Analysis and Risk Warning of Financial Markets Based on Communication Network Optimization Algorithms

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Abstract. This paper uses communication network optimization algorithms to study financial market evolution and systemic risk warning. The Dijkstra algorithm optimizes the financial market network. Data processing like noise reduction improves risk analysis accuracy. The research focuses on systemic financial risks, covering their definition, measurement, warning mechanisms, and complex network model applications. A complex financial network framework is built. Methods such as optimal threshold determination and community detection are used to analyze market network characteristics in pre - pandemic, pandemic, and post - pandemic stages. The minimum spanning tree retains key risk paths, with optimal thresholds of 0.55, 0.62, and 0.67 for each stage. Community detection by the Fast - Newman algorithm shows pandemic impacts on financial market industry interconnections. Findings show pre - pandemic, the market was well - connected and stable. During the pandemic, connections weakened and risk isolation rose. Post - pandemic, the market recovered but not fully. Network topology indicators serve as risk warning metrics, with a 25% fluctuation threshold for early warnings. This research offers new ways to understand market vulnerabilities, optimize risk management, and forecast market trends during crises. The use of optimization algorithms and self - healing mechanisms in risk warning has great theoretical and practical value.

Keywords: Communication Networks, Routing Algorithms, Systemic Financial Risk, Community Detection, Risk Forecast

1. Introduction

The outbreak of the COVID - 19 pandemic in 2020 brought about extensive and profound impacts on the global economic landscape. Factories halted operations, consumer demand slumped, international trade was impeded, and the unemployment rate soared. The financial market was no exception. The risks borne by the real economy rapidly permeated into the financial sector. Investors were in low spirits, market confidence plummeted, and global stock markets experienced severe volatility. For instance, in China, on the first trading day after the Spring Festival holiday in 2020, thousands of stocks in the A - share market hit the daily limit down, presenting a historic scenario. Subsequently, the stock markets of many countries and regions, including the United States, also declined significantly in March of the same year, plunging the global financial system into crisis[1]. Due to the development of economic globalization and integration, trade, investment, and consumption activities among countries have become increasingly intertwined, enhancing the contagiousness and diffusibility of risks. Systemic financial risks thus spread rapidly on the global stage.

During the pandemic, the financial system played a crucial role in helping the real economy tide over difficulties. It not only had to fully support epidemic prevention and control and the resumption of work and production but also shoulder the significant mission of maintaining financial stability and preventing systemic financial risks. Before the pandemic, China's financial system already faced numerous challenges, especially issues such as the global economic slowdown, the increasing local debt burden, and the over - leveraged real estate industry[2]. The emergence of the COVID - 19 pandemic undoubtedly posed a formidable test to the stability of the financial system and put forward long - term and essential requirements for preventing systemic financial risks.

Regarding the definition of systemic financial risk, there is currently no unified and consensual definition in the academic community. Most scholars and regulatory agencies around the world approach it from the perspective of the financial market. The financial market encompasses various sub - fields such as the stock market, futures market, foreign exchange market, and national debt market, among which the stock market is of particular importance. Therefore, this paper also bases itself on the financial market, collates relevant research on systemic risk, and draws on scholars' understanding of systemic financial risk to gain a scientific understanding of systemic risk in the financial market[3]. The definitions of systemic financial risk by researchers can be summarized into two aspects. One is defined by the consequences of systemic financial risk. The International Monetary Fund and others, based on research on global and national financial markets, pointed out that systemic financial risk refers to the functional impairment of the entire financial system caused by problems in part or the whole of the financial system. The European Central Bank also has a unique view, believing that systemic financial risk is rooted in the inherent instability of the financial system, that is, the fragility of the financial system, which can damage the operation of the financial system itself and then affect its service function to the social economy defined systemic financial risk as risk factors that threaten the stability of the financial system and public confidence.

In China's financial system, the banking sector is central, significantly supporting SMEs, pandemic response, and economic recovery during COVID-19. Despite strict interbank risk controls, the 2008 U.S. subprime crisis underscores the catastrophic impact of banking collapses on the broader financial and real economies. The 2013 "money shortage" highlights latent banking risks. With financial markets evolving, non-bank institutions' growing role and interconnectedness amplify systemic risks. Studying financial institutions' interconnectedness is crucial for systemic risk prevention.

2. Research on Financial Market Evolution Analysis

The innovation of this paper lies primarily in the use of the optimal threshold method to construct a financial complex network, and the improvement of community detection algorithms for more precise monitoring and analysis of systemic risks in financial markets.

2.1. Proposal of the Optimal Threshold Method for the Correlation Matrix

Based on the correlation coefficient matrix, this paper innovatively proposes optimal thresholds for the three stages: pre-pandemic at 0.55, during the pandemic at 0.62, and post-pandemic at 0.67, which are used as the connection standards for constructing the financial complex network [5]. These thresholds effectively filter out key risk transmission links, excluding weakly correlated edges, and allow the network model to focus on the primary paths of systemic risk propagation.

2.2. Improvement of the Financial Market Community Detection Algorithm

In terms of community detection, this paper integrates routing optimization algorithms from communication networks and proposes an improved strategy based on the Fast-Newman algorithm[6]. Routing optimization algorithms in communication networks are typically used to find the shortest paths and optimize the efficiency of data flow transmission. Similarly, risk propagation in financial markets can be viewed as a process of information flow. Therefore, these algorithms can be adapted to optimize the risk propagation paths within financial markets. Specifically, this study analyzes the node connection relationships in financial markets, employs Dijkstra and PRIM algorithms to identify the shortest risk propagation paths, and uses the optimal threshold method to filter key paths. By identifying the risk propagation paths within the financial market, we can further refine the community detection strategy, thereby more accurately identifying the core risk areas in the market.

2.3. Use of Network View Statistical Inference Indicators

The network and community structures constructed in this paper not only provide an intuitive network view but also conduct in-depth community statistical inference. By comparing the model selection process with the Stochastic Block Model (SBM), the role of homogeneity in the propagation of systemic risks is assessed. This helps in understanding the mechanisms of risk concentration and diffusion, providing scientific early warning signals and strategic responses for policymakers and market participants [7].

3. Construction of the Financial Complex Network Based on the Optimal Threshold Method

3.1. Data Sources and Preprocessing

3.1.1. Data Sources

The data used in study is derived from the real trading records of stocks in the CSI 300 Index, focusing primarily on the performance of 276 stocks in response to financial market volatility since the outbreak of the COVID-19 pandemic in 2020 [8]. The data spans from 2015 to 2024, with a central focus on several key indicators that reflect market trends, such as opening prices, closing prices, and trading volumes [9]. The dataset is directly sourced from the Wind database, ensuring both the timeliness and reliability of the data.

3.1.2. Data Preprocessing

This study collects daily trading volume data for the 276 constituent stocks of the CSI 300 Index from January 2, 2015, to April 1, 2024. Based on this comprehensive dataset, the logarithmic returns for each day are further calculated to serve as the basis for the research analysis.

$$DC(v_i) = \frac{d(v_i)}{N-1} DC(v_i) = \frac{d(v_i)}{N-1} DC(v_i) = \frac{d(v_i)}{N-1} = 100(\ln(P_{i,t}) - \ln(P_{i,t-1})) \tag{1}$$

The logarithmic return for stockiat time t is represented as $R_{i,t}$, where $P_{i,t}$ and $P_{i,t-1}$ are the current and previous period stock prices, respectively.

In communication engineering, signal transmission is often subject to noise interference, requiring noise reduction techniques to improve signal quality. Similarly, financial market data can be affected by various anomalous fluctuations and disturbances. To obtain more accurate and reliable log-return data, noise reduction methods similar to those in communication engineering are applied.

First, the log-return time series data is treated as a signal sequence, where the total number of data points is denoted as NNN. Filtering algorithms, such as low-pass filtering, can be employed to eliminate high-frequency noise. The principle of low-pass filtering is to allow low-frequency signals to pass while suppressing high-frequency signals.

When $t \le m$:

$$\hat{R}_{i,t} = \frac{1}{t}\sum_{k=1}^{t} R_{i,k} \tag{2}$$

When $t > m$

$$\hat{R}_{i,t} = \frac{1}{m}\sum_{k=t-m+1}^{t} R_{i,k} \tag{3}$$

By applying the above noise reduction technique, anomalous fluctuations and noise interference in the log-return time series can be effectively reduced, allowing the data to better reflect the true trend of stock price changes. The filtered log-return time series curve provides higher-quality data support for subsequent studies, such as the construction of financial complex networks and risk analysis.

The time series curve of the logarithmic returns derived from Equation (1) (2) (3) is shown in Figure 1:

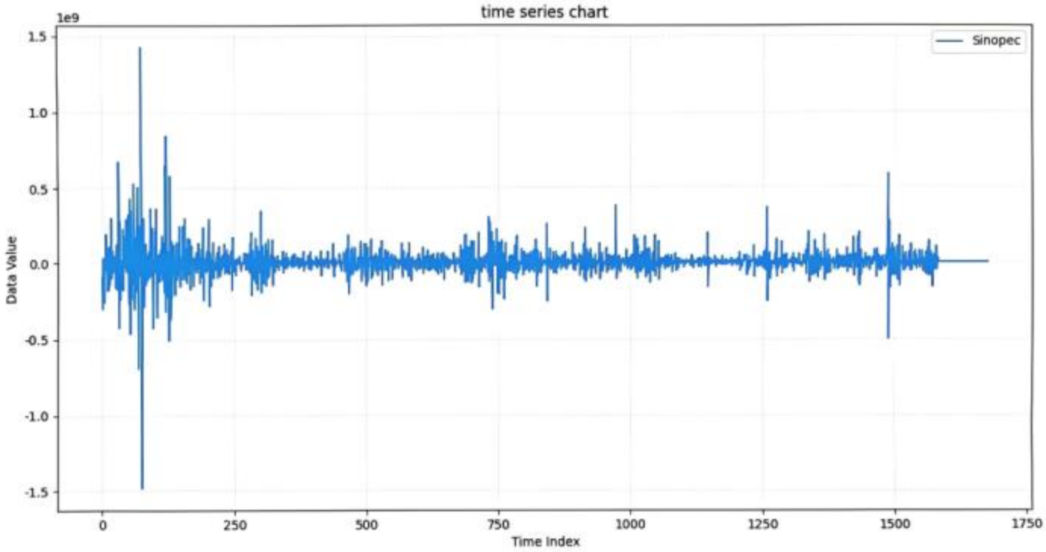

Figure 1. Time Series Plot

3.2. Optimal Threshold Method

This section aims to determine appropriate thresholds to filter key connections from the stock correlation data and streamline the financial complex network. Using the outbreak of the COVID-19 pandemic as a reference point, the historical data of the past decade is divided into three periods. The Brownian distance between stocks is measured, generating a 276×276 Brownian distance matrix. The Routing optimization Dijkstra algorithm and Prim algorithm is employed to construct the minimum spanning tree for each stage, revealing the closely correlated paths between stocks. Node centrality is then calculated to identify the 100 most influential nodes, and the K-shell algorithm is used to filter out the 25 key nodes. The maximum Brownian distance between these key nodes is set as the network connection threshold, retaining only the strong correlations (below the threshold) between the core nodes. This ensures that the network model focuses on the core risk propagation paths, simplifying the model and improving the accuracy of the early warning analysis.

3.2.1. Brownian Distance

In complex network analysis, selecting an appropriate method to compute the distance between nodes and visualizing it in the network structure is crucial. An improper distance metric may lead to a network graph that misrepresents the actual relationships between nodes. To better capture the correlation between stocks during different periods, and based on existing methods in the literature, this paper proposes a time-series correlation coefficient to calculate the distance between two stocks in the network, which represents their correlation. The detailed calculation formula is shown in Equation (2).

$$R_{n_1,n_2} = \frac{\sum_{m=1}^{M}[T_{n_1,m}-(T_{n_1})]\times[T_{n_2,m}-(T_{n_2})]}{\sqrt{\sum_{m=1}^{M}[T_{n_1,m}-(T_{n_1})]^2 \sum_{m=1}^{M}[T_{n_2,m}-(T_{n_2})]^2}} \tag{4}$$

Where n_1,n_2 represent different stocks in the sequence, m represents different days, and M denotes the total number of days in the 10-year dataset. Then, $T_{n_1,m}$ represents the logarithmic return data for stock n_1 on day m, and similarly, $T_{n_2,m}$ represents the logarithmic return data for stock n_2 on day m.

This study divides the historical data from the past 10 years into three stages based on the COVID-19 pandemic: pre-pandemic (2015-2019), pandemic (2020-2022), and post-pandemic (2022-2024). The data for these three periods is input into the formula to calculate the correlation coefficients between stocks, resulting in three 276×276 correlation matrices. When using Brownian distance correlation to construct the financial network and minimum spanning tree, the distance used in the complex network is defined as: $d_{XY} = 1 - R(X, Y)$.

3.2.2. Dijkstra Algorithm

Path optimization formula: "To optimize the risk propagation path in the financial market, we introduced the Dijkstra shortest path algorithm, which calculates the shortest risk path between nodes using the following formula:

$$d(s,v) = \min_{u \in V} \{d(s,u) + w(u,v)\} \tag{5}$$

where $d(u,v)$ represents the shortest path from the source node u to the target node v,and $w(u,v)$ denotes the connection weight between nodes u and v,which represents the intensity of risk propagation. Through this algorithm, we can analyze the shortest path of risk propagation from a given financial institution (node) to other institutions, thus identifying potential risk transmission paths.

The goal of the community detection algorithm is to group nodes in the market based on their similarities, thereby identifying potential risk clusters.

3.2.3. Prim Algorithm

The minimum spanning tree (MST) can eliminate secondary edges, retain critical connections, reveal efficient risk transmission pathways, and simplify network structures, thereby providing strong support for financial risk monitoring, early warning, and causal analysis. The Prim algorithm is employed to construct the minimum spanning tree.

Figure 2. Minimum Spanning Tree

As shown in Figure 2, the previously computed three 276×276 correlation matrices represent the degree of connectivity or correlation between stocks during the respective time periods. These matrices define the distances between nodes, serving as the standard for measuring edge lengths in the Prim algorithm. This process is repeated across three time periods—pre-pandemic, during the pandemic, and post-pandemic. The data from each stage reflects different market conditions and the strength of inter-stock relationships, ultimately allowing for the construction of minimum spanning trees corresponding to each period while preserving the key

3.2.4. Node Importance Calculation

In network structures, the "degree" of a given node v_i refers to the number of other nodes directly connected to it. If a node has a larger number of adjacent nodes, its degree value will correspondingly be higher. Degree centrality is a standardized metric that evaluates the centrality of a node within the overall network based on its degree. The degree centrality of a node v_i can be calculated using the following formula:

$$DC(v_i) = \frac{d(v_i)}{N-1} \tag{6}$$

Where $DC(v_i)$ represents the degree centrality index of node v_i, $d(v_i)$denotes the actual degree of node v_i, i.e., the number of directly connected nodes, and N represents the total number of nodes in the network. The term $N-1$ theoretically corresponds to the maximum possible degree of any given node in the network.

In addition, K-shell centrality is an index used to assess the influence of a node based on its hierarchical embedding within the network structure. This concept originates from the K-shell decomposition algorithm, which follows an iterative node removal process. The algorithm assigns a K-shell value to each node in the network through a stepwise pruning approach

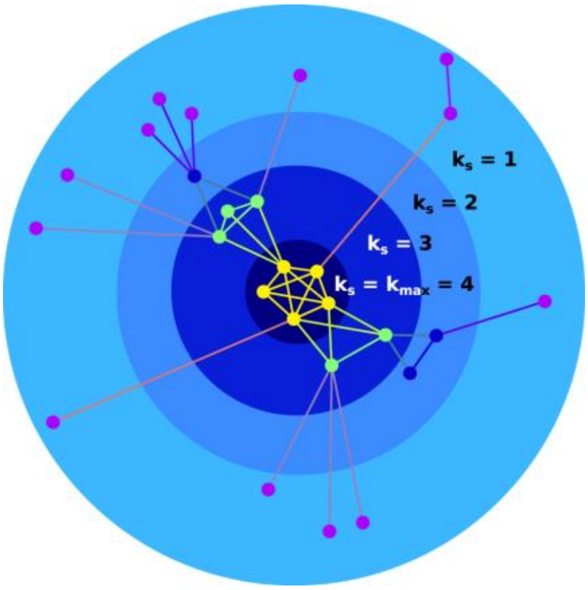

Figure 3. Schematic Diagram of the K-shell Algorithm Principle

As is evident from Figure 3, during the entire K-shell decomposition process, the larger the K-shell value assigned to a node, the closer its position is to the core area of the network, indicating that its influence within the network is more significant.

3.2.5. Determining the Minimum Threshold

Finally, to further refine the network, we base the connections between these 25 key nodes on weighted edges. The smallest correlation coefficient among these edges is chosen as the threshold for network connections. This threshold implies that edges with correlations below this value will not be considered, thus simplifying the network and ensuring that only the most tightly connected and critical risk propagation channels are retained.

Through these steps, a meaningful threshold construction method is established, which can be used for subsequent risk monitoring and the construction of evolution networks. Using this approach, the network thresholds for the three stages are determined as 0.55 before the pandemic, 0.62 during the pandemic, and 0.67 in the post-pandemic era.

3.3. Network Construction

In the stage of constructing the financial complex network, this paper has successfully computed the Brownian distance matrices between stocks for three different periods: pre-pandemic, during the pandemic, and post-pandemic. The optimal thresholds for each period were determined as 0.55, 0.67, and 0.62, respectively. Based on these data, the following steps were employed to create three unweighted, undirected complex network graphs [6].

Using the thresholds for each period as standards, edges with Brownian distances below the threshold were filtered out. This implies that there are no edges connecting two stocks with a relatively large distance between them. The filtered connection information was then used to construct unweighted, undirected network graphs corresponding to the three periods. In each graph, the nodes represent individual stocks, and the presence of an edge signifies a significant correlation between two stocks in the financial market during the respective period. The absence of edge weights means that all connections are considered equally important.

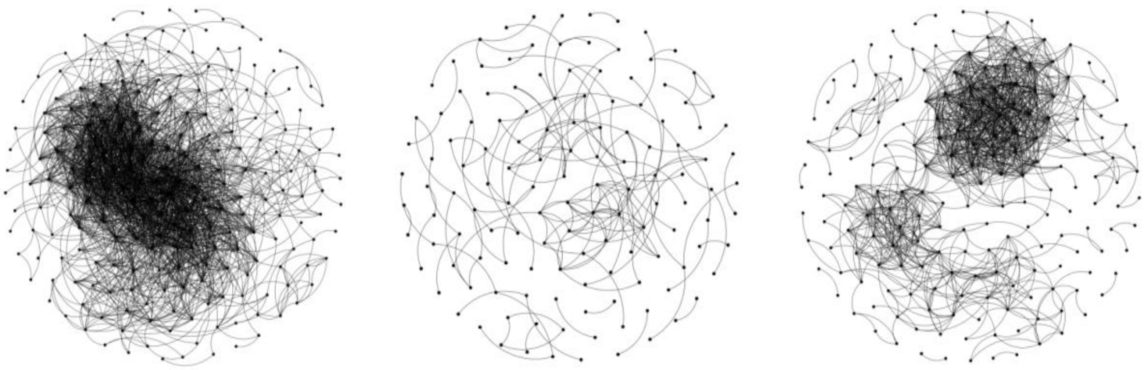

Figure 4. Complex Network Graphs

By analyzing these three graphs of Figure 4 comprehensively, insights can be gained into the immediate impact of the pandemic on the financial market structure, the dynamic adjustments in the medium term, and the long-term systemic changes. This provides a visually intuitive and quantitative foundation for understanding the evolution of financial market risks.

4. Financial Network Evolution Analysis and Risk Warning

4.1. Evolution of Community Structure

The Fast-Newman algorithm incorporates a greedy strategy, starting with each node in the network as an independent community. Through a series of iterative merging steps, it selects pairs of communities to merge that either maximize or minimize the decrease in modularity. The ultimate goal is to achieve the optimal community division by maximizing modularity.

In the operation of the algorithm, the initial modularity is set to 0, and the initial values of the parameters are as follows:(

$$e_{ij} = \begin{cases} \frac{1}{2M},\ If\ \ node\ v_i\ and\ node\ v_j\ exist\ line \\ \qquad\qquad 0, Other\ \frac{d(v_i)}{2M} \end{cases} \tag{7}$$

Where $d(v_i)$ represents the degree of node v_i, and M represents the adjacency matrix of the network, with m being the total number of edges in the network. Since node degrees in the network may be equal, the complex network is treated as an undirected graph, and the modularity increment is calculated using the following formula:

$$\Delta Q_{ij} = e_{ij} + e_{ji} - 2a_i a_j = 2(e_{ij} - a_i a_j) \tag{8}$$

Running the Fast-Newman algorithm produces a hierarchical tree structure for the community decomposition. At different levels, community merges are broken, allowing for the acquisition of multiple network community partitioning schemes. The partition with the highest modularity value is selected, resulting in the optimal network community structure.

By applying this algorithm, the community partitioning results of the complex networks for the three periods are obtained. Analyzing the dynamic changes in the community structure enables a deeper understanding of financial market behavior. The analysis of the community distribution and degree of aggregation in the three phases (pre-pandemic, during the pandemic, and post-pandemic) reveals the financial market's adaptation and adjustment mechanisms in response to external shocks.

Figure 5. Distribution Pre-Pandemic

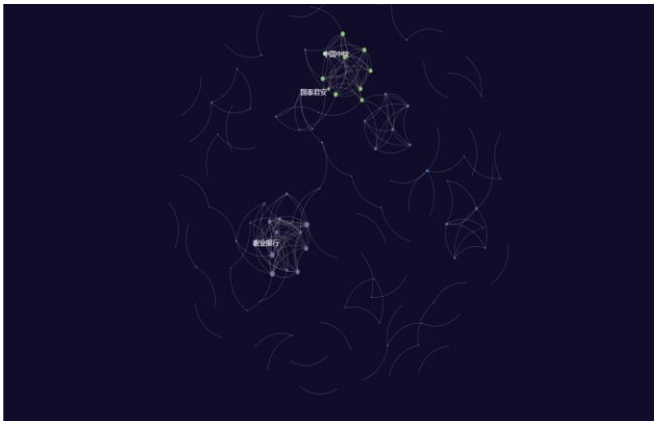

Figure 6. Distribution During the **Pandemic**

As shown in Figure 5, before the pandemic, the community structure was stable, with close collaboration across sectors, strong internal cohesion within communities, orderly market operations, balanced community layouts, active inter-industry exchanges, and broad connections among market participants. Systemic risk aggregation was mitigated.

From Figure 6, during the pandemic, the community structure and density changed significantly. The degree of community aggregation decreased, leading to risk dispersion. Some communities had clear boundaries with tightly-knit internal relationships, while the connections between communities became sparse, forming a risk isolation pattern. Certain communities became "islands" of risk, with core sectors acting as "bridges" for risk transmission. The connecting lines between communities represented potential risk mitigation zones and monitoring blind spots.

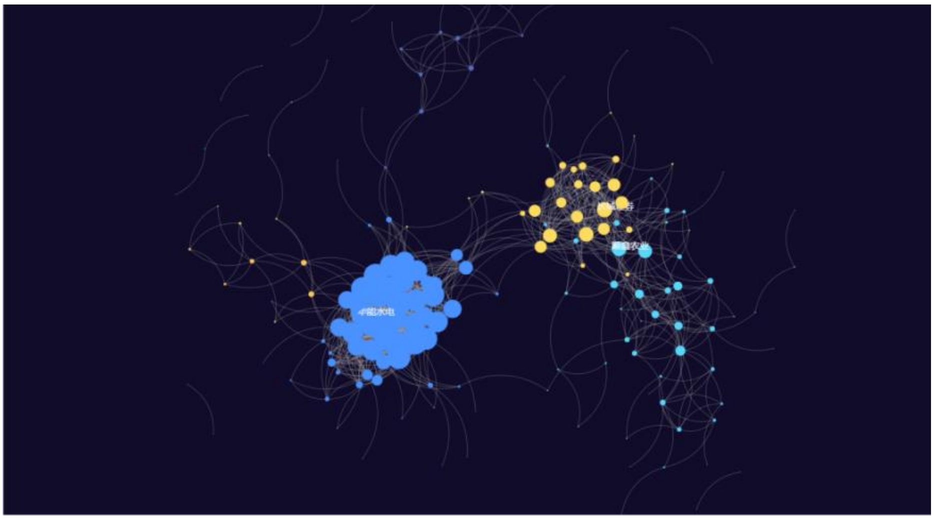

Figure 7. Community Distribution in the Post-Pandemic Era

As shown in Figure 7, in the post-pandemic era, the community structure moves towards a new balance, though still differing from the pre-pandemic period. The internal cohesion within communities begins to revive, indicating a self-healing process in the market. Sectors demonstrate resilience and rebuild internal cooperative networks. Community connections and structures become more diverse. Some communities have a looser structure, exploring new resource allocation and risk diversification paths, while others are highly concentrated, suggesting emerging risk convergence points and market structure adjustments.

4.2. Network Topological Indicators

In the study of financial complex network structures, this paper employs several suitable topological indicators to effectively analyze the network's topology. These topological indicators not only help in analyzing the properties and characteristics of the network graph itself but also allow for financial market risk early warning through comparisons between different indicators.

4.2.1. Graph Density

Network density refers to the ratio between the actual number of edges in the network and the maximum possible number of edges theoretically. This value can be calculated using the following formula:

$$\rho = \frac{2M}{N(N-1)} \tag{9}$$

Where M represents the actual number of edges in the network, and N is the total number of nodes. The network density value ranges from 0 to 1. It can be used to evaluate the overall tightness of the network structure and also serve to analyze the local connectivity of the network. When the network density approaches 1, it indicates that the network is more tightly connected.

4.2.2. Average Path Length

For a general network with N nodes, the shortest distance between any two nodes is denoted as $d_{i,j}$, then the average path length L of the network is:

$$L = \frac{1}{N^2}\sum d_{i,j} \tag{10}$$

Where N is the total number of nodes, $d_{i,j}$ represents the shortest distance between nodes i and j.

Thus, the average path length L can be restated as the average of the shortest paths between all pairs of nodes in the network:

$$L = \frac{2}{N(N-1)}\sum d_{i,j} \tag{11}$$

In complex networks, the average path length LLL typically reflects the efficiency of information transfer or risk contagion. A shorter average path length suggests that the nodes are more tightly connected, thereby increasing the efficiency of information transfer or risk contagion within the network.

4.2.3. Clustering Coefficient

Let the degree of a node v_i be k_i , then the maximum number of potential connections between its neighboring nodes is $k_i(k_i - 1)/2$. However, in practice, these neighboring nodes are not fully connected. Based on this, the clustering coefficient of a node v_i can be calculated using the following formula:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \tag{12}$$

Where E_i is the actual number of edges between the neighbors of node v_i , and k_i is the degree of the node.

4.2.4. Community Statistical Inference

This paper uses a novel community detection framework based on non-parametric Bayesian methods, focusing on inferring assortative community structures within the network. Compared to previous methods (e.g., modularity maximization), this approach can more accurately identify statistically significant assortative modules, avoiding the overfitting issues found in artificial and real networks. Moreover, it is not subject to resolution limits and can theoretically detect any number of communities as long as sufficient statistical evidence is available. This framework, through the model selection process, can be compared with more general methods based on the Stochastic Block Model (SBM) to determine whether assortativity is a key feature of large-scale mixed patterns in the network.

4.2.5. Indicator Analysis

In examining the evolution and risk early warning of the financial market's complex network, the topological indicator values at different stages provide a dynamic view of the financial market’s response to systemic shocks [10].

Table 1. Topological Indicators for Different Periods

	Average Clustering	**Average Path Length**	**Graph Density**	**Average Degree**	**Community Statistical**
Pre-Pandemic	0.921	1.98	0.093	20.22	6149.168
During Pandemic	0.539	4.219	0.02	5.623	2258.524
Post-Pandemic	0.619	2.818	0.059	11.232	3329.936

As shown in Table 1, before the pandemic, the network's average clustering coefficient reached 0.921, indicating high internal connectivity and collaboration within sectors, with a compact and stable market structure. The average path length of 1.98, graph density of 0.093, and average degree of 20.22 suggested rapid information and risk transmission, with strong node influence. The community statistical inference value of 6149.168 indicated high industry connectivity and a balanced market segmentation structure.

During the pandemic, the financial market experienced turbulence, with significant changes in topological indicators, which became an important basis for market warning. The average clustering coefficient dropped to 0.539, indicating a looser market connection; the average path length increased to 4.219, suggesting that information and risk transmission paths were lengthened, and market segmentation and risk isolation were enhanced. The graph density dropped to 0.02, and the average degree decreased to 5.623, indicating weakened market interactions and node connections. The community statistical inference value dropped to 2258.524, reflecting a reshaped market structure and a reconfiguration of risk aggregations.

In the post-pandemic era, as the market recovered, topological indicators exhibited a new normal. The average clustering coefficient rose to 0.619, indicating that connectivity had been restored but not fully recovered; the average path length decreased to 2.818, indicating improved operational efficiency but with some gaps remaining. The graph density and average degree increased to 0.059 and 11.232, respectively, indicating enhanced market interactions and node connections. The community statistical inference value increased to 3329.936, reflecting the reconstruction of the market structure, with risk distribution evolving towards diversification and decentralization.

4.3. Financial Risk Early Warning

The average clustering coefficient (0.921), average path length (1.98), graph density (0.093), average degree (20.22), and community statistical inference value (6149.168) before the pandemic serve as standard values for market stability, and the changes in these indicators from June 2019 to June 2020 are compared. The early warning threshold is set to trigger when the fluctuations of each topological indicator exceed 25% relative to the baseline value. Through this method, key early warning threshold values for topological indicators are identified:

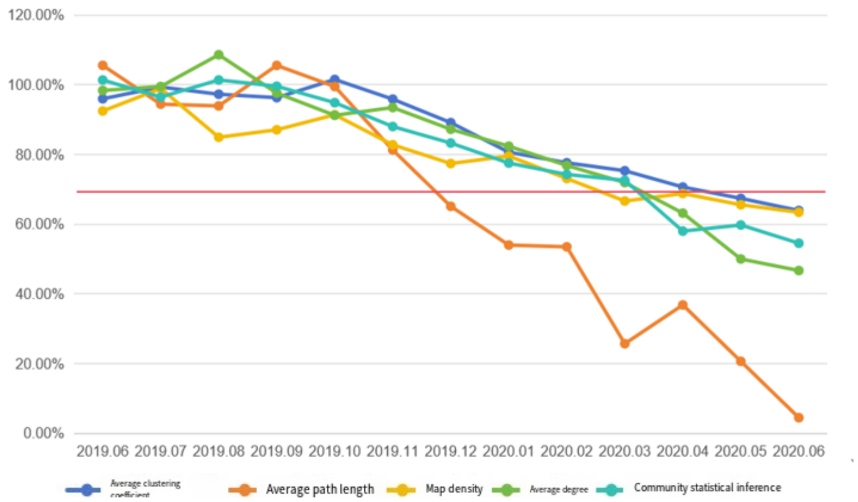

Figure 8. Systemic Financial Risk Early Warning Chart

As shown in Figure 8, these early warning values reveal the market's sensitivity to risk transmission pathways, providing timely signals to policymakers and market participants, and helping to prevent systemic financial risks [11]. A decrease in the average clustering coefficient indicates weakened market cohesion; an increase in the average path length and a decrease in graph density suggest poorer market connectivity and reduced efficiency in information and risk transmission. A decline in the average degree and changes in community statistical inference reflect deep adjustments in the market structure and risk distribution [12]. A comprehensive analysis of these indicators provides a scientific basis for real-time monitoring and early warning systems in financial markets.

5. Conclusion

This study integrates communication network optimization algorithms to analyze the evolution of the financial market across different stages of the pandemic. Using the Dijkstra algorithm, the optimal network thresholds for the three stages were determined (0.55, 0.62, and 0.67), simplifying the network model and identifying critical risk propagation paths. The Fast-Newman algorithm was employed to analyze community structures, revealing the profound effects of the pandemic on industry linkages and structural adjustments in the financial market. The results demonstrate that, before the pandemic, the market had fast information flow, tight risk propagation, and structural stability. During the pandemic, market connections weakened, information transmission efficiency decreased, and risk isolation was enhanced. In the post-pandemic era, the market showed gradual recovery but had not yet fully returned to pre-pandemic conditions. Based on network topology indicators and community statistical analysis, a risk warning mechanism with a threshold of 25% fluctuation is proposed, which effectively identifies potential risk signals and offers new insights for financial market risk management and emergency response. The findings highlight the importance of communication network optimization algorithms and self-healing mechanisms in financial market risk warning systems, providing technical support for optimizing market monitoring and risk identification.

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