risk. The correlation structure between stocks affects the risk transmission between them and plays an important role in the contagion effect. Therefore, it is important to understand the risk transmission and characteristics of the stock market under the impact of the epidemic, together with typical characteristics of a "black swan" incident.

Against this background, we are interested in understanding the impact of the three representative major emergencies—the GFC of 2007/2008, stock disaster in 2015, and COVID-19 event—on the correlation structure on China's stock market, and the differences between them: What are the key nodes and industries in the stock market, and how do they contribute to its systemic risk? How does the stock market network structure change over time? The answers to these questions can help us grasp the overall risk characteristics of the stock market, manage risks and formulate risk management measures under the impacts of different types of emergencies, and optimize portfolios.

This study uses China's stock market as its research object, with the unique research value of China's financial market. First, China's financial market plays a critical role in the global financial market. China is the world's second largest economy, while the renminbi (RMB) accounted for 2.15% of the global payment market in 2019, ranking fifth in the global payment market. With the opening of China's financial and foreign exchange markets, the RMB may become an increasingly important anchor point in the global foreign exchange market. The Shanghai Stock Exchange and Shenzhen Stock Exchange ranked third and fourth among the world's top 10 stock exchanges in terms of turnover, at $10.43 trillion and $7.72 trillion, respectively. Second, China's stock market boasts a unique system design. The stock market adopts the price limit of rises and falls, "$T + 1$" trading, restrictions on foreign shareholding, while the main board market's issuance system remains the approval system. The unique system design implies differences between China and developed countries' stock markets. Third, the proportion of individual investors in China's stock market is large: in 2019, individual investors still accounted for more than 90% of market participants and contributed more than 80% of trading volume. Institutional and individual investors exhibit different patterns of behavior: the latter are more sensitive to returns (Barber et al., 2006), which distinguishes the characteristics and correlation structure of market returns from those of developed countries.

In this study, we combine network analysis and sliding time window to build static and dynamic volatility networks of the stock market. We empirically analyze the constituent stocks of the Shanghai and Shenzhen 300 Index. First, we find that when the stock market is impacted by major events, the correlations between the stocks increases significantly, the network structure is more compact, showing a cluster phenomenon, while the stages and duration of the above agglomeration effect are inconsistent due to the different impacts of sudden events. In the 2015 stock disaster and the COVID-19 incident, the volatility threshold network of the stock market showed the characteristics of the overall holding in the face of shock, which lasted until the later stock disaster. The impact of the 2008 GFC on China's stock market was different from those of the stock disaster and COVID-19 events. The market agglomeration effect occurred after the crisis, not during the crisis, the cluster effect of the financial crisis events was smallest compared with those of the stock disaster and epidemic events, and the cluster effect of the epidemic event occurred most rapidly. Moreover, the dynamic change in the correlation degree of the stock market network showed that the information connection structure of the market changed with time and was affected by the impact sources and node differences. Second, key nodes in the stock market network have greater risk transmission ability. The characteristics of industry agglomeration in the stock market network amplify the risk transmission caused by node changes. The key nodes change due to the impact of the market and external influence. With the different event stages, key industries rotate. The manufacturing industry plays a crucial role during the later stages of all impact events, whereas the financial industry plays an important role during the epidemic's recovery period. Third, the stock market network structure has a certain indicative effect on the systemic risk contribution, which is consistent in three different markets: the A-share, U.S., and Hong Kong stock markets. Although the heterogeneity of the impact events leads to changes in the degree and direction of impact, some network indicators have the same impact on the systemic risk contribution. Generally, the greater the eigenvector centrality of a stock in an emergency, the greater its systemic risk contribution, while the greater its closeness centrality and clustering coefficient, the smaller it's systemic risk contribution.

Given the uncertainty regarding the impacts of major emergencies on the stock market and the uniqueness of China's stock market, the financial market regulatory authorities, financial institutions, researchers, and investors may be interested in our research results. The contributions of this study lie mainly in its new research questions and conclusions: First, the sudden major events significantly increased the overall relevance of the financial market system. The major external shocks were easily spread and transmitted, and the systemic risk of the financial market could not be ignored. The impacts of the three major events were extensive and continue to this day. Using the complex network method, this study can provide a more comprehensive and intuitive research perspective, explore the characteristics and general laws of the impacts of major emergencies on the stock market, and provide decision-making bases for investors and policy makers. Second, the study examines the changes in the network structure of China's stock market under the impacts of major emergencies. It captures the important structural characteristics of the stock market volatility network before, during, and after the major emergencies. Additionally, we establish how the network structure of the stock market evolves over time. Third, through the correlation and network analysis of different stages of the event, we identify the risk transmission ability of key stocks and industries during each stage, discuss the impact on the systemic risk contribution from the perspective of network structure, and analyze differences and similarities between different markets. The analysis enriches the research on the impact of emergencies on the financial market and the systemic risk contribution, and provides empirical evidence for the short-term impact on the stock market. The study is not only about expanding and deepening our understanding of the effects of major emergencies on the financial market, but is also a useful supplement to the research on sudden shocks and the correlation structure between complex network applications and China's stock market.

The remainder of the paper is organized as follows: Section 2 summarizes the literature on the impacts of major emergencies on the financial market, the identification of financial market risks, and the application of complex networks in the financial market. Section 3 introduces the research design and methods. Section 4 presents and discusses the empirical results, while Section 5 concludes.

2. Literature review

The impacts of major emergencies on financial markets have been widely investigated by financial supervision departments, academia, and investment institutions. A growing body of literature has accumulated on stock, foreign exchange, and commodity futures markets for specific emergencies. Ramiah et al. (2019) considered the impact of terrorist attacks on commodity futures markets that resulted in abnormal fluctuations in returns and long, continuous, response time. Similar studies include the impact of the Madrid and London bombings on the capital market (Kollias et al., 2011) and that of political risk events on the stock market (He et al., 2021a). Some studies examined the impact of natural disasters on stock markets in different stock markets and investigated the contagion effect of the trading market caused by this kind of emergencies (Huang et al., 2018). Concerning the impact of a financial crisis on the financial market, Bloom (2009) proposed a structural framework to investigate, at the company level, the impact on the financial market of uncertain events such as the Cuban missile crisis, crude oil price shock, and 911 terrorist attacks; the author then used a parametric model to simulate the macro uncertain impact. Ahmad et al. (2013) examined how the European debt crisis affected stock markets and risk transmission in emerging market countries by constructing a dynamic correlation coefficient. Similar studies include the stability of the stock market under sudden shocks (Heiberger, 2014), the impact of major sudden shocks such as a financial crisis, an election, war, and monetary policy changes on the stock index (Charles and Darné, 2014), and the impact of "black swan" events on the money market (Taylor and Williams, 2009). Since the outbreak of the epidemic, scholars have also focused on its impact on the market from multiple perspectives, such as the financial market, micro enterprises, and the macro economy (Zhang et al., 2020; Yousfi et al., 2021; He et al., 2021b; Yoo et al., 2021).

Under the impacts of major emergencies on the financial market, financial assets are exposed to common risk, which leads to the "herding effect," which results in market contagion and a stock market collapse. Therefore, risk identification in the event of a shock is an important research issue. Regarding the identification of financial market risk, researchers have extensively examined systemic financial risk factors. Adams et al. (2014) established a state dependent VAR model and investigated the spillover effect of financial institutions' systemic risk. Laeven et al. (2016) analyzed the determinants of systemic risk by using ΔCoVaR and found that the scale of bank assets was a crucial systemic risk factor. In addition, macroeconomic imbalances such as excessive credit expansion, the common risk exposure and risk contagion caused by the herding effect, information mismatch, and negative externalities were all relevant factors that led to systemic financial risks.

With the continuous development of modern econometric methods, investigating the financial market from the perspective of network topology has become a new perspective. Using the network approach, scholars have investigated information transmission among currency, commodity, stock, and bond markets (Yoon et al., 2019), the impact of a financial crisis on the network topology of the stock market in South America (Majapa and Gossel, 2016), financial crises and stock market network (Nobi et al., 2014; Coletti and Murgia, 2016; Memon and Yao, 2019), and differences in the impacts of financial crises and local crisis on stock market networks (Xia et al., 2018). Research on China's stock market network has appeared in recent years. Li et al. (2016) established return and volatility networks, and found that the link between global stock market returns and volatility was enhanced, and that China's connection to global stock markets was strengthened during the financial crisis. Ning and Tu (2019) used mutual information (MI) to define the nonlinear relationship between each stock price volatility and found that risk was rapidly transmitted to the whole market through nodes with a large number of connections, and that the operation of the stock market appeared to show industry agglomeration.

Generally, the impacts of major emergencies on the financial market have always been a research hotspot, and have mainly focused on events such as financial crises, natural disasters, and terrorist attacks. Most of the studies conclude that there is a short-term negative impact. Second, due to the advantages of complex networks in processing high-dimensional data sets and rich and intuitive analysis methods, their use as a useful measure in examining the impacts of major emergencies on the stock market network has gradually increased in recent years, including in examining the impact of financial crises. However, there has been insufficient direct research on the impacts of major public health emergencies on the stock market (Aslam et al., 2020b). In addition, some scholars have studied the impact of the 2008 GFC on different markets (Kao et al., 2019), and found that only the Chinese market was not affected by the U.S. market, indicating that the impacts of major emergencies would be significantly different due to different event characteristics or impact objects.

Second, risk identification when a major shock occurs has important economic and social significance. Asset correlation is a key element of modern financial risk measurement and management; however, traditional research methods focus more on pairwise interactions between variables, and ignore the overall network correlation structure of financial risk (Van de Leur et al., 2017). The network topology method can not only effectively describe the impacts of systemic financial risks on the financial market, but can also accurately measure their contributions to systemic financial risks; thus, it effectively unifies traditional research methods such as CoVaR and MSE into a common research framework. Existing studies have investigated stocks' contributions to systemic risk (Acemoglu et al., 2015) and the evolution of global systemic financial risks (Yang and Zhou, 2020) from the perspective of network correlation structure.

The existing literature on the impact of major events on the financial market has been relatively extensive; however, there are few comparative studies from the perspective of the correlation structure of the stock market network. Second, the current research on the identification of the systemic risk of the correlation structure of the financial market mainly focuses on financial institutions' local networks (Huang et al., 2016; Asgharian et al., 2021; there is no special choice for the time and stage of the data. The current study is a beneficial extension and deepening of previous research. We enrich the research on the impacts of major emergencies on the stock market. We study different major impact events and supplement the comparison of relevant relationship network topology indicators and industry changes during different stages of the events. Third, in the research on the identification of the systemic risk of the correlation structure of the financial market, this study expands the research object from financial institutions' local networks to the global network of the stock market, focuses on the characteristics during sudden events, and compares multiple markets. To our knowledge, there remains a lack of research on how different types of major emergencies affect the correlation structure characteristics of volatility in China's stock market and the identification of systemic risk. This study represents a useful supplement in addressing this deficiency.

We select three major emergency events with a deep impact on society and the economy that spread widely and are representative: The GFC in 2008 was a major global emergency that indirectly impacted China's stock market. The stock disaster in 2015 occurred in China, with a direct impact on China's stock market. COVID-19 first broke out in China, impacting the Chinese market first. Research on emergency events suggests that when an impact occurs, policy uncertainty increases investors' risk aversion, resulting in stock market fluctuation and a change in stocks' correlation structure. For the whole stock market, the trend in this change is consistent; thus, the network structure of the stock market is more compact when a shock occurs, while the time of occurrence of this effect may be different for different events. For individual stocks, inconsistent changes in network topology characteristics lead to changes in the key nodes of the network; this change in the association structure in turn leads to changes in its systemic risk contributions.

3. Research methods and data

3.1. Research methods

In this study, we select the constituent stocks of the CSI 300 index as the research object, and construct a minimum spanning tree (MST) to reflect the correlation structure of the stock market and identify close relationships within the stock markets. We use the constituent stocks of the CSI 300 index as nodes for network analysis and regard the edges as representing the relationships between them. There may be a complex correlation structure between stock markets. The correlation coefficient matrix can describe the overall behavior of the financial market, which can be expressed in the form of network analysis from the perspective of topology. The overall correlation structure of the stock market may not be stable under the impacts of major emergency events, while the positions of some industries or individual stocks may be more important in some periods of risk transmission. We use the degree, clustering coefficient, and centrality of the network to investigate the time-varying characteristics and stability of the network structure of the stock market, and identify the core marginal position in the stock market.

The network approach used in this study has unique advantages. Previous studies typically used complex measurement methods to estimate the impacts of major emergency events on the underlying assets; it was difficult to examine the impact of exogenous shocks on the stock market from the overall perspective of the stock market. We use the threshold method and an MST in our network analysis. Only the correlation matrix is used as the starting point of the analysis, with no additional presumptions about the price relationships between assets. In addition, an MST has the advantage that it can be used to simultaneously investigate the characteristics of the overall stock market behavior during major emergency events. It captures the important static structure characteristics of the stock market network under major emergency events while its shows the dynamic characteristics of the evolution of the stock market network structure.

3.1.1. Volatility of stock market prices

This study uses realized volatility to measure stock price uncertainty. Compared with the return index commonly used in existing studies, volatility is a more important core index at the level of risk management (Christoffersen and Diebold, 2000). Consider n stocks in the stock market, constituting a set, $I = \{i|i = 0, \dots, n\}$, where each stock corresponds to the *ith* element of set *I*. We define $P_i(t)$ as the closing price of the *ith* stock in period *t*, while the return, $r_i(t)$, after the time interval, (Δt), of the *ith* stock can be calculated using the following formula:

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

We use daily frequency data to construct the volatility network. The daily frequency volatility is a latent variable that cannot be directly observed. As the daily frequency data are generally available, long-range observations can be obtained. The estimation of volatility is typically estimated using the GARCH (Bollerslev, 1987), stochastic volatility (Taylor and Williams, 2009), and Black-Scholes option pricing models (Black and Scholes, 1973). We use the GARCH model to estimate each stock's realized volatility. The form of the GARCH (p, q) model is as follows:

$$P_i(t) = \mu + \varepsilon_i(t), \tag{2}$$

where $\varepsilon_i(t) = \sigma_i(t) z_i(t)$, and

$$\sigma_i(t) = \kappa + \gamma_1 \sigma_i^2(t-1) + \dots + \gamma_P \sigma_i^2(t-P) + \alpha_1 \varepsilon_i^2(t-1) + \dots + \alpha_Q \varepsilon_i^2(t-Q), \tag{3}$$

where $\kappa > 0; \gamma_i \geq 0,\ \alpha_i \geq 0$; and $\sum_{i=1}^{P} \gamma_i + \sum_{j=1}^{Q} \alpha_j < 1$.

3.1.2. Stock market network with an MST

To use an MST to construct the stock market network, we first need to determine the distance between the nodes of the stock market network. Pearson's correlation coefficient is widely used in the existing literature (Mantegna, 1999; Onnela et al., 2004) to measure network connection and nodes' distance. However, Pearson's correlation coefficient is only applicable when one measures the linear correlation between variables; it is difficult to use to capture nonlinear correlation information between price volatility variables, while financial time series variables often show a nonlinear correlation pattern (Guo et al., 2018). Therefore, we use MI to measure the correlation between stock volatilities and construct the MST.

MI is a measure of useful information in information theory. It can be regarded as the amount of information on one random variable contained in another random variable (Dionisio et al., 2004). It is often used to measure nonlinear correlation between variables. The definition of information entropy is as follows:

$$H(X) = -\sum_i p(x_i) \log_2 p(x_i), \tag{4}$$

where $p(x_i)$ represents the probability distribution of *X*. For two-dimensional random variables, *(X,Y)*, the joint entropy is defined as follows:

$$H(X,Y) = -\sum_i \sum_j p(x_i, y_j) \log_2 p(x_i, y_j), \tag{5}$$

where $p(x_i, y_j)$ represents the joint probability distribution of *(X,Y)*. The MI of *X* and *Y* is defined as:

$$I(X,Y) = H(X) + H(Y) - H(X,Y) \tag{6}$$

If and only if *X* and *Y* are independent, is MI, $I(X,Y) = 0$. To standardize the MI in the interval, [0,1],

$$N(X,Y) = \frac{2I(X,Y)}{H(X) + H(Y)} \tag{7}$$

This study adopts the interval number of 10 * 10 and converts the MI of stocks *i* and *j* into distance (Guo et al., 2018):

$$D(X,Y) = 1 - \frac{I(X,Y)}{H(X,Y)} \tag{8}$$

The main purpose of an MST is to filter the redundant connections of a network, extract the important connection information in a stock market, and maintain the simplest structure of the stock market network (Mantegna, 1999; Onnela et al., 2004). For a network with *N* nodes, all possible connection bits equal $N(N-1)/2$. An MST selects the *(N-1)*th strongest connection, which corresponds to the shortest path of all vertices on the overlay. We use Prim's algorithm to construct an MST, following Prim (1957).

3.1.3. Network topology indicator

3.1.3.1. Degree centrality.

In a stock market network, the degree of an asset is defined as the number of assets connected with it. The degree and degree distribution of assets are used to reflect the market position of assets and to investigate the changes of relative positions among assets in dynamic analysis (Gong et al., 2019; Onnela et al., 2003). Degree centrality characterizes the importance of nodes in a local network composed of their adjacent nodes. The greater the degree centrality, the more important a stock is.

$$k_i = \sum_{j=1}^{n} A_{ij} \tag{9}$$

$$D(i) = \frac{k_i}{(n-1)} \tag{10}$$

Here, k_i and $D(i)$ are the degree of an asset and degree centrality, respectively, A_{ij} is the adjacency matrix of the financial market network. If and only if assets *i* and *j* exist in an MST, $A_{ij} = 1$; otherwise, $A_{ij} = 0$. *n* is the number of assets in a stock market network.

3.1.3.2. Betweenness centrality. The betweenness centrality of a market is a key indicator for measuring the network centrality (Huang and Wang, 2018; Ji and Fan, 2016):

$$B(i) = \frac{2}{(N-2)(N-1)} \sum_{(j,l)} \frac{\sigma_{jl(i)}}{\sigma_{jl}}, j \neq i \neq l, \tag{11}$$

where $B(i)$ is the betweenness centrality of asset i, $\sigma_{jl(i)}$ is the shortest path from asset j to asset l via asset i, and σ_{jl} is the shortest path from asset j to asset l. Betweenness centrality, $B(i)$, reflects the extent to which other assets in an asset network depend on asset i. The greater the value of $B(i)$, the higher the central position of asset i in the asset market.

3.1.3.3. Closeness centrality. Closeness centrality is defined as the reciprocal of the sum of the shortest distances, i, to all other nodes multiplied by the number of other nodes (Costenbader and Valente, 2003; Ji et al., 2018). The greater the closeness value of a node, the more the node lives in the center of a network, and the more important it is in the network.

$$C(i) = \frac{1}{L_i} = \frac{N-1}{\sum_{(i,j)} d_{ij}} \tag{12}$$

3.1.3.4. Eigenvector centrality. The importance of a node depends on the number and importance of adjacent nodes. The method for calculating eigenvector centrality is similar to that for calculating degree centrality. The difference is that, for the former, to calculate the number of edges connected with adjacent nodes, each edge is weighted by the degree centrality of adjacent nodes, and then summed. Eigenvector centrality can absorb the quantity and quality information of adjacent nodes. A larger value of eigenvector centrality indicates that node i can transmit information to more individuals and extract more information through these individuals. The calculation formula is as follows, where λ is a constant and the largest eigenvalue of the adjacency matrix (Bonacich, 2007):

$$e_i = \lambda \sum_{J=1}^{N} A_{ij} e_j \tag{13}$$

3.1.3.5. Clustering coefficient. A clustering coefficient describes the possibility that individuals' adjacent nodes in a network are neighbors to each other. We cannot calculate the node clustering coefficient of an MST network; therefore, we use the original network based on MI. Since the network is a completely weighted, undirected network, we choose the weighted clustering coefficient (Saramäki et al., 2007). The clustering coefficient of node i is defined as

$$CC_i^t = \frac{1}{N(N-1)} \sum_{j,k} \left(\left|\rho_{i,j}^t\right| \times \left|\rho_{i,k}^t\right| \times \left|\rho_{j,k}^t\right| \right)^{\frac{1}{3}}, \ i \neq j, i \neq k, j \neq k \tag{14}$$

3.1.4. ΔCoVaR of stock market

VaR stands for value at risk, which is used to measure the maximum loss that relevant assets or an asset portfolio may encounter under a certain confidence level in a certain period. A regulated institution uses it to determine the capital level that financial institutions need to set aside to deal with market risks (Huang et al., 2016). Given the returns, X_t^i, of an asset and the confidence level, $1-q$, $VaR_{q,t}^i$ is defined as:

$$Pr\left(X_t^i \leq VaR_{q,t}^i\right) = q \tag{15}$$

Adrian and Brunnermeier (2016) proposed a measure for systemic risk, namely, conditional value-at-risk (CoVaR). $CoVaR_{q,t}^{j|i}$ is the VaR of asset i when the confidence level is $1-q$ under the condition that $C(X^i)$ of asset i occurs at time t:

$$Pr\left(X_t^j \leq CoVaR_{q,t}^{j|C(X^i)} \middle| C(X^i)\right) = q \tag{16}$$

$\Delta CoVaR_{q,t}^{j|i}$ is the risk contribution to asset j, or the whole system when the asset is in trouble, and is defined as the difference between the $CoVaR$ conditional on the distress of asset i and the $CoVaR$ under normal conditions. It reflects the marginal contribution of asset i to the overall systemic risk, which is expressed as follows:

$$\Delta CoVaR_{q,t}^{j|i} = CoVaR_{q,t}^{j|C(X^i)} - CoVaR_{q,t}^{j|X_i = Median^i} \tag{17}$$

$CoVaR_{q,t}^{j|X_i=Median^i}$ indicates that the value of VaR under the confidence level of the system is $1-q$ when the return rate of asset i is in the median state.

We use a quantile regression model to estimate $CoVaR$. A quantile regression model is suitable for dealing with heteroscedasticity, and can describe a conditional distribution in detail, the estimator is not easily affected by outliers, and the parameter estimation result is more robust. First, quantile regression is conducted for stocks' daily return data:

$$X_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i \tag{18}$$

$$X_t^{system|i} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_t + \varepsilon_t^{system|i}, \tag{19}$$

where X_t^i represents the return of stock i at t, $X_t^{system|i}$ represents the return of the system at t, and M_t represents the state variable. This study uses the conditional variance of the return rate of the index as the state variable. Based on the estimation results of Eqs. (18) and (19), the corresponding VaR and $CoVaR$ can be calculated:

$$VaR_{q,t}^i = \widehat{\alpha}_q^i + \widehat{\gamma}_q^i M_t \tag{20}$$

$$CoVaR_{q,t}^i = \widehat{\alpha}_q^{system|i} + \widehat{\beta}_q^{system|i} VaR_{q,t}^i + \widehat{\gamma}^{system|i} M_t \tag{21}$$

$\Delta CoVaR_{q,t}^{j|i}$ is calculated based on Eq. (17).

3.1.5. Evolution and stability of financial markets

To analyze the characteristics and stability of a stock market network structure over time, we investigate the performance of statistical characteristics such as MI and its standard deviation, network centrality, and edge density, over time, and evaluate the dynamic statistical characteristics of the financial market network. We use a sliding time window to calculate the time-varying values of the above indicators. The choice of window size is a trade-off between excessive noise and excessive smoothing. We set the window size to 100 days, based on similar studies (Ji and Fan, 2016). The specific procedure is as follows: Calculate 100 observations at a time and estimate these measurements recursively, then move along the time scale, and the window step size is 1.

3.2. Data and descriptive statistics

3.2.1. Data

We use the closing prices of the constituent stocks of the CSI 300 index as the research object for empirical analysis. The stock market value of the CSI 300 index component accounts for approximately 60% of the total market value of the A-shares, while its main income market share is basically stable, at approximately 70%. These stocks command high market value, are highly liquid, and exhibit obvious industry characteristics. Therefore, the constituent stocks of the CSI 300 index are highly representative and indicative. Considering the availability of actual data, we selected data from a recent five-year period, i.e., from January 9, 2007 to December 18, 2020, with a total of 3394 observations, and obtained a total of 3294 windows with complete examples. The data involved the GFC in 2008, the stock disaster in 2015, and the COVID-19 outbreak in 2020. Considering the long time span of the three events and the regular adjustment of the CSI 300 index's sample stocks, each shock's data observations were screened separately. We selected the complete stock price data for the three shock events in the study period. Among the data were 263 stocks during the GFC, 280 stocks during the stock disaster, and 300 stocks during the COVID-19 outbreak. With reference to the industry classification standards by the CSRC for listed companies, we classified the sample stocks as follows: (1) financial industry, (2) real estate industry, (3) construction industry, (4) power, heat, gas and water production and supply industry (utilities), (5) mining industry, (6) wholesale and retail industry, (7) transportation, warehousing and postal industry, (8) information transmission software and information technology service industry, (9) manufacturing, (10) culture, sports and entertainment, (11) agriculture, forestry, animal husbandry and fisheries, (12) scientific research and technology services, (13) health and social work, (14) leasing and business services, (15) water conservancy, environment and public facilities management, (16) education, and (17) comprehensive. The research sample for this study comprises daily frequency data. To construct a volatility network for China's stock market, we use a GARCH process to estimate each asset's historical volatility as a proxy variable, since volatility is a latent variable and cannot be directly observed.

Based on the event research method, we use the following research design: the sample period for the 2008 U.S. subprime crisis is from January 15, 2008 to November 18, 2008. On January 15, 2008, Citigroup, Merrill Lynch, UBS, AIG, and other large banks and insurance companies reported huge losses. Mortgage institutions' bankruptcy risk spread to the financial field and marked the official outbreak of the subprime mortgage crisis. On November 18, 2008, the Chinese government launched an economic stimulus plan, which temporarily alleviated the crisis. The sample period for the stock disaster in 2015 is from June 12, 2015 to January 8, 2016. On June 12, 2015, the regulatory authorities began to clean up the over-the-counter capital allocation, which induced leveraged investors to rapidly sell a large number of financing trading positions to repay. The massive sell-off caused a shortage of liquidity, resulting in a steep decline in stocks' market prices. In early 2016, the circuit breaker mechanism was triggered twice; on January 8, 2016, the circuit breaker mechanism was canceled and the stock market stabilized. The COVID-19 epidemic case in 2020 was from January 11, 2020 to March 10, 2020. January 11, 2020 is the first day of the National Health Council's announcement of data on COVID-19, and the first day of the first death case report. Thus, we use January 11, 2020 as the start date of the novel coronavirus epidemic event. On March 10, 2020, the last batch of patients were cured and left hospital. All the shelter hospitals in Wuhan were officially closed. The epidemic was effectively contained and the period of recovery from the epidemic began. By the middle of March, the overseas epidemic had spread globally, and led to four circuit breakers in the U.S. stock market and a decline in the Chinese stock market. Therefore, from this time onward, the performance of the stock market was affected less by the epidemic and more by external pressure.

We use the same trading days before the start date of the event as in the pre-event window, and the same trading days after the end date of the event as in the post event window. Therefore, the time range for the selected data sets for the three impact events is from March 15, 2007 to September 17, 2009, November 13, 2014 to August 8, 2016, and November 21, 2019 to April 30, 2020, respectively, for the GFC, stock market disaster, and COVID-19 epidemic. The sample data were obtained from the Wind financial terminal. In addition, for the sudden events that occur on legal holidays and weekends, when the financial market is closed, we use the first trading day after the event instead.

Table 1 shows the time division before, during, and after the three events in this study.

3.2.2. Data description

On January 15, 2008, major financial institutions in the U.S. suffered extensive losses, and the subprime mortgage crisis spread globally. The CSI 300 index continued to decline from 5696 points to an historical low of 1663 on October 31, 2008, a decline of nearly 71%. In November of the same year, the government issued the "four trillion" rescue plan, and the index reached the bottom before it rebounded. In June 2015, the regulatory authorities began to clean up off-site capital allocation and deleveraging, causing market panic. The CSI 300 index began to decline from 5225 points to a lowest point of 3025 on August 26, 2015, a decrease of nearly 42%. A standard reduction policy was issued at the end of August, when the stock market temporarily stabilized. In early 2016, the circuit breaker mechanism was triggered twice, and was urgently stopped four days after its implementation. In the following month, the market fell nearly 1000 points and rebounded at the end of the month. The first COVID-19 death occurred on January 11, 2020. On January 20, 2020, the fact that the epidemic was transmitted to humans was confirmed. The Health Commission took measures to prevent and control class A infectious diseases. From January 20, 2020, the CSI 300 index dropped by 497 points in 5 trading days, and dropped to nearly 12% points from 3688 points on February 3, 2020. Then, over 20 trading days, it rose to 4206 points on March 5, 2020, an increase of approximately 14%. The descriptive statistics for the CSI 300 index are presented in Table 2. Due to lack of data on the highest, lowest, and closing prices caused by suspension, this study uniformly uses the stock closing price data of the day before the loss (De Truchis and Keddad, 2016) to calculate volatility.

Table 1
Sample time interval description.

	Sample interval	Start date	End date
2008-GFC	Pre-crisis	March 15, 2007	January 14, 2008
	crisis	January 15, 2008	November 18, 2008
	Post-crisis	November 19, 2009	September 17, 2009
2015-Stock Disaster	Pre-disaster	November 13, 2014	June 11, 2015
	disaster	June 12, 2015	January 8, 2016
	Post- disaster	January 11, 2016	August 8, 2016
2020-COVID-19	Pre-epidemic	November 21, 2019	January 10, 2020
	During-epidemic	January 11, 2020	March 10, 2020
	Post-epidemic	March 11, 2020	April 30, 2020

As shown in Fig. 1, of the three shock events, the impact of the stock disaster in 2015 was the largest, while the volatility was the highest in the sample period; the second is the GFC, which lasted for a long time and fluctuated extremely. Compared with the fluctuations due to the stock disaster and GFC, the stock market fluctuation caused by the epidemic was smaller.

4. Results of empirical research and corresponding analysis

4.1. Change in stock market correlation structure in sudden shock

In what follows, we start with the overall structure of the stock market network, and examine the changes in the stock market correlation structure under the major emergency events using static and dynamic comparative analyses.

4.1.1. Stock market threshold network comparison

In this section, we use the threshold method (Namaki et al., 2011) to construct the stock market network. We use MI to calculate the correlation of stock price volatility among the three events, and compare the correlation coefficients of the three events at different stages, as shown in Table 3. Evidently, the average MI after the GFC in 2008 was higher, showing a stronger cluster effect than that under the impact of the crisis. In the stock disaster events in 2015, the average correlation coefficient during and after the stock disaster was higher than that before the stock disaster. The MI increased by 58.78% and 53.13%, respectively,

Table 2
Descriptive statistics of the CSI 300 index.

Time	Mean value	Standard deviation	Skewness	Kurtosis	Maximum value	Minimum value
2007.1.9–2020.12.18	3281.5	804.99	0.53	2.98	5877.2	1627.8
2008-GFC	3210.8	1033.80	0.29	2.06	5696.4	1627.8
2015-Stock Disaster	3762.7	431.92	1.30	5.33	5335.1	3025.7
2020-COVID-19	4048.3	123.75	−1.00	3.55	4206.7	3688.4

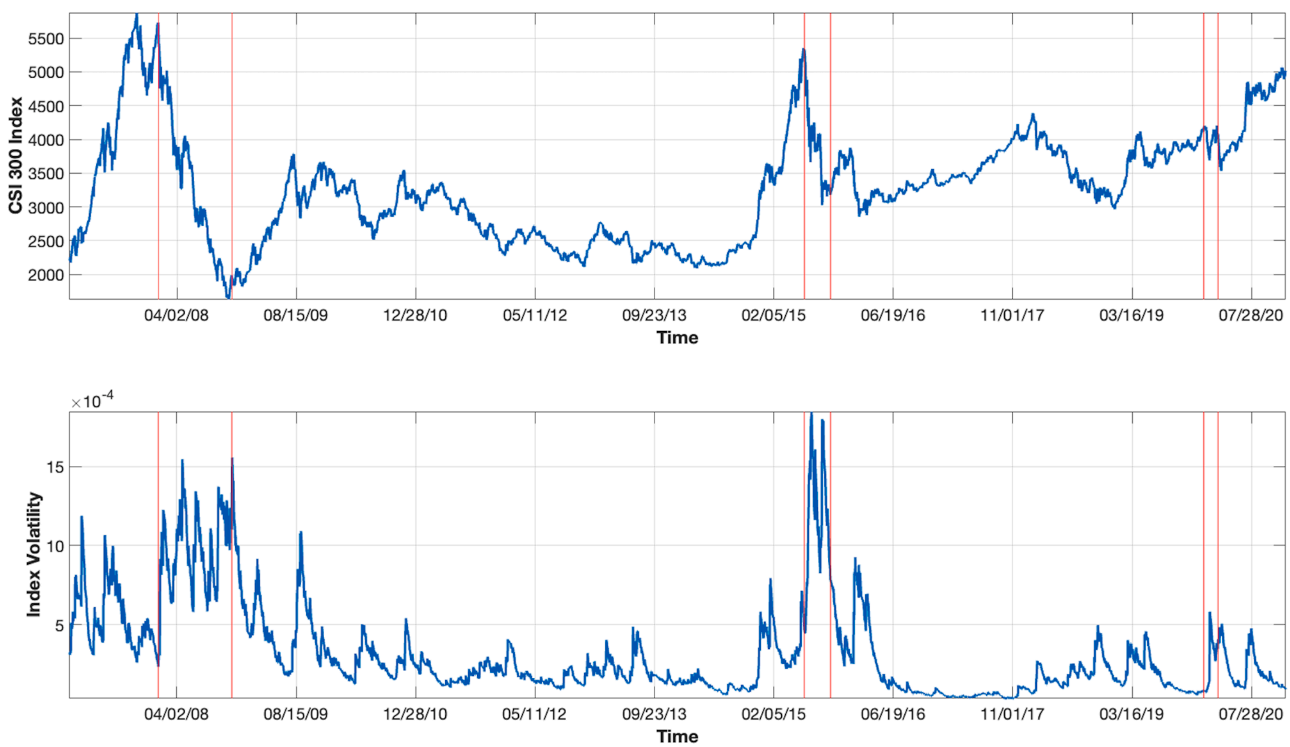

Fig. 1. Trend of the CSI 300 index and volatility (from January 9, 2007 to December 18, 2020).

Table 3
Comparison of correlation indexes during different stages of each event.

		MI Mean	Max	Min	DMI Mean	Max	Min
2008-GFC	Pre-crisis	0.07	0.50	0.00	0.91	1.00	0.11
	crisis	0.07	0.50	0.00	0.92	1.00	0.12
	Post-crisis	0.09	0.50	0.00	0.90	1.00	0.12
2015-Stock Disaster	Pre-disaster	0.10	0.50	0.00	0.88	1.00	0.13
	disaster	0.15	0.50	0.00	0.80	0.99	0.12
	Post-disaster	0.15	0.50	0.00	0.81	1.00	0.30
2020-COVID-19	Pre-epidemic	0.15	0.50	0.00	0.82	0.99	0.25
	During-epidemic	0.17	0.50	0.01	0.79	0.99	0.06
	Post-epidemic	0.16	0.41	0.00	0.78	0.97	0.31

compared with the values before the disaster. The strong correlation between the stock markets suggests that all the stocks were impacted during the stock disaster, while the impact of this common shock lasts for a period after the disaster. The highest average correlation coefficient is recorded during the epidemic period, and the MI is 0.17; the correlation between stock markets during the recovery period has declined, although it remains higher than the pre-epidemic level.

Next, based on the stock standard MI correlation matrix, we construct the stock market network of each shock event and analyze the parameter information changes in the threshold network at different stages. Using θ[0.1, 0.2] as the interval and 0.05 as the step, we establish nine adjacency matrices for the three impact events. Table 4 shows the differences in the graph density, average degree, and clustering coefficient of the stock market network under different thresholds. With an increase in θ, the density of the threshold network decreases significantly (Xu et al., 2017). To ensure sparsity and connectivity, we select the threshold network with reasonable graph density for event comparison and analysis. We find that in any threshold network, the density, average degree, and clustering coefficient of the network are smallest during the GFC, followed by those during the stock disaster network. The highest values occur in the COVID-19 network. This shows that, with the continuous development of the stock market, the correlation between stocks in the market increasingly strengthens.

When $\theta = 0.1$, the network density, average degree, and clustering coefficient during the financial crisis in 2008 decreased compared with those before the crisis but increased significantly after the crisis. This indicates that the correlation between stocks is stronger after the financial crisis, which is inconsistent with the conclusion in Memon and Yao (2019)'s study, in which the overall performance of the stock market during the financial crisis was stronger. A possible explanation is that, on the one hand, the impact of the GFC on China was smaller than that on other developed countries (Kao et al., 2019). On the other hand, China issued a stronger economic stimulus plan for the financial crisis, with a greater impact on China's stock market, resulting in a significant increase in the integrity of China's stock market after the financial crisis, which was even higher than that before the financial crisis.

When $\theta = 0.2$, the clustering coefficient before the outbreak of the

Table 4
Threshold network density, average degree, and clustering coefficient during different stages of each event.

		$\theta > 0.1$ network density	average degree	clustering coefficient	$\theta > 0.15$ network density	average degree	clustering coefficient	$\theta > 0.2$ network density	average degree	clustering coefficient
2008-GFC	Pre-crisis	28.91%	69.09	0.66	12.74%	22.05	0.42	10.53%	8.95	0.19
	crisis	23.60%	58.06	0.58	5.22%	10.23	0.37	6.43%	4.95	0.12
	Post-crisis	37.39%	92.35	0.69	22.37%	40.71	0.46	16.81%	17.98	0.22
	Pre-disaster	49.46%	133.54	0.77	20.14%	48.13	0.60	9.91%	17.63	0.38
2015-Stock Disaster	disaster	76.05%	206.10	0.88	54.36%	145.15	0.82	45.86%	106.85	0.66
	Post-disaster	76.06%	203.84	0.87	60.95%	155.41	0.79	46.19%	104.40	0.64
2020-COVID-19	Pre-epidemic	81.10%	241.67	0.91	50.62%	150.84	0.76	18.65%	54.84	0.55
	During-epidemic	85.12%	253.65	0.90	84.94%	163.73	0.76	27.03%	80.54	0.65
	Post-epidemic	91.18%	271.71	0.95	65.42%	194.30	0.82	27.99%	82.01	0.61

stock disaster in 2015 was 0.38, and increased rapidly to 0.66 during the disaster. After the stock disaster, the clustering coefficient did not change significantly, remaining at 0.64. The comparison of average degree and density is similar. This suggests that during the stock disaster, the correlation between stocks is stronger, and the stock market tends to behave as a unit; this impact continues until after the stock disaster. When $\theta = 0.2$, the network density before the COVID-19 epidemic was 18.65%. Compared with that during the early stage of the epidemic outbreak, the density during the epidemic increased by 45% – 27.03%, while the density during the epidemic's recovery period was even higher, at 27.99%. This suggests that there was a stronger correlation between stocks after the outbreak of the epidemic, and the phenomenon of agglomeration had not been significantly alleviated during the period of recovery from the epidemic. It may be because the overseas epidemic broke out in late March, China's stock market was affected by the global capital market, and the impact of the epidemic continued.

4.1.2. Stock market MST network dynamic analysis

From the comparative static analysis in 4.1.1, we find that the correlation structure of the stock market system is unstable; thus, it is critical to examine the dynamic evolution of the stock market structure over time. In this subsection, we use Prim's algorithm (Prim, 1957) to construct an MST network based on an MI distance matrix. We use the sliding time window specified in 3.1.5 to calculate the mean and standard deviation of the MI distance matrix, which are used to construct the MST, and investigate its time-varying characteristics.

To ensure data consistency, the stocks used in this section are the constituent stocks of the CSI 300 index that were common during the whole sample period, numbering 67. The dynamic change in the MI distance (DMI) distribution is shown in Fig. 2. The DMI value evolves extremely unstably with time. The basic law is that in the case of major emergencies and major market events, the volatility of the stock market will rise, and the average DMI will decline; that is, the correlation between stocks will rise, as evident from Fig. 2. During the three shock events in this study, the average DMI decreased significantly. During the

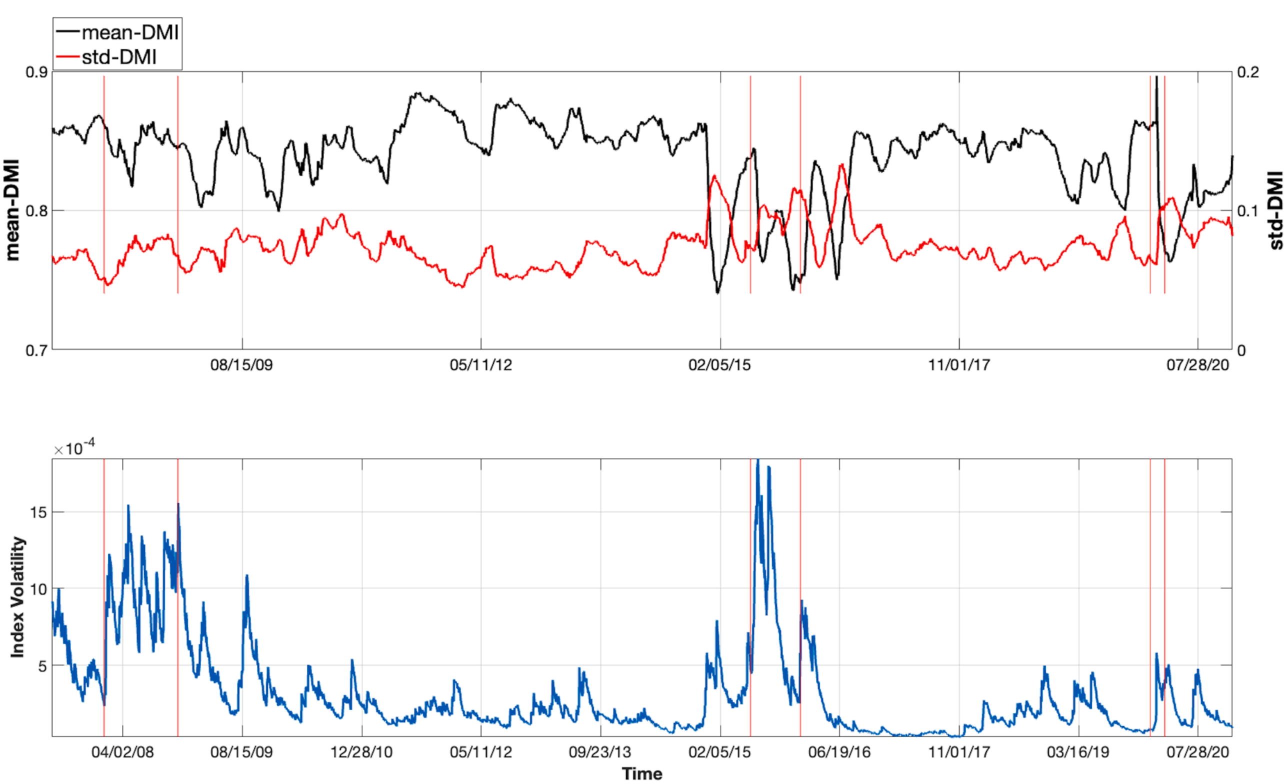

Fig. 2. Dynamic structure of stock market network.

GFC in 2008, the DMI decline was smallest, at 5.0%, while there were many declines of the same magnitude after the crisis. This shows that the stock market correlation improved during the financial crisis; however, it appears to have been stronger after the crisis, which is similar to the results from 4.1.1. During the stock disaster in 2015, the average DMI decreased significantly, from 0.84 to 0.76, and then rose briefly to 0.80, before it decreased to 0.74; the phenomenon of stock market agglomeration was obvious and continued until after the disaster. During the epidemic outbreak period, the average DMI rose to the highest point in the sample, reaching 0.89. With the development of the event, the DMI value rapidly dropped to 0.78, and gradually increased in the late stage of the epidemic.

Of the three shocks, the stock market agglomeration effect was the smallest in the GFC in 2008. During the stock disaster in 2015, the fluctuation range widened the most in the whole sample, whereas that of the average DMI narrowed the most in the whole sample. The phenomenon of stock conglomeration was obvious, and the standard deviation of the average MI distance (std-DMI) changed most dramatically, which shows the great impact of this event on the stock market. The epidemic and stock disaster have a similar impact on the overall relevance of the stock market. However, the impact of the epidemic on the stock market was more rapid: The DMI declined the most in a short time, with a decrease of 14.9% in 30 trading days, while the stock disaster lasted longer than half a year.

The analysis of the dynamic structure of the stock market MST network reflects that the information connection structure of the market changes with time. Affected by the different impact sources and nodes, the major impact events break the original structure and trigger new information connections.

4.2. Stock market risk identification during a major emergency event

In this subsection, we start with individual stocks, identify the industry characteristics and key nodes in each event through the network topology, and discuss their risk transmission ability and systemic risk contribution in the stock market network. We construct MST networks for each shock event in different stock markets, including three-stage subsamples and full-stage samples. Using the Shanghai and Shenzhen stock market as an example, we examine the cluster characteristics and key node changes during different stages of the impact events, and compare the network topology structures of the Chinese, U.S., and Hong Kong stock markets to identify the systemic risk contributions.

4.2.1. Distribution characteristics of network nodes

Based on the node degree frequency distribution, we construct a degree distribution and linear fitting diagram (in double logarithmic coordinates) for the whole stage network for the three events. From the degree distribution diagram (see Fig. 3), few nodes with large degrees occur in the stock market network. The number of corresponding nodes decreases exponentially with an increase in degree, which shows the characteristics of the scale-free networks. Barabási and Albert (1999) proposed that the degree of nodes in a scale-free network exhibited the characteristics of a power-law distribution, that is, $P\ (K \geq k) \propto k - \gamma$, where $p\ (K \geq k)$ is the degree distribution function and k is the number of degrees. It has been found that financial networks obey a scale-free structure (Onnela et al., 2003).

Based on the degree value of the network, we divide stock nodes into three categories: The first group is of the nodes with a degree value greater than 6; the number of such stocks is small but the impact is significant. Generally, they are typically the first to be affected by stock market fluctuations, and will transfer the risk to the connected stocks to a great extent. The second group is of the secondary nodes with a degree

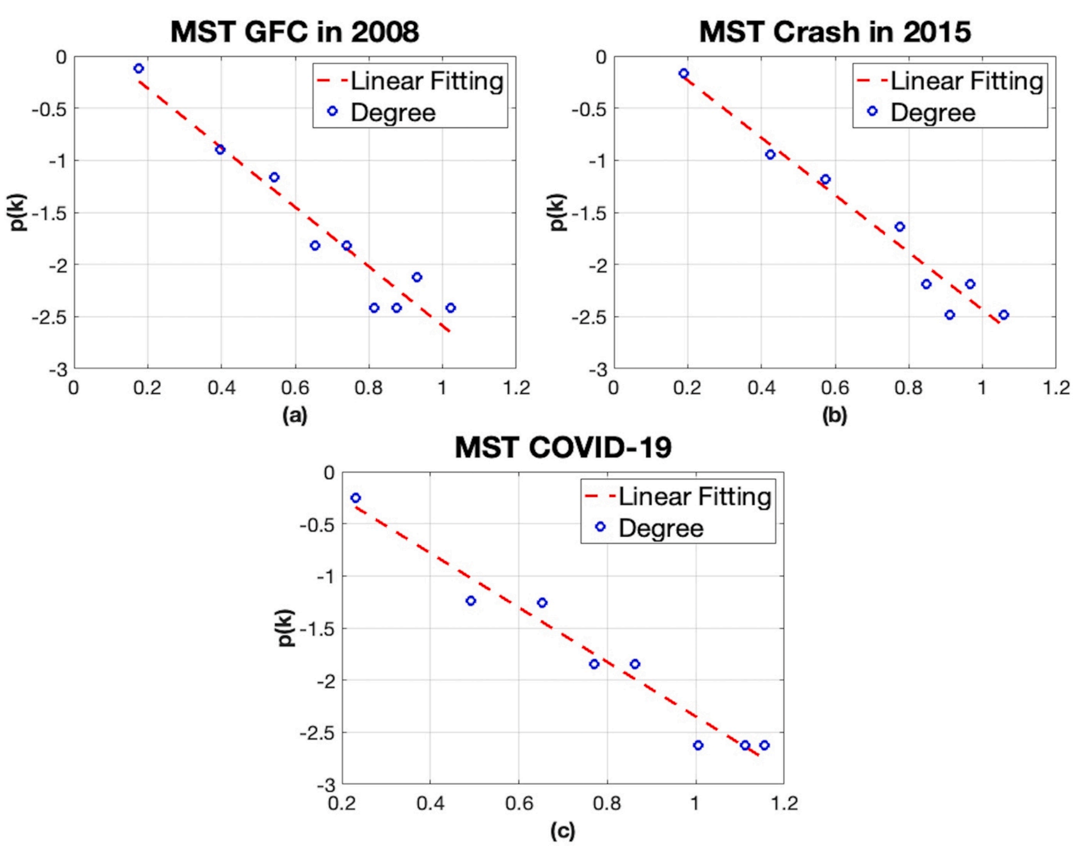

Fig. 3. Degree distribution of MST in double logarithmic coordinates.
Note: (a), (b), and (c) are the MST network distribution and fitting graphs for GFC, Stock disaster, COVID-19.

value between 2 and 6, which transmit the risk of key nodes to other nodes. The third group is of the nodes with degree 1. This kind of stock is at the edge of the network and has little impact on the network.

In the whole-stage network for the GFC, only 9 nodes with a degree value greater than 6, accounting for 3.4% of the total nodes, are distributed in the center of the network graph, and 50.8% with degree 1 are distributed at the edge of the network graph. In the stock disaster whole stage network, there were 13 nodes with a degree value greater than 6, accounting for 4.6% of the total nodes, and the nodes with degree 1 accounted for 52.0% of the total. The COVID-19 whole-stage network has 15 nodes with degree values greater than 6, accounting for 5.0% of the total number of nodes, and 57.2% with degree 1.

4.2.2. Cluster characteristics of network node distribution

A network diagram can intuitively reflect the internal correlation of stock fluctuations. The MST network contains rich information about the correlation structure of the stock market. Figs. 4, 5, and 6 show the MST stock network diagrams of the Shanghai and Shenzhen Stock Markets for the 2008 GFC, 2015 stock market disaster, and COVID-19 epidemic, respectively, including subsamples at each stage of the three events. Node size represents the number of connections with other stocks (degree), while different industries are represented by different colors.

We find that the industry distribution is different during each stage. The number of manufacturing industries has always been the largest. In addition, during the financial crisis, the stock market was mainly dominated by the transportation, real estate, and energy industries. During the stock market disaster and epidemic, the number of firms in the financial industry increased significantly, and the influence was greater. The connection of the stock market system most intuitively reflects the connection and tightness between stocks. Most of the closely connected nodes belong to one industry, which is especially true for stocks that are directly connected to the central node. Moreover, the connection mode between these nodes shows a significant phenomenon of industry agglomeration, which is related to the similar products and services that are provided by enterprises that belong to the same industry, with similar responses to external factors. For example, in the financial crisis event, there are multiple manufacturing clusters, while the wholesale and retail and transportation industries connect multiple manufacturing clusters. During the stock disaster and epidemic events, there are obvious industry clusters in the manufacturing and financial industries. During the stock disaster, there are also cultural and entertainment and energy industry clusters. The financial industry is highly concentrated during the epidemic events, with numerous important nodes that play an important role in protecting the market during the outbreak. During the epidemic's recovery period, the industry is widely connected with manufacturing, real estate, and other industries, and continues to play a role in stabilizing the economy.

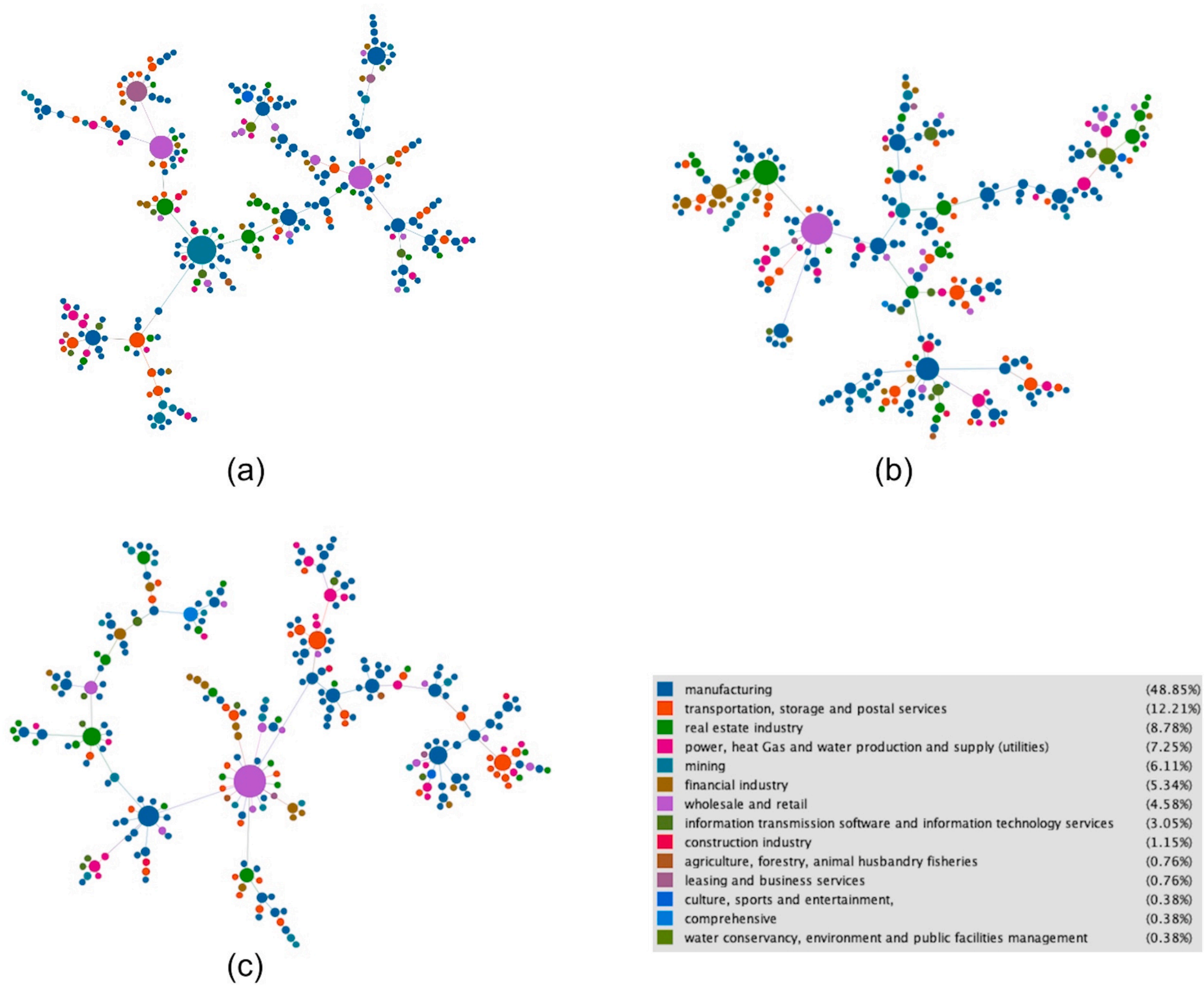

Fig. 4. MST of the three stages in the 2008 GFC.
Note: (a), (b), and (c) are the MST networks before, during, and after the event.

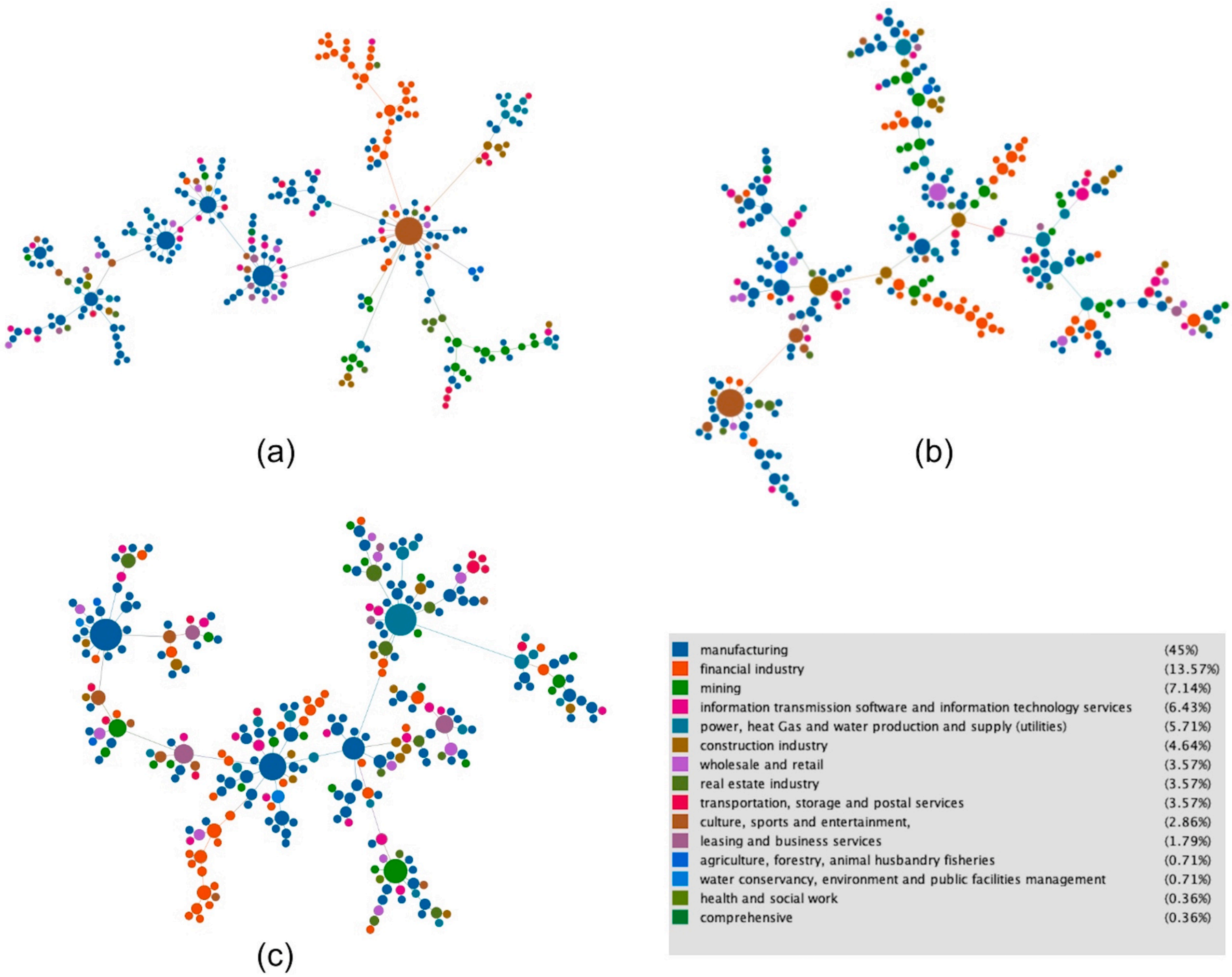

Fig. 5. MST of the three stages in the 2015 Stock disaster.
Note: (a), (b), and (c) are the MST networks before, during, and after the event.

4.2.3. Network centrality indicates key nodes

Degree, betweenness, closeness, and eigenvector centralities are four indicators that measure the importance of nodes in a network (Gao et al., 2016). The economic meaning of each centrality indicator in the stock market network, as well as and the evaluation angle of node importance are different. The degree centrality calculates the proportion of the stocks that are connected to one node in the whole network, reflecting the position of the stock in the market. The stocks with greater degree centrality carry a greater weight of the stock market volatility network, with a stronger local risk contagion ability. The betweenness centrality reflects the dependence of other stocks on one stock in the stock market network. The greater the value, the stronger the intermediary role of the stock is, indicating that the stock can be more affected by, and generate stock price income spillover to, other stocks, and has more risk transmission paths. Closeness centrality measures the reciprocal of the sum of the shortest distances from one stock to all the other stocks in the network multiplied by the number of other stocks. The greater the closeness centrality, the smaller the distance from the node to other nodes in the stock market network (not only the nodes adjacent to the node), and the faster the risk infection rate. The eigenvector centrality describes the importance of adjacent stocks to one stock. While it calculates the number of edges connected with adjacent nodes, it also uses the degree centrality of nodes for a weighted summation. The larger the value, the more information the stock can absorb and transmit, and the more vulnerable the stock is to infection.

We comprehensively use these four centrality indicators to analyze the network at different stages of each event and identify the core stocks and core industries in the network to explore the characteristics of risk transmission in the network. Table 5 lists the top 20 stocks in the four centralities for each event.

The stocks with large centrality are the key nodes in the network. The stocks with large values for the four centrality indicators have strong infection ability, many infection paths, rapid infection, and are more likely to be infected in the network. We find that due to the different causes of the different events, the industries that play a core role in the ensuing impact are also different. During the early stage of the financial crisis, the real estate and mining industries were the absolute core industries in the market. When the crisis occurred, the core positions of the manufacturing and wholesale and retail industries emerged, and continued their key roles in the market after the crisis. The real estate industry is in the core position during the whole financial crisis. The cultural and entertainment and construction industries are at the core during the early and middle stages of the stock disaster. In addition, the manufacturing and financial industries are key industries during the early stage of the stock disaster, while the energy and manufacturing industries play a more significant role during the later stage of the stock disaster. During the COVID-19 outbreak and recovery periods, the financial and manufacturing sectors are at a crucial position; especially during the outbreak, the financial industry plays a crucial role in the recovery of the stock market. After the epidemic, the economy resumed

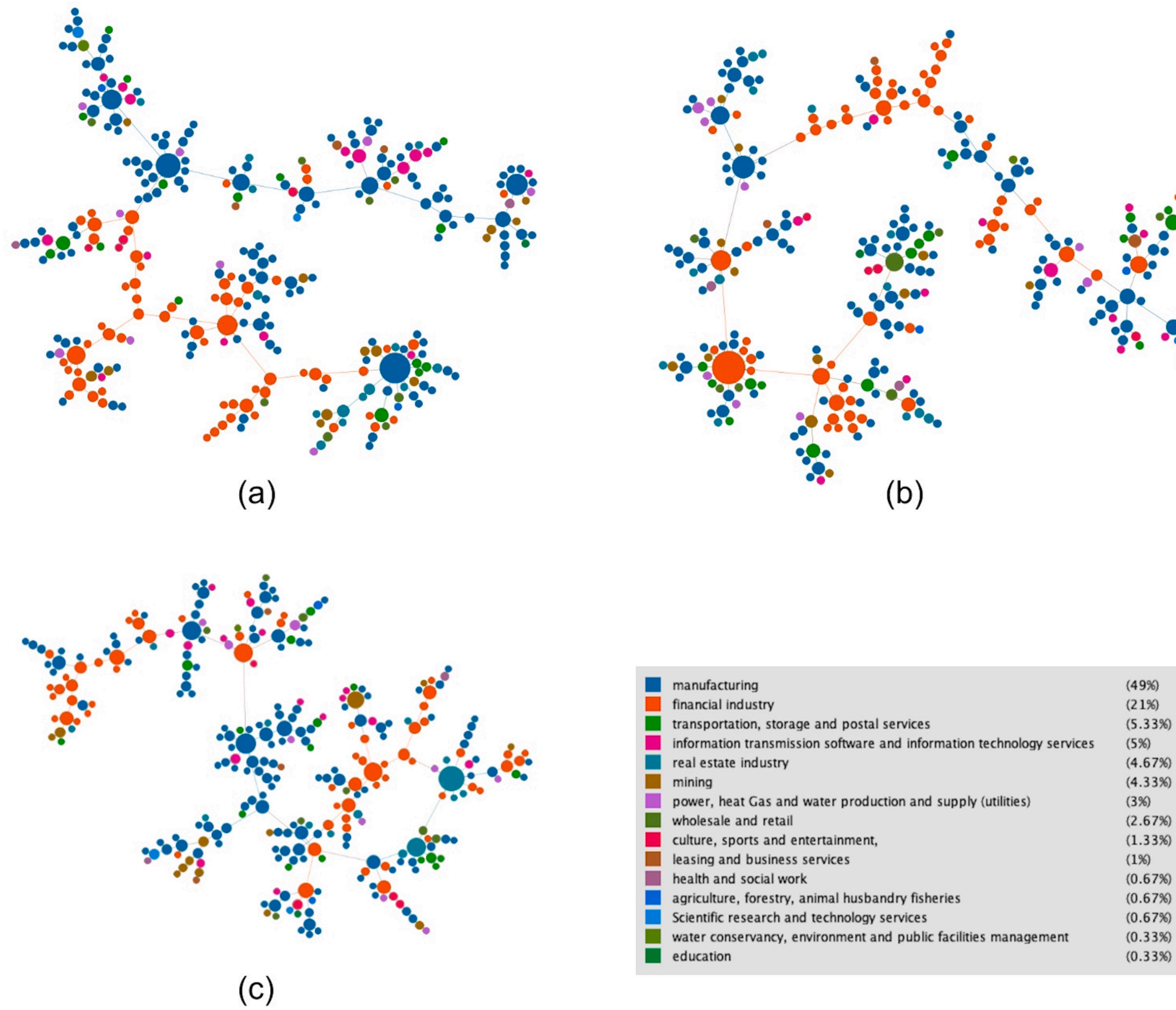

Fig. 6. MST of the three stages in the COVID-19 epidemic.
Note: (a), (b), and (c) are the MST networks before, during, and after the event.

Table 5
Stocks in the top 20 of the four centrality indicators for each event.

Key node (industry)						
2008-GFC	Pre	600,348.XSHG (mining)	600,158.XSHG (real estate industry)	000,069.XSHE (real estate industry)		
	In	002,024.XSHE (wholesale and retail)	000,651.XSHE (manufacturing)	600,158.XSHG (real estate industry)	600,961.XSHG (manufacturing)	
	Post	002,024.XSHE (wholesale and retail)	600,158.XSHG (real estate industry)	000,651.XSHE (manufacturing)		
2015-Stock Disaster	Pre	300,133.XSHE (culture, sports and entertainment)	002,475.XSHE (manufacturing)	600,999.XSHG (financial industry)	601,117.XSHG (construction industry)	
	In	601,117.XSHG (construction industry)	601,098.XSHG (culture, sports and entertainment)			
	Post	600,642.XSHG (power, heat Gas and water production and supply (utilities))	002,202.XSHE (manufacturing)	000,623.XSHE (manufacturing)		
2020-COVID-19	Pre	–	–	–	–	–
	In	601,939.XSHG (financial industry)	000,898.XSHE (manufacturing)	600,015.XSHG (financial industry)	600,016.XSHG (financial industry)	
	Post	601,186.XSHG (financial industry)	000,728.XSHE (financial industry)	601,155.XSHG (construction industry)	600,372.XSHG (manufacturing)	000,063.XSHE (manufacturing)

operation, and the construction, real estate, and manufacturing industries returned to the core position.

During different stages of the event, the functions of core nodes are also different. For example, there are 4 and 5 core stocks in the top 20 during the middle and later stages of the epidemic event, respectively, but not during the early stage, indicating that the four centralities of core stocks are quite different during the financial crisis, as are the risk contagion functions. Similar situations can also be seen during the financial crisis and stock disaster.

The results suggest that the key nodes in the different stages are not the same. They change with time, showing the rotation of different sectors and industries, which is related to the market status, impact reasons, and market feedback during each stage. Special attention should be paid to key nodes, because when the market is affected by emergencies, fluctuations and risks will first spread rapidly through them to the whole market. Meanwhile, the industry agglomeration characteristics of the network node distribution show that a change in the association structure characteristics of nodes leads to fluctuations in relevant industries, that is, it amplifies the risk transmission caused by node changes. Therefore, the intervention and management of these stocks is an effective measure to rapidly control and mitigate financial risks, which helps to reduce the cost of management regulation. In the process of risk prevention, we should always pay attention to the financial status and other important indicators of key node enterprises, find and reduce potential risks timely, and minimize the occurrence of risk events and the possibility of severe market fluctuations.

4.2.4. *The relationship between network topology and ΔCoVaR*

Billio et al. (2012) pointed out that systemic risk was a systemic event that had an obvious impact on numerous financial institutions or financial markets, and one that seriously damaged the normal operation of the financial system. The core idea is that risk is transmitted from a single financial institution or assets in financial markets to other institutions or other assets. Under the impact of major emergencies, if the stock market risk is transmitted to the whole financial market, it may cause systemic risk, which hinders economic development and leads to welfare loss.

We identify the contagion ability of core stocks in the stock network from the perspective of the centrality in 4.2.3. In what follows, the analysis is from the perspective of systemic risk. We use the $\Delta CoVaR$ data and topology variables of the CSI 300 component stocks under the different events to study the impact of network topology on the contribution of systemic risk.

First, we calculate the daily $\Delta CoVaR^i_{q,t}$ for each stock according to the method in 3.1.4. Huang et al. (2016) show that asset scale, leverage, and profitability are important factors in the risk contribution of an asset system. We introduce the natural logarithm of assets (ln Assets), equity ratio (Equity, equity/assets), and return on assets (ROA) as additional independent variables. The data on these variables are obtained from financial institutions' quarterly, semiannual, or annual reports, with a frequency of 3 months, from the WIND financial terminal. We convert their quarterly frequency to daily to match other variables. To avoid spurious regression, we first conduct a stationarity test on the variables. The test results are shown in Table 6.

Except for the logarithm of assets and equity ratio, all the variables reject the unit root hypothesis. After taking the first-order difference of the asset logarithm and equity ratio, the test shows that it is stable. The Hausman test is then used to choose between the random and fixed effects models, resulting in the choice of the latter. The following regression equation is established:

$$\Delta CoVaR^i_{q,t} = \alpha_i + x_i\beta_i + u_i, \tag{22}$$

where $i = 1, 2, \ldots, N$. $\Delta CoVaR^i_{q,t}$ is the explained variable $(T\times\ 1)$, x_i is the explanatory variable matrix $(T\times\ 8)$, $x_i = (CC^t_i, D^t_i, B^t_i, C^t_i, e^t_i, \ln Assets\_diff^t_i, leverage\_diff^t_i, ROA^t_i)$, and α_i is a constant term in the intercept $(T\times\ 1)$, which will be different because each stock is different. u_i denotes the residual results $(T\times\ 1)$. Table 7 shows the regression results for the three events.

From the full sample of the three events of the CSI 300 component network, the network indicators significantly affect the systemic risk contribution. Among them, five indicators during the financial crisis have significant effects. During the stock disaster events, the betweenness and closeness centralities and clustering coefficient are significant. During the COVID-19 event, the closeness and eigenvector centralities and clustering coefficient have significant effects. Moreover, the closeness and eigenvector centralities and clustering coefficient of stock nodes have the same influence direction on the systemic risk contribution in the three events, which shows that when a sudden shock occurs, the influence of network structure on the systemic risk contribution is similar. Among them, closeness centrality and clustering coefficient have a positive effect on $\Delta CoVaR$, that is, the greater the closeness centrality and clustering coefficient of nodes, the greater the $\Delta CoVaR$, and the smaller the systemic risk contribution. The eigenvector centrality has a negative effect on $\Delta CoVaR$. The larger the value, the smaller the $\Delta CoVaR$, and the greater the systemic risk contribution.

Furthermore, we discuss the relationship between the network topologies of stock markets in the U.S. and Hong Kong and the systemic risk contribution. We select the return data on the constituent stocks of the U.S. Dow Jones Industrial Average and Hong Kong Hang Seng indexes at different event stages, construct the MST network, calculate the $\Delta CoVaR$ value of each stock, and investigate and compare the relationship between the network topology and $\Delta CoVaR$ in the three stock markets (see Table 8).

We select two global emergencies, the financial crisis and the COVID-19 epidemic, and compare the regression results for the three markets.

Table 7
The regression results for the different events.

	2008-GFC	2015-Stock Disaster	2020-COVID-19
lnA_d	0.0315***	0.137***	−0.00333
	(2.77)	(2.97)	(−0.18)
l_d	0.00972	−0.149	−0.0111
	(1.48)	(−1.31)	(−0.27)
ROA	0.00879***	0.0215**	−0.00549
	(3.28)	(2.58)	(−0.73)
B	−0.000000143***	−8.39e-08*	1.14e-08
	(−8.18)	(−1.83)	(0.56)
C	12.89***	7.882***	2.181**
	(23.68)	(8.10)	(2.43)
e	−0.0396***	−0.0206	−0.0302**
	(−8.76)	(−1.47)	(−2.25)
D	0.0231**	0.0161	−0.0181
	(2.55)	(0.51)	(−1.17)
CC	0.0121***	0.0528***	0.00528***
	(13.33)	(30.92)	(3.02)
_cons	−0.0468***	−0.0733***	−0.0235***
	(−51.53)	(−56.78)	(−17.21)
N	118,076	85,101	21,165

Note: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
Stationarity test results.

Variable	$\Delta CoVaR$	CC	D	B	C	e	lnA	L	ROA
ADF_1	1790.87	1748.97	4716.46	7454.97	4890.63	13,208.7	600.067	554.627	599.755
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)
ADF_2	−30.5646	−29.9835	−54.8296	−68.5117	−59.011	−99.6509	2.00778	0.39326	−6.17567
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.977)	(0.652)	(0.000)

Note: ADF1 and ADF2 represent statistics of ADF-Fisher Chi-square and ADF-Choi Z-stat, respectively.

Table 8
The regression results for the different events in three stock markets.

	2008-GFC			2020-COVID-19		
	HS300	DJI	HSI	HS300	DJI	HSI
lnA_d	0.0315***	−0.00409***	−0.00140***	−0.00333	0.181	−0.0132***
	(2.77)	(−3.00)	(−5.62)	(−0.18)	(0.24)	(−6.06)
l_d	0.00972	−0.000567***	0.000117	−0.0111	2.796**	0.000549***
	(1.48)	(−3.34)	(0.88)	(−0.27)	(2.10)	(4.97)
ROA	0.00879***	−0.00930**	0.00000424	−0.00549	0.117***	−0.00138
	(3.28)	(−2.34)	(1.24)	(−0.73)	(6.64)	(−0.68)
B	−0.000000143***	−0.00000584	−0.00000560	1.14e-08	0.0000519*	0.00000204
	(−8.18)	(−1.34)	(−0.88)	(0.56)	(1.74)	(0.27)
C	12.89***	0.123*	0.500***	2.181**	−1.987***	1.669**
	(23.68)	(1.94)	(3.45)	(2.43)	(−3.66)	(2.38)
e	−0.0396***	−0.000276	−0.0141	−0.0302**	0.0129	−0.0745
	(−8.76)	(−0.04)	(−0.67)	(−2.25)	(0.21)	(−1.49)
D	0.0231**	0.00355	0.00378	−0.0181	−0.0193	−0.0175
	(2.55)	(0.68)	(0.32)	(−1.17)	(−0.42)	(−0.44)
CC	0.0121***	0.0970***	0.101***	0.00528***	0.101***	0.0615***
	(13.33)	(18.57)	(14.64)	(3.02)	(11.89)	(9.83)
_cons	−0.0468***	−0.103***	−0.117***	−0.0235***	−0.111***	−0.0841***
	(−51.53)	(−22.21)	(−18.51)	(−17.21)	(−14.81)	(−12.47)
N	118,076	11,268	10,388	21,165	2214	2754

Note: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

First, we find that the network indicators significantly impact the systemic risk contribution in the different stock markets. Of the indicators, closeness centrality and clustering coefficient significantly impact the systemic risk contribution in the three markets. Second, due to the different nature of the emergencies and market differences, the relationship between the network indicators and systemic risk contribution is also different, which is reflected not only in the significance of each impact, but also in their direction. For example, due to the different events, the nodes' betweenness centrality of the three markets negatively impact $\Delta CoVaR$ during the financial crisis event, but positively impact it during the epidemic event, while the degree centrality positively impacts $\Delta CoVaR$ during the financial crisis event, but has the opposite effect during the epidemic event. Regarding the effect of the differences between the markets, the relationship between the network structure and $\Delta CoVaR$ for U.S. stocks during the epidemic event is different from that for the A shares and Hong Kong stocks.

However, the impacts of the emergencies on the stock markets are also similar. First, there are similar characteristics among the different markets during the different emergencies. During the financial crisis, the five network indicators in the three markets have the same direction in terms of the systemic risk contribution. During the epidemic event, the network indicators for the A- and Hong Kong shares have the same direction in terms of the systemic risk contribution. The U.S. stocks show some differences, which may be related to the selected time period of the epidemic events. The epidemic broke out earlier in China, whereas the overseas epidemic broke out only after the recovery period began in mid-March 2020. This shows that, when affected by sudden shocks, the relationship between network structure and systemic risk contribution is similar. Second, under emergencies, the effect of some network indicators on the contribution to systemic risk is consistent, which is reflected in the above comparison of different events in the same market. Moreover, this law is found in different markets, that is, eigenvector centrality has a negative effect on $\Delta CoVaR$. The larger the value, the smaller the $\Delta CoVaR$, and the greater the contribution to systemic risk. While the closeness centrality and clustering coefficient positively impact $\Delta CoVaR$, the greater the closeness centrality and clustering coefficient of nodes, the smaller the contribution to the systemic risk. This is inconsistent with Huang et al. (2016), who examined the network structure and systemic risk contribution of financial institutions, and may be related to the industry characteristics of financial institutions.

The above results indicate that the network topology characteristics of a stock market can explain the systemic risk contribution, and the ability to explain is significant during major emergencies. The key nodes indicated by the network topology characteristics are among the main sources of the systemic risk of the stock market, and the risk spreads them to the whole stock market to build systematic risk. This study facilitates the identification of key nodes, advance interventions for key nodes, and setting up a "firewall" mechanism to discover and reduce risks in time by strengthening key stock monitoring, improving leverage, and managing speculative accounts of key stocks through "penetrating" account management and other measures.

5. Conclusions

The purpose of this study is to examine the characteristics of stock market network structure under different sudden shocks. We select three representative major emergencies (the GFC in 2008, stock disaster in 2015, and COVID-19 epidemic in 2020) and use a variety of network analysis methods to construct a comparative static and dynamic network of different events based on the return rate of the constituent stocks of the CSI 300 index. We find that first, when the stock market is impacted by major events, the correlation between stocks increases significantly, the network structure is more compact, showing a cluster phenomenon, and the stages and duration of the agglomeration effect are inconsistent due to the differences in the nature of the events. The cluster effect of the financial crisis events is smallest compared with those of the stock disaster and epidemic events, while the cluster effect of the epidemic events occurs most rapidly. Second, the key nodes in the stock market network have greater risk transmission ability, and the characteristics of industry agglomeration amplify the risk transmission caused by node changes. We should always pay attention to the important indicators, such as the financial status of key node enterprises, find and reduce potential risks in time, and reduce the occurrence of risk events and the possibility of severe market fluctuations as much as possible. The key nodes will change due to the market and external impacts; key industries rotate. The manufacturing industry plays a crucial role during the later stages of all the impact events, whereas the financial industry plays an important role during the epidemic's recovery period. Support for these key industries can effectively support the recovery of the market after sudden emergencies. Third, through the panel data regression analysis, the systemic risk contribution is linked with the stock topology in the network. It is found that the stock market network structure has an indicative effect on the systemic risk contribution, which is consistent in the three different markets of the A-shares and U.S. and Hong Kong stocks. Although the heterogeneity of the impact events will lead to changes in the degree and direction of impact, some network indicators have the same impact on the contribution to systemic risk, to which special attention should be paid. Generally, the greater the eigenvector centrality of a stock in an emergency, the greater its systemic risk contribution, while the greater the closeness centrality and clustering coefficient, the smaller its systemic risk contribution.

Our results have important implications for the risk management of stock market operation and portfolio risk management. The research results on the structural change and dynamic evolution of China's stock market describe the different performances of China's stock market in stable periods and under the major shocks, as well as the correlation between stocks and the time-varying characteristics of the stock market network. The identification and rotation interpretation of key industries in the stock market, as well as the indicative role of network topology on the systemic risk contribution, can provide more perspectives for regulators to evaluate the stability of the stock market and have better foresight and predictability for the stock market's systemic risk.

This paper discusses the characteristics of the stock market network and the identification of systemic risk contribution from the overall perspective of the market. The discussion on the characteristics of the various industries' local networks and the indicative role of systemic risk contribution will enrich the existing conclusions, and represents the focus of future research.

CRediT authorship contribution statement

Chengying He: Resources, Writing – review & editing. **Zhang Wen:** Data curation, Writing – review & editing. **Ke Huang:** Methodology, Software. **Xiaoqin Ji:** Conceptualization, Methodology.

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