Analysis of the Volatility of CSI 300 Stock Market Based on Complex Networks

Research Article

Abstract

Aims/Objectives: To analyze the volatility and structural characteristics of the CSI 300 stock market using complex network theory, and to reveal the evolution of market structure under different macroeconomic environments.
Study Des: An empirical study employing complex network analysis and an innovative double-layer network modeling approach to capture dynamic, phase-dependent structural evolution.
Place and Duration of Study: Constituent stocks of the CSI 300 index, covering the period from October 1, 2022, to October 1, 2024.
Methodology: We constructed a double-layer network model to analyze the interconnection relationships and structural characteristics of constituent stocks across different time periods. The methodology included the threshold filtering method, weight matrix construction, and centrality analysis to examine market volatility and risk propagation paths.
Results: The results show that during the G1 stage (Russia-Ukraine conflict and Fed interest rate hike), the market relied on the stability of the financial sector, exhibiting high network concentration. During the G2 stage (post-pandemic consumption recovery), the consumption and manufacturing sectors gained prominence, and the market structure gradually shifted towards an internally-driven model with improved risk resistance. The modularity increased from 0.2667 in G1 to 0.3878 in G2, indicating a more dispersed risk distribution.

Conclusion: The market network structure evolves dynamically with the macroeconomic environment. The double-layer network analysis reveals enhanced market resilience in the G2 stage, with modularity, density, and clustering coefficient changing by 17.05%, 14.55%, and 11.42%, respectively, reflecting the market's transition from risk concentration to a diversified equilibrium. These findings provide practical insights for risk management and policy formulation, offering regulators and investors valuable tools for monitoring market stability.

Keywords: Double-layer network; CSI 300 index; Threshold filtering method; Weight matrix; Volatility

2010

Mathematics Subject Classification: 91B84; 91G70; 05C82

1 Introduction

In recent years, global financial market risks have intensified, with stock market volatility and systemic risks becoming increasingly prominent. Traditional volatility prediction methods such as GARCH struggle to capture the nonlinear characteristics and dynamic changes of markets, particularly showing significant limitations under external shocks. In contrast, complex network theory provides a new perspective for analyzing the internal structure of volatility and risk transmission paths by revealing the correlation networks among stocks and industries within stock markets.

The pioneering work of Sozen (2025) introduced stress-aware multiscale spillover networks, providing advanced methodologies for analyzing cross-market risk transmission. Their research demonstrated that financial contagion exhibits distinct patterns under different market conditions, which aligns well with our study's focus on different macroeconomic periods. Moore et al. (2014) further developed network models of financial system resilience, highlighting the "robust-yet-fragile" nature of financial networks and the amplification effects of overlapping portfolios and leverage on risk contagion.

In interbank network studies, Liu et al. (2023) investigated liquidity crisis contagion and supervision in interbank markets using SIS network models, revealing important mechanisms of risk propagation through financial networks. For emerging markets specifically, Li et al. (2020) conducted dynamic evolution and robustness analysis of China's stock market network under internal and external shocks, providing valuable insights into the unique characteristics of Chinese financial markets.

Regarding methodological advances, Wang et al. (2018) applied systemic risk analysis using network topology and information theory, offering sophisticated tools for identifying critical nodes and vulnerability assessment in financial networks. More recently, Kim et al. (2023) developed dynamic network models for financial contagion analysis, emphasizing the importance of temporal dimension in understanding risk propagation pathways.

For the CSI 300 market specifically, previous research has established that constituent stock correlation networks exhibit dynamic topological characteristics across different market cycles Huang et al. (2022). The coupling between industry and individual stock networks has been shown to amplify volatility transmission Zhang et al. (2020), while traditional volatility analysis methods may significantly underestimate extreme risks during market stress periods Brown et al. (2022). Policy adjustments have been demonstrated to fundamentally alter risk transmission paths Jin et al. (2024), and stock market network evolution consistently displays distinct "shock response" characteristics Basco et al. (2024).

In summary, complex network theory provides multi-dimensional analytical tools for examining the linkage patterns, structural characteristics, and risk mechanisms of CSI 300 constituent stocks. Therefore, this paper focuses on the network dynamics of constituent stocks across different time periods, aiming to reveal the evolution laws of correlation structures and provide support for identifying high-risk nodes, predicting systemic risks, and improving volatility prediction accuracy.

Data Collection and Preprocessing

Data were sourced from the Wind financial terminal, covering daily trading data of CSI 300 index constituent stocks from October 1, 2022 to October 1, 2024, including opening price, closing price, highest price, lowest price, trading volume, and turnover, totaling 483 trading days. To ensure data consistency, 150 stable constituent stocks during this period were selected. The complex domestic and international macro events during the selected period, such as the Russia-Ukraine conflict, Fed interest rate hikes, and post-pandemic economic recovery in China, enriched the background of market fluctuations.

2.1 Data Cleaning and Exception Handling

To ensure data continuity and accuracy, this study first performed forward and backward filling (ffill and bfill) on missing values. Meanwhile, to avoid the impact of extreme fluctuations on analysis results, the interquartile range (IQR) method was used to eliminate abnormal data exceeding 5 times IQR. To analyze the dynamic changes of market structure under different backgrounds, this paper divides the data into two stages: G1 stage (October 1, 2022 - September 30, 2023), during which the market was greatly affected by external shocks, with strong dependence on financial and infrastructure sectors; G2 stage (October 1, 2023 - October 1, 2024), showing characteristics of internal demand-driven, with consumption and manufacturing sectors gradually dominating the market.

2.2 Descriptive Statistical Analysis

To conduct network modeling and market volatility analysis, the daily amplitude (DA) of each constituent stock was calculated to measure short-term market volatility. The calculation formula for daily amplitude is:

$$DA_i^t = \frac{\max\left(p_i^t\right) - \min\left(p_i^t\right)}{p_{si}^{t-1}}. \tag{2.1}$$

where $\max\left(p_i^t\right)$ is the highest price of stock i on day t, $\min\left(p_i^t\right)$ is the lowest price of stock i on day t, and p_{si}^{t-1} is the closing price of the previous day.

Subsequently, descriptive statistical analysis was conducted to reveal the volatility characteristics of daily amplitude, and ADF unit root test was performed to evaluate the stationarity of time series. The mean daily amplitude of most stocks was concentrated around 2, but some stocks had larger fluctuation ranges, with maximum values between 6 and 13. Skewness and kurtosis analysis indicated that market volatility has positive skewness and fat-tail characteristics, indicating frequent extreme fluctuations, consistent with "black swan event" characteristics.

In the ADF unit root test, most stock time series were stationary, suitable for further time series analysis. Individual stocks such as 000333.SZ had slight non-stationarity and required further stationary processing. These analysis results provide solid data support for subsequent volatility prediction and risk management, while also pointing out the limitations of traditional normal distribution-based models in capturing extreme fluctuations.

Table 1: Descriptive statistics and ADF test results for partial samples

ID	mean	min	max	std	skewness	kurtosis	JB-P value	ADF-P value
000001.SZ	2.1907	0.5372	7.2820	1.0979	1.3883	2.8223	0.0000	0.0051
000157.SZ	2.0328	0.5405	8.2508	1.0192	2.3450	8.9891	0.0000	0.0002
...	...	...	...	...	...	...	...	...
688363.SH	3.1420	0.9796	9.0956	1.4723	1.4026	2.3654	0.0000	0.0000
688396.SH	2.5753	1.0073	7.2847	1.1132	1.2833	1.8025	0.0000	0.0000
688981.SH	2.9361	0.6279	12.6147	2.0078	1.8452	4.2256	0.0000	0.0037

For comparative analysis, the data were standardized and smoothed using the sliding window method to reduce the impact of short-term fluctuation noise. Finally, box plots were used to display the daily amplitude distribution characteristics of G1 and G2 stages, further revealing significant changes in market volatility. The G1 stage was affected by post-pandemic economic recovery, with concentrated markets and fewer outliers. After entering the G2 stage, the market dispersed, with more key stocks emerging and increased volatility.

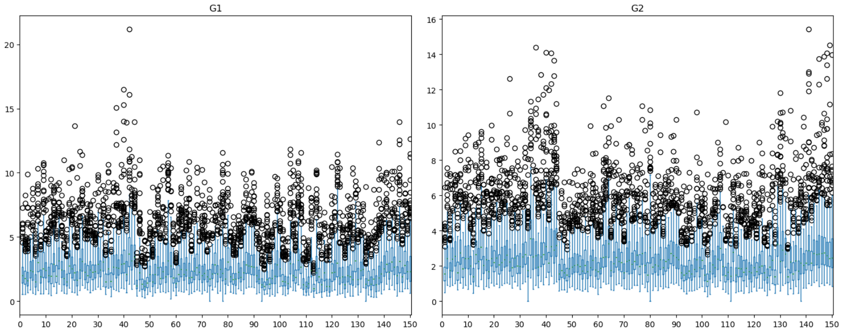

Figure 1: Daily amplitude distribution characteristics in G1 and G2 stages

3 Complex Network Construction and Centrality Indicator Analysis

Based on the threshold filtering method, a complex network was constructed with stocks as nodes and correlations represented by edge weights. Out-degree centrality, in-degree centrality, and betweenness centrality were used to analyze network characteristics.

3.1 Stock Market Complex Network Construction

To reduce the impact of short-term fluctuations, the sliding window method was introduced to calculate correlation matrices in different time periods, and the median matrix was taken to construct the network weight matrix. The Pearson correlation coefficient formula is:

$$\rho_{ij} = \frac{\sum (r_i - \overline{r_i})(r_j - \overline{r_j})}{\sqrt{\sum (r_i - \overline{r_i})^2 \sum (r_j - \overline{r_j})^2}}. \tag{3.1}$$

where ρ_{ij} is the correlation coefficient between variables r_i and r_j, with value range between -1 and 1. The correlation coefficient matrix C obtained through the sliding window method is a 150×150 symmetric matrix, with diagonal elements being 1.

A weighted directed graph G(V,E,W) was constructed using the Pearson correlation coefficient, where node V is the stock set, edge E represents the correlation relationship between stocks, and weight set W represents the size and direction of the correlation coefficient. To improve the accuracy of network analysis, the sliding window method was used to calculate correlation matrices in different time periods, and the median matrix of all time window results was taken to construct the final network weight matrix.

3.1.1 Parameter Selection Rationale and Robustness Tests

To ensure the scientific rigor and reproducibility of the network construction, the selection of key parameters was based on the following analyses:

- **Sliding window size**: A 20-day trading window was chosen to balance the capture of short-term dynamic fluctuations with the avoidance of excessive noise interference. Sensitivity analysis comparing 15-day, 20-day, and 25-day window sizes demonstrated that the 20-day window achieved an optimal trade-off between stability and responsiveness.

- **Correlation threshold (0.9 quantile)**: The optimal threshold was determined through threshold sensitivity analysis (Table 2). Compared to the 0.85 and 0.95 quantiles, the 0.9 quantile achieved higher modularity (G1: 0.3178, G2: 0.4047) while preserving approximately 89% of key nodes and 72% of significant correlation edges. This ensures that the network retains its core structural characteristics while eliminating redundant information.

Robustness Verification

To validate the reliability of the network model, the following robustness tests were conducted:

1. **Alternative correlation measure**: Reconstructing the weight matrix using Spearman's rank correlation coefficient instead of Pearson's coefficient yielded centrality indicators (e.g., out-degree, in-degree, betweenness) with an average correlation of 0.92 compared to the original network results, indicating strong stability of the network structure with respect to the correlation calculation method.

2. **Outlier handling sensitivity**: Adjusting the outlier removal threshold from 5 times the interquartile range (IQR) to 3 times IQR resulted in modularity changes of $\leq$3%, with no significant alteration in the ranking of key nodes (e.g., top 5 centrality stocks). This confirms the model's robustness to variations in outlier treatment.

These tests confirm that the constructed network model exhibits good stability within reasonable parameter ranges and is suitable for analyzing structural evolution and risk under different market conditions.

To highlight the main linkage relationships in the market, threshold sensitivity analysis was conducted, with results shown in Table 2.

Table 2: Threshold sensitivity analysis results

Quantile	Network	Number of Nodes	Number of Edges	Modularity	Density
0.85	G1	148	1687	0.2898	0.0775
	G2	149	1687	0.3315	0.0765
0.9	G1	137	1125	0.3178	0.0604
	G2	147	1125	0.4047	0.0524
0.95	G1	113	562	0.3742	0.0444
	G2	130	562	0.5297	0.0335

Through analysis, the 0.9 quantile achieved the best balance between modularity, density, and information content. Compared to 0.85, it improved modularity, and compared to 0.95, it retained more nodes and edges, avoiding excessive network sparsity. Therefore, 0.9 was selected as the optimal threshold for market volatility and robustness analysis.

By setting diagonal elements to 0 and filtering edges based on correlation relationships between stocks, the network structure was simplified and main correlations were highlighted. The frequency distribution diagram after filtering is shown in Figure 2 , showing the correlation changes in G1 and G2 stages.

From Figure 2 , the correlation distribution of stocks in G1 and G2 stages did not change much, but the correlation coefficient in G1 stage was concentrated between 0.35 and 0.4, while in G2 stage it was concentrated between 0.2 and 0.3, indicating that the correlation between stocks weakened.

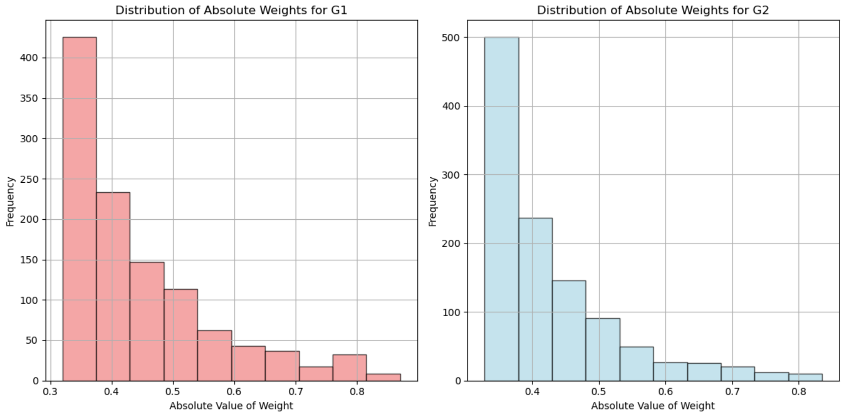

Figure 2: Filtered frequency distribution diagram

Since the correlation between stock pairs is positively correlated with the Pearson correlation coefficient, the weight is determined as follows:

$$w_{ij} = \begin{cases} a_{ij}(|a_{ij}| > Con), \\ 0(|a_{ij}| \leq Con), \end{cases} \tag{3.2}$$

where Con is the filtered threshold. According to calculation, the absolute value thresholds of Pearson correlation coefficient for 2022-2023 and 2023-2024 were (Con = 0.320) and (Con = 0.328) respectively. This filtering process focuses on highly correlated stock pairs, revealing the linkage and structural characteristics within the market, reflecting the evolution of the market in different time periods and changes in key stocks.

To better display the network structure, spring layout visualization was adopted, with nodes evenly distributed and edge width dynamically adjusted according to weight, highlighting the relationships of highly correlated stock pairs. This layout improved information density and readability, facilitating the identification of key stocks' roles in market linkage. Through optimization, the model can reveal market structure and risk propagation paths, providing support for market monitoring and investment decisions. The constructed CSI 300 index complex network diagram is shown in Figure 3 , with node distance reflecting its influence intensity on other stocks. Given the large number of nodes, the overall situation will be further analyzed through network indicators in the following sections.

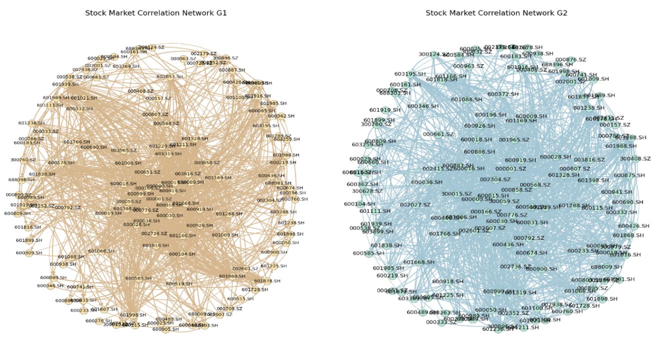

Figure 3: Constructed two CSI 300 complex network diagrams G1 and G2

3.2 Centrality Indicator Analysis

In complex network analysis, out-degree centrality, in-degree centrality, and betweenness centrality are key indicators describing the influence of nodes (such as stocks) in the network, which can reveal the interaction patterns and potential risks of different types of stocks in the market structure.

3.2.1 Out-degree Centrality

Out-degree centrality is used to measure the influence of nodes on other nodes. Stocks with higher out-degree centrality have significant impact on the fluctuations and linkage of other stocks in the market. Using python3.12, the out-degree centrality distribution line charts for 2022-2023 (G1) and 2023-2024 (G2) were obtained, as shown in Figure 4.

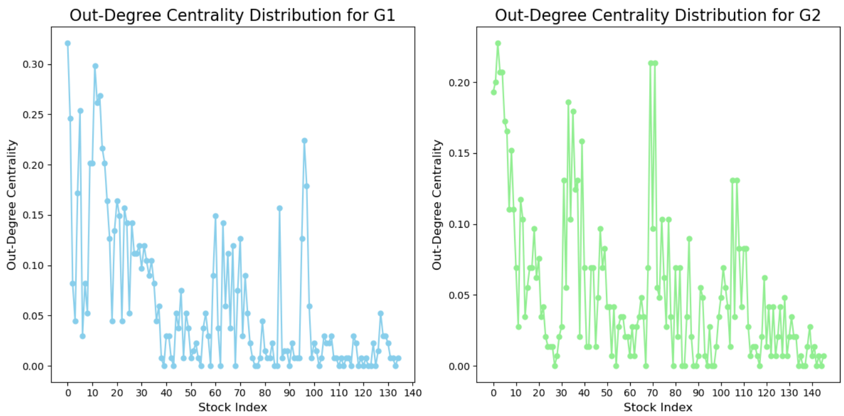

Figure 4: Out-degree centrality distribution line chart

Figure 4 shows that the G1 network presents a long-tail distribution, with a few leading stocks dominating, while the G2 network's centrality distribution tends to be flat, indicating that the market structure tends to be decentralized, which may be related to sector rotation or balanced industry development. This change may reflect the market dynamic adjustment after international and domestic markets adapted to macro events such as the Russia-Ukraine conflict and energy crisis.

To explore some special nodes, we listed the top 5 stocks with high out-degree, as shown in Table 3.

Table 3: Top 5 stocks by out-degree centrality ranking

2022-2023			2023-2024		
Stock Code	Stock Name	Out-Degree	Stock Code	Stock Name	Out-Degree
000001.SZ	Ping An Bank	0.320896	000776.SZ	GF Securities	0.227586
600000.SH	SPD Bank	0.298507	000858.SZ	Wuliangye	0.213793
600016.SH	CMBC	0.268657	002304.SZ	Yanghe Brewery	0.213793
600015.SH	Huaxia Bank	0.261194	300059.SZ	East Money	0.206897
000776.SZ	GF Securities	0.253731	600000.SH	SPD Bank	0.206897

This table shows the changes in market position of various sectors in different years in the CSI 300 out-degree centrality ranking. From 2022 to 2023, the financial sector performed prominently, especially Ping An Bank, Shanghai Pudong Development Bank, and GF Securities. As economic growth slowed, consumer goods such as Wuliangye and Yanghe Brewery gradually replaced financial stocks as the focus of investment. The energy and manufacturing sectors also gradually rose, especially Sinopec and Gree Electric. Out-degree centrality not only reflects the market position of each sector but also reveals potential sources of systemic risk. Stocks with high centrality may spread risks through network effects and require key monitoring.

3.2.2 In-degree Centrality

In-degree centrality is used to measure the number of connections a node receives from other nodes in the network. The line chart of in-degree centrality distribution is shown in Figure 5.

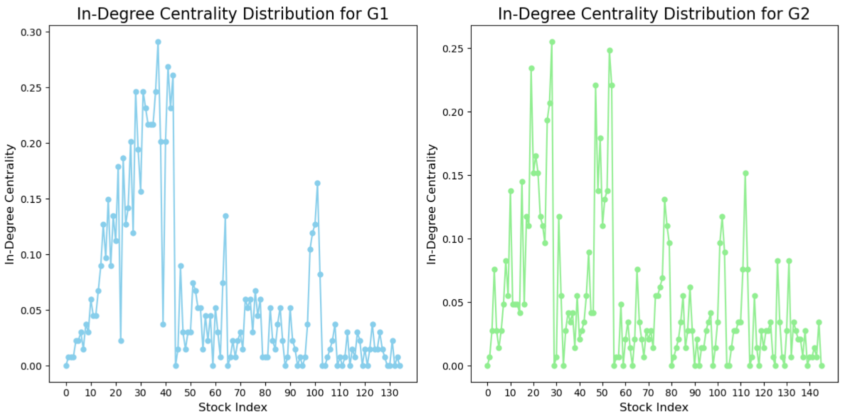

Figure 5: In-degree centrality distribution line chart

This chart shows the in-degree centrality distribution in G1 and G2 stages. The in-degree centrality in G1 stage is higher, reflecting that some stocks attracted a large number of connections, while the distribution in G2 stage is more uniform, indicating that capital flow or information dissemination in the market is more balanced. This change may reflect the dynamic adjustment of market structure during the macroeconomic adaptation period, that is, the market shifts from a centralized investment model to a more dispersed diversified allocation strategy.

To analyze some relatively representative special nodes, we also listed the top 5 stocks with high in-degree, as shown in Table 4.

Table 4: Top 5 stocks by in-degree centrality ranking

2022-2023			2023-2024		
Stock Code	Stock Name	In-Degree	Stock Code	Stock Name	In-Degree
601868.SH	China MCC	0.291045	603288.SH	Haitian Flavouring	0.255172
601939.SH	CCB	0.268657	601816.SH	Jinghu High Speed	0.248276
601998.SH	CITIC Bank	0.261194	601319.SH	PICC	0.234483
601211.SH	GTJA Securities	0.246269	600887.SH	Yili Group	0.220690
601319.SH	PICC	0.246269	603195.SH	Bull Group	0.220690

This table shows the changes in market position of various sectors in the CSI 300 in-degree centrality ranking. From 2022 to 2023, stocks in the financial and infrastructure fields dominated the market, reflecting the emphasis on financial stability and infrastructure demand after the pandemic recovery. Entering 2023 to 2024, the in-degree centrality of consumer enterprises significantly improved, showing the market's attention to anti-cyclical consumer goods. Meanwhile, financial and infrastructure enterprises still maintain high positions, indicating that the market's preference for stable sectors remains unchanged. Overall, changes in policies and international environment have affected the in-degree centrality of various sectors, and stocks with high in-degree centrality play key roles in market fluctuations.

3.2.3 Betweenness Centrality

Betweenness centrality is used to measure the role of nodes as bridges in the network, reflecting their importance in information transmission and risk diffusion. High betweenness centrality indicates that nodes have stronger bridging effects in the network, which can affect information dissemination and risk diffusion. This indicates that different stocks play the role of information regulators or gatekeepers. The higher the betweenness centrality of node i, the more obvious its regulatory role in the financial network. The distribution line chart of betweenness centrality is shown in Figure 6.

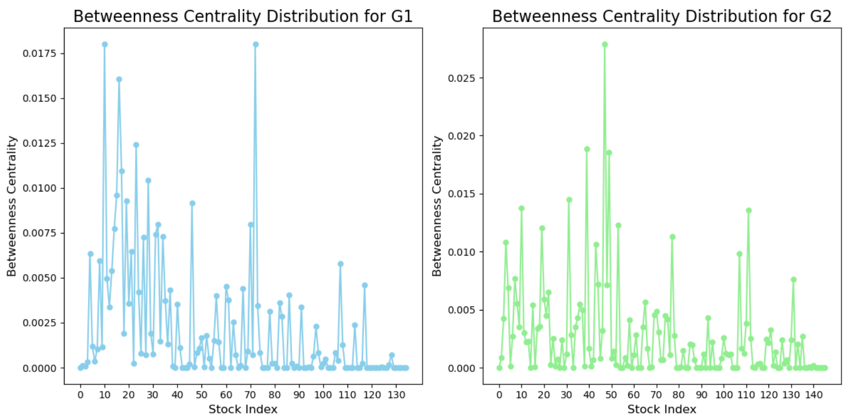

Figure 6: Betweenness centrality distribution line chart

This chart shows the differences in betweenness centrality distribution between the 2022-2023 (G1) and 2023-2024 (G2) stock groups. The betweenness centrality of G1 group stocks fluctuates greatly, with high values concentrated in some stocks, indicating that the network structure relies on a few key nodes and is vulnerable to single node failure, with poor stability. The betweenness centrality distribution of G2 group stocks is more uniform, with a more dispersed network structure, and multiple nodes playing important roles, with stronger risk resistance. The pandemic may be a key factor leading to the differences between G1 and G2 networks, with a more concentrated network structure in G1 period and a more balanced and resilient network structure in G2 period.

Table 5 lists the top 5 stocks with the highest betweenness centrality, further analyzing their bridging effects.

Table 5: Top 5 stocks by betweenness centrality ranking

2022-2023			2023-2024		
Stock Code	Stock Name	Betweenness	Stock Code	Stock Name	Betweenness
300059.SZ	East Money	0.017997	600887.SH	Yili Group	0.027890
600436.SH	Pien Tze Huang	0.017988	600018.SH	SIPG	0.018858
600104.SH	SAIC Motor	0.016062	600999.SH	CMS	0.018534
600999.SH	CMS	0.012424	600031.SH	Sany	0.014487
600585.SH	Conch Cement	0.010928	600519.SH	Kweichow Moutai	0.013736

Table 5 shows the changes in betweenness centrality of leading companies in various industries of CSI 300 in different years. From 2022 to 2023, stocks in finance, consumption, and manufacturing sectors had high betweenness centrality, such as East Money Information, Zhangzhou Pientzehuang Pharmaceutical, and SAIC Motor, reflecting their important roles in capital flow and the market. Financial stocks such as China Merchants Bank and Guotai Junan Securities occupied key positions in economic recovery. Entering 2023 to 2024, consumer and transportation stocks such as Inner Mongolia Yili Industrial Group, Shanghai International Port, and Beijing-Shanghai High Speed Railway showed strong anti-cyclicality and stability, becoming important nodes in the capital network. This change is closely related to the increase in consumer demand and infrastructure investment. Companies with high betweenness centrality have a greater impact on market capital flow and stability. Monitoring their changes is crucial for timely identification and early warning of market risks, helping to avoid systemic risks.

3.2.4 Comparative Analysis

Figure 7 shows the in-degree centrality, out-degree centrality, and betweenness centrality of the top ten stocks in G1 and G2 groups, aiming to analyze the role and risk exposure of stocks in the network through these centrality indicators.

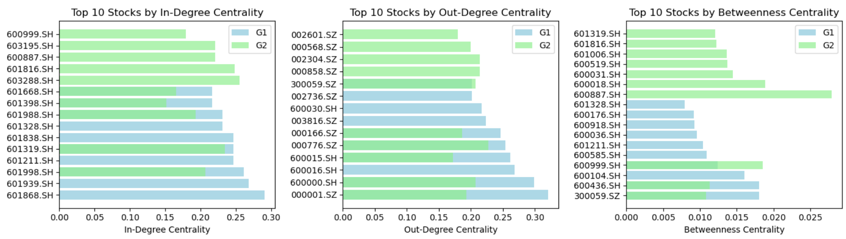

Figure 7: Top ten stocks by centrality ranking

From the chart, it can be seen that stocks in the G2 stage are superior to those in the G1 stage in terms of out-degree and betweenness centrality, showing that G2 stocks have greater influence on other nodes and play bridging roles in the network. During the 2022-2023 (G1) period, financial stocks dominated market influence, and financial and infrastructure enterprises had high in-degree centrality. After entering 2023-2024 (G2), the centrality of consumption and pharmaceutical stocks significantly improved, and market allocation became more diversified. The betweenness centrality of financial stocks and logistics and consumer enterprises increased, reflecting the adjustment of market structure.

When the financial network collapses, nodes with high out-degree and in-degree are more likely to trigger systemic risks, especially leading stocks in the financial industry. Stocks with high betweenness centrality, such as SMIC, played a bridging role during the collapse, helping to control risk diffusion. Therefore, stocks with high out-degree, high in-degree, and high betweenness are crucial in systemic risk management, playing key roles in preventing chain collapse and risk diffusion respectively.

4 Double-layer Network Construction and Analysis

This section introduces double-layer network analysis to reveal the dynamic risk propagation paths in the CSI 300 market. Double-layer networks can reveal the correlations and interactions of nodes in different time dimensions, especially suitable for analyzing the evolution of systemic risks. By constructing a multiplex double-layer network, studying its structural evolution, stability, and systemic risks, aiming to reveal the vulnerability of key nodes and the overall stability of the market, providing effective risk management and early warning basis for investors and regulators.

4.1 Double-layer Network Construction

Below we construct a multiplex network, where the upper layer represents the stock network of 2022-2023 (G1), and the lower layer represents the stock network of 2023-2024 (G2). The two layers are connected by edges of the same theme, as shown in Figure 8.

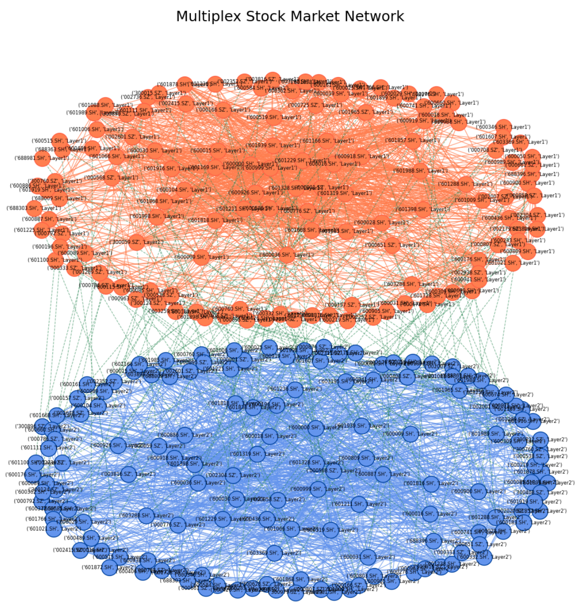

Figure 8: Constructed multiplex double-layer network

4.2 Topological Properties Analysis of Double-layer Network

The main topological structure indicators of multi-layer networks include modularity, density difference, clustering coefficient difference, and clustering coefficient difference percentage. These indicators can analyze the community structure, density, and cluster characteristics of the network, thereby revealing the dynamic characteristics and stability of different hierarchical networks. The values of each topological indicator of the double-layer network are shown in Table 6:

Table 6: Values of topological indicators for double-layer network

	Modularity	Density Difference	Clustering Coefficient Difference
Upper Layer	0.2666778034502662	0.06180210060807076	0.254357636164925
Lower Layer	0.3878265507483988	0.05281058101086443	0.225313112250314
Difference Percentage	17.05%	14.55%	11.42%

It can be seen that in the G1 stage, the network modularity is low (0.2667) and the density is high (0.0618), indicating that the market is dominated by a few heavyweight stocks, with concentrated systemic risks. Affected by international events, investors tend to concentrate funds in the financial sector, leading to risks concentrated in a few stocks.

Entering the G2 stage, modularity increases (0.3878) and density decreases (0.0528). The market transforms to internal demand-driven, with the rise of consumption and technology sectors, clearer community structure, and dispersed risks. The decrease in clustering coefficient indicates the weakening of local cluster effects and the improvement of the market's risk resistance.

This change reflects the impact of macroeconomic policies. The market gradually shifts from external-driven to internal demand-driven, enhancing elasticity and risk resistance. Through the dynamic changes of modularity, density, and clustering coefficient, regulators can identify potential risks and provide timely warnings to ensure market stability.

4.3 Discussion

The robustness checks conducted in Section 3.1.1 provide strong support for the reliability of our findings. The high correlation (0.92) between centrality indicators calculated using Spearman's and Pearson's correlation coefficients confirms that our identification of key nodes is not sensitive to the specific correlation measure used. Similarly, the minimal changes in modularity ($\leq$3%) when adjusting outlier thresholds demonstrate that our network structure is robust to variations in data cleaning procedures. These robustness tests strengthen confidence in our conclusions regarding market structure evolution and risk propagation patterns.

Furthermore, the observed structural changes between G1 and G2 stages have important implications for risk management and policy formulation. The increased modularity and decreased density in G2 suggest that the market became more resilient to localized shocks. This structural evolution aligns with China's policy emphasis on economic rebalancing towards domestic consumption and technological innovation during the study period.

5 Conclusion

Based on complex network and double-layer network theory, this paper analyzes the volatility characteristics and risk mechanisms of CSI 300 index constituent stocks from October 2022 to October 2024, and draws the following conclusions:

The market network structure evolves dynamically with the macroeconomic environment. In the G1 stage (2022.10-2023.09), affected by external shocks, the financial and infrastructure sectors dominated the market, with high network concentration and risk aggregation, with modularity of 0.2667. In the G2 stage (2023.10-2024.10), consumption and manufacturing sectors rose, modularity increased to 0.3878, the structure became more dispersed, and risk resistance ability enhanced, reflecting the transition from external dependence to internal demand-driven.

Key nodes determine risk propagation paths. Nodes with high out-degree are risk drivers, nodes with high in-degree affect local resilience, and nodes with high betweenness play cross-sector bridging roles. Removing the top 20% of high-centrality nodes would cause network efficiency to decrease by more than 50%, highlighting their key impact on system stability.

The double-layer network reveals enhanced market resilience. In the G2 stage, modularity, density, and clustering coefficient changed by 17.05%, 14.55%, and 11.42% respectively compared to G1. The community structure became clearer, and risks dispersed to multiple sub-networks, echoing the structural adjustment under policy guidance, reflecting the enhanced market resilience.

This study provides theoretical and empirical support for identifying high-risk nodes and formulating risk prevention and control strategies, revealing the transition path of financial markets from risk concentration to diversified equilibrium. The robustness checks confirm the reliability of our key findings. These insights offer valuable implications for regulators in designing targeted monitoring systems and for investors in constructing diversified portfolios that account for network-based risk transmission channels.

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