Journal of Southeast University (English Edition) Vol. 39, No. 3, pp. 233 – 239 Sept. 2023 ISSN 1003—7985

A multilayer network model of the banking system and its evolution

Jiang Qiao[1] Liu Xiaoxing[1,2] Ma Qianting[2,3]

([1] School of Cyber Science and Engineering, Southeast University, Nanjing 211189, China)
([2] School of Economics and Management, Southeast University, Nanjing 211189, China)
([3] College of Finance, Nanjing Agricultural University, Nanjing 210095, China)

Abstract: A multilayer network model of the banking system is constructed based on the Pearson, Spearman, and Kendall correlations among stock returns. The three correlations correspond to the multilayer network's Pearson, Spearman, and Kendall layers. This paper empirically analyzes the evolutionary characteristics of the multilayer network structure of the banking system from 2011 to 2020, using data from China's listed banks. The following are the principal findings based on empirical research. Firstly, the large state-owned banks are more active within the banking system. Secondly, the interlayer correlation of the multilayer banking network exhibits volatility, with the Spearman and Kendall layers showing a higher correlation than the Pearson layer. Thirdly, the constructed bank multilayer network exhibits small-world characteristics. Fourthly, all bank nodes influence each layer of the banking multilayer network. The present research reveals the dependency structure between various correlations of bank yield fluctuations, which has a specific theoretical reference value for maintaining the banking system's smooth operation.

Key words: multilayer network model; banking system; network evolutionary characteristics; small-world characteristics; dependency structure

DOI: 10.3969/j. issn. 1003 – 7985. 2023. 03. 003

Commercial banks are a significant part of the modern financial system and an indispensable financial intermediary for the economic system's health and stability. Commercial banks form intricate business associations through various forms, such as interbank lending and investment[1]. A complex network can represent the complex credit and debt relationships among commercial banks, with commercial banks serving as the network's nodes and the credit and debt relationships serving as the network's edges. Complex network relationships between commercial banks facilitate the efficient and rational allocation of liquidities in the interbank financial market. Simultaneously, however, it causes the risk of a single financial institution to rapidly spread to other banks, thus transforming it into a systemic risk for the entire banking industry[2]. Therefore, studying the complexity of interbank linkages from the perspective of complex networks will aid in a deeper understanding of the banking system's complex microstructure. In addition, it has significant reference value for preserving the stability of the interbank market and enhancing the quality and efficacy of the development of commercial banks.

The complex network theory is widely employed in the study of the structural characteristics of the banking network, and it is an effective tool for studying the correlation between financial entities. Current research focuses extensively on the single-layer correlation among banks. Scholars have discovered that Japan's interbank payment network[3], Brazil's interbank risk exposure network[4] and Russia's interbank loan network[5] show scale-free properties. Both the US interbank payment network[6] and the UK interbank payment network[7] show small-world attributes. Meanwhile, the structure of the Austrian[8], Colombian[9], and German interbank lending networks[10] is hierarchical. Moreover, the Brazilian[11] and the Dutch interbank market interbank lending network[12] have a money center structure. Lastly, the interbank overnight lending market network in Italy[13] and the interbank risk exposure network in Mexico[14] show dynamic evolution characteristics.

In addition, some scholars have begun studying the multilayer relevance among banks. For example, Langfield et al.[15] constructed the bank's risk exposure network and capital network, and they found that the risk exposure network has a more pronounced core edge structure than the capital network. In Mexico, Poledna et al.[16] built a four-layered banking network comprised of interbank deposits and loans, securities cross-holdings, derivatives, and foreign exchange relations. They found that the degree distribution of these four-layer networks has a thick power-law tail, and the correlation between

Received 2023-04-10, **Revised** 2023-07-02.

Biographies: Qiao Jiang (1972—), male, Ph. D. candidate; Ma Qianting (corresponding author), male, doctor, mqt2626@njau.edu.cn.

Foundation items: The National Natural Science Foundation of China (No. 72173018), the 71st General Program of China Postdoctoral Science Foundation (No. 2022M711649).

Citation: Jiang Qiao, Liu Xiaoxing, Ma Qianting. A multilayer network model of the banking system and its evolution[J]. Journal of Southeast University (English Edition), 2023, 39(3): 233 – 239. DOI: 10.3969/j. issn. 1003 – 7985. 2023. 03. 003.

different network layers is distinct. Meanwhile, Bargigli et al. [17] built a multilayer network of Italian banks based on interbank guarantee relationships and different maturity dates. They discovered that medium-sized banks were occasionally at the core, whereas large banks were always at the core. Aldasoro and Alves[18] evaluated interbank assets and liabilities and built a multilayer network of European banks with varying maturities. They found distinct core-periphery structures between different layers. Moreover, Berndsen et al. [19] constructed a three-layer network based on the financial payment relationship between Colombia's sovereign bond, foreign exchange, and interbank markets. The average path length of these networks was found to be short, whereas the aggregation coefficient was large scale. Hüser et al. [20] constructed a multilayer bond cross-holding network based on the debt types and debt grades of European banks. They showed that the multilayer aggregation network has a high degree of aggregation.

The aforementioned research focuses primarily on the direct relationship between the banking system's single-layer network and the multilayer network. In fact, direct correlations exist among financial institutions. However, many indirect correlations, such as common asset correlations and yield volatility correlations, also exist. Li et al. [21] built an interbank common loan network based on the banks-enterprise loan relationship. They determined that the co-loan network always shows a core-peripheral structure and a small-world property with a nine-year lifespan. The multiple constructed from financial data by Musmeci et al. [22] reveals significant changes in the network's internal multiplex properties that are associated with periods of financial stress.

Considering that studies on the indirect correlation between banks are scarce, this present paper aims to analyze in depth the micro-dependency structure of the indirect multilayer correlation between banks from the perspective of different yield fluctuation correlations. Accordingly, this study focuses primarily on the three correlations of bank return volatility: Pearson correlation[23], Spearman correlation[24], and Kendall correlation[25]. The micro basis of complex multilayer bank correlations is deconstructed by analyzing the dependency structure between the different correlations of bank yield fluctuations. Compared with existing research, this study contributes to the existing literature in the following ways. First, a method for constructing the bank multilayer network model is proposed. Second, it investigates the structural features and evolutionary characteristics of the bank multilayer network. Third, this article reveals the inherent relationship between multilayer correlations between banks and stock market prices.

1 Model

This study develops a multilayer network model for banks using bank stocks as nodes and the correlation of returns between stocks as edges. Among them, three kinds of correlations between stocks are mainly considered, namely, the Pearson, Spearman, and Kendall correlations, which are represented by the Pearson, Spearman, and Kendall correlation coefficients, respectively.

1.1 Correlation calculation

1.1.1 Pearson correlation

The Pearson correlation coefficient is one of the most commonly used linear correlation coefficients suitable for continuous variables; the data obey normality[23]. The following equation presents the Pearson correlation coefficient $\rho_{i,j}^{(1)}$:

$$\rho_{i,j}^{(1)} = \frac{<Y_iY_j> - <Y_i><Y_j>}{\sqrt{(<Y_i^2> - <Y_j>^2)(<Y_j^2> - <Y_j>^2)}} \tag{1}$$

where $<Y_i>$ denotes the mathematical expectation of the sequence $\{Y_i^{(1)}, Y_i^{(2)}, \ldots, Y_i^{(L)}\}$. The value of the coefficient is always between -1 and 1. Variables approaching 0 are uncorrelated, whereas those close to 1 or -1 are strongly correlated.

1.1.2 Spearman correlation

The Spearman correlation coefficient is a rank correlation coefficient, also known as the rank correlation coefficient, which is suitable for continuous variables and does not necessarily obey normality[24]. The Spearman correlation coefficient $\rho_{i,j}^{(2)}$ is as follows:

$$\rho_{i,j}^{(2)} = 1 - \frac{6\sum_{m=1}^{n} d_m^2}{n(n^2-1)} \tag{2}$$

where d_m is the rank difference between $Y_i^{(m)}$ and $Y_j^{(m)}$. The rank difference of a number is the position of the number in a column after it is sorted from small to large. The value of the coefficient is always between -1 and 1. Variables approaching 0 are uncorrelated, whereas variables close to 1 or -1 are strongly correlated.

1.1.3 Kendall correlation

Kendall correlation coefficient is a rank correlation coefficient, also known as a rank correlation coefficient, which applies to categorical variables[25]. The following is the Kendall correlation coefficient $\rho_{i,j}^{(3)}$:

$$\rho_{i,j}^{(3)} = P[(Y_i^{(a)} - Y_i^{(b)})(Y_j^{(a)} - Y_j^{(b)}) > 0] - P[(Y_i^{(a)} - Y_i^{(b)})(Y_j^{(a)} - Y_j^{(b)}) < 0] \tag{3}$$

where $P[(Y_i^{(a)} - Y_i^{(b)})(Y_j^{(a)} - Y_j^{(b)}) > 0]$ denotes the probability when Y_i and Y_j change in the same direction, $P[(Y_i^{(a)} - Y_i^{(b)})(Y_j^{(a)} - Y_j^{(b)}) < 0]$ represents the probability when Y_i and Y_j change in the opposite direction. The value of the coefficient is always between -1 and 1. Variables approaching 0 are uncorrelated, whereas those close to 1 or -1 are strongly correlated.

1.2 Multilayer network construction

Assume there are N bank stocks on the market, and the period is T days. Let $Y_i(k)$ be the log-return series of the stock i in the k-th window. This study develops a multilayer network model for banks using bank stocks as nodes and the correlation between stock returns as edges. It constructs three-layer banking networks based on three correlations of banking return volatility: the Pearson, Spearman, and Kendall layer networks. The corresponding correlation matrices are $\boldsymbol{\rho}^{(1)} = [\rho_{ij}^{(1)}(k)]$, $\boldsymbol{\rho}^{(2)} = [\rho_{ij}^{(2)}(k)]$, and $\boldsymbol{\rho}^{(3)} = [\rho_{ij}^{(3)}(k)]$, respectively.

At the same time, the concept of "distance" is introduced. At time t, the distance matrix $\boldsymbol{d} = [d_{i,j}(k)]$ and the weight matrix $\boldsymbol{w} = [w_{i,j}(k)]$ of the distance between stock i and stock j in the k-th correlation network are shown in the following equations.

$$d_{i,j}(k) = \sqrt{2(1-\rho_{i,j}(k)} \tag{4}$$

$$w_{i,j}(k) = \mathrm{e}^{d_{i,j}(k)} \tag{5}$$

where $\rho_{i,j}(k)$ denotes the correlation coefficient and $\rho_{i,j}(k) \in [-1,1]$, $d_{i,j}(k) \in [0,2]$, $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, N$. Let $\rho_{i,j}(k) = \rho_{i,j}^{(1)}(k)$, $\rho_{i,j}(k) = \rho_{i,j}^{(2)}(k)$, and $\rho_{i,j}(k) = \rho_{i,j}^{(3)}(k)$ in the Pearson, Spearman, and Kendall layer networks, respectively. For the k-th stock correlation network, the starting and ending times are $1 + (k-1)\delta$ and $(k-1)\delta + E$, respectively.

Based on the preceding calculation process, this paper constructs the aforementioned three network layers. Notably, we are constructing a fully interconnected network, so network edges are inevitable. In addition, this article constructs a weighted network, so the degree of nodes is not an integer. The weight matrix corresponds to the weights of the network's edges. The banking multilayer network model has been constructed thus far.

2 Empirical Analysis

2.1 Data

We initially selected 37 banking stocks based on the Wind database. In addition, we eliminated 16 stocks suspended for less than 30 consecutive trading days and whose daily log return is not zero for 30 consecutive trading days. Therefore, we collected 16 stocks of Chinese listed banks in 2 432 trading days from January 1, 2011 to December 31, 2020. Using forward weighting, we processed all stocks' daily closing price data. Following the initial data processing, we can obtain the daily log-return data for 16 stocks for a total of 2 431 trading days. In this study, the time window E is 1 month, the network interval δ is 1 month, and there are 120 total stock correlation networks. We divide the 16 stocks into three categories based on the Wind database's bank classification standard: large state-owned banks, national joint-stock banks, and regional banks.

2.2 Node degree of multilayer network

The bank multilayer network's node degree is a simple and essential concept for describing the characteristics of bank nodes. The larger the node degree, the more influential the node is in the banking system. Referring to Boccaletti et al.'s[26] work, the node degree of the multilayer network adopts the vector form. Vector $\boldsymbol{k}_i$ is the degree of node i in the multilayer network, and $\boldsymbol{k}_i = \{k_i^{[1]}, k_i^{[2]}, \ldots, k_i^{[M]}\}$, where $k_i^{[\alpha]}$ is the degree of node i in layer α, and M is the number of layers in the multilayer network. The total degree of node i in the multilayer network can be expressed as follows:

$$o_i = \sum_{\alpha=1}^{M} k_i^{[\alpha]} \tag{6}$$

Tab. 1 measures the node degree of the bank multilayer network and its sub-networks in the Chinese interbank market's 120th stock correlation network. As shown in Tab. 1, the mean value and volatility of the Pearson layer network are high, whereas those of the Kendall layer network are low. This indicates that the Pearson layer network shows a better degree of correlation.

Tab. 1 Node degree of banking multilayer network

Network classification	Min	Max	Mean	Std
Pearson layer network	6.227 0	8.198 3	7.442 4	0.542 3
Spearman layer network	5.924 2	7.329 7	6.905 9	0.348 3
Kendall layer network	5.460 8	6.417 3	6.105 4	0.227 5
Multilayer network	17.612 0	21.945 4	20.453 7	1.055 5

To better describe the internal characteristics of the bank multilayer network, we show in Fig. 1 the node degree distribution of the bank multilayer network in the 120th stock correlation network, where the abscissa and the ordinate represent the bank number and the node degree, respectively. Among them, numbers 1-5 represent large state-owned banks, 6-13 represent national joint-stock banks, and 14-16 represent regional banks. The large state-owned banks have relatively high node degrees of the banking multilayer network, whereas the national joint-stock banks and regional banks have relatively low node degrees. It also indicates that large state-owned banks have a greater level of banking system activity.

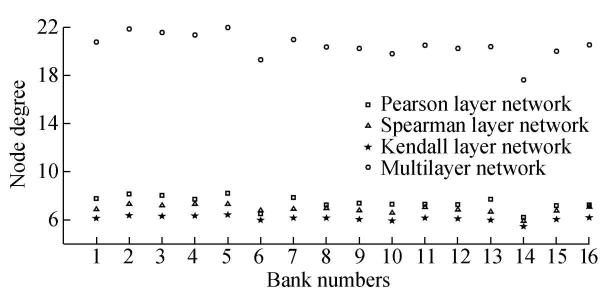

Fig. 1 Node degree distribution of banking multilayer network

2.3 Degree correlation of multilayer network

The degree correlation of the bank multilayer network is a crucial indicator for characterizing the relationships between various network layers. Specifically, the degree correlation of the bank multilayer network describes the correlation strength between different layers in the multilayer network. The higher the interlayer correlation value, the stronger the positive correlation between the two layers. Referring to the research of Battiston et al. [27], we expressed the degree correlation of the multilayer network $\boldsymbol{W}$ as follows:

$$\rho^{[\alpha,\beta]} = \frac{\sum_i (R_i^{[\alpha]} - \bar{R}^{[\alpha]})(R_i^{[\beta]} - \bar{R}^{[\beta]})}{\sqrt{\sum_i (R_i^{[\alpha]} - \bar{R}^{[\alpha]})^2 \sum_j (R_j^{[\beta]} - \bar{R}^{[\beta]})^2}} \tag{7}$$

where $R_i^{[\alpha]}$ is the moderate rank of node i in layer α, $\bar{R}^{[\alpha]}$ and $\bar{R}^{[\beta]}$ are the average rank of nodes in each layer, respectively.

Fig. 2 depicts the 120-period evolution of the degree correlation of the bank's multilayer network over time. It primarily illustrates the correlation between the degree of any two of the three network layers (i. e., the Pearson, Spearman, and Kendall layer networks). As shown in Fig. 2, the interlayer degree correlation of multilayer networks shows volatility. The mean value of the Pearson-Spearman interlayer degree correlation curves is 0.848 1, most of which are above 0.5. Meanwhile, the mean value of the Pearson-Kendall interlayer degree correlation curves is 0.853 9, most of which are above 0.5. Moreover, the mean value of the Spearman-Kendall interlayer degree correlation curve is 0.996 1, and most are above 0.95.

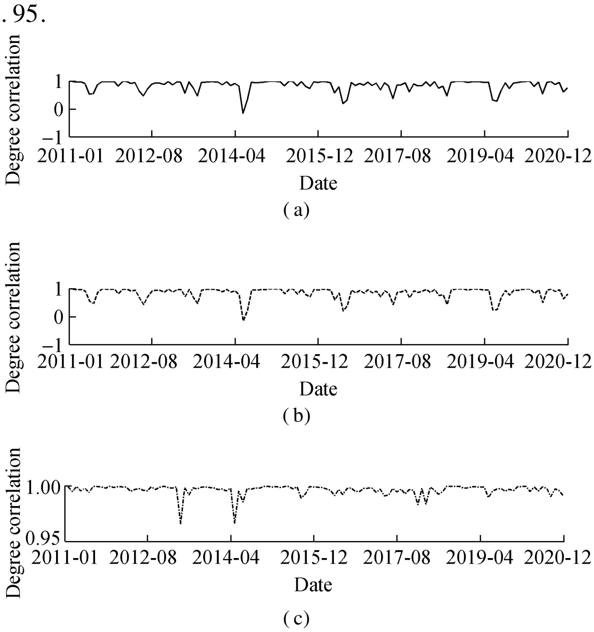

Fig. 2 Degree correlation of banking multilayer network. (a) Pearson-Spearman; (b) Pearson-Kendall; (c) Spearman-Kendall

This indicates that the overall correlation between the three-layer networks is positive, and the interlayer degree correlation between the Spearman and Kendall layer is higher. This could be due to the fact that both correlation indicators are rank correlations. In addition, the interlayer correlation of the multilayer network between banks presents a degree of volatility; in June 2014, in particular, the interlayer correlation showed a significant decline, indicating that market conditions may have a notable impact on it. Similarly, Poledna et al. [16] constructed a multilayer financial network in Mexico and found that the interlayer degree correlation demonstrates a certain degree of volatility. The bank multilayer network structure constructed in the present paper replicates this characteristic of actual financial networks, thereby validating the model's rationality.

2.4 Clustering coefficient of multilayer network

The clustering coefficient of a multilayer network is used to describe the proximity of clustering among nodes in a multilayer network. In particular, it is used to describe the degree of interconnection between neighboring nodes of any node in a multilayer network. The aggregation of multilayer networks should consider not only the aggregation of intralayer connections but also the aggregation of interlayer connections, which have a greater apparent multilayer complexity than single-layer networks.

Referring to the research of Boccaletti et al. [26], we denote $N(i)$ as the set of all neighbor nodes of node i in the projection network proj($\boldsymbol{W}$), and $\bar{E}_\alpha(i)$ as the set of corresponding edges. Then, for any network layer $\alpha \in \{1, 2, \ldots, M\}$, its subgraph in the projection network is represented as $\bar{S}_\alpha(i) = (N_\alpha(i), \bar{E}_\alpha(i))$, where $N_\alpha(i) = N(i) \cap X_\alpha$ and $\bar{E}_\alpha(i)$ satisfies the following equation.

$$\bar{E}_\alpha(i) = \{(k, j) \in E_\alpha;\ k, j \in N_\alpha(i)\} \tag{8}$$

The clustering coefficient of node i in the multilayer network $\boldsymbol{W}$ is expressed as:

$$C_W(i) = \frac{2\sum_{\alpha=1}^{M} |\bar{E}_\alpha(i)|}{\sum_{\alpha=1}^{M} |N_\alpha(i)|(|N_\alpha(i)| - 1)} \tag{9}$$

Further, the clustering coefficient of the entire multilayer network can be defined as the average value of all nodes.

Fig. 3 depicts the evolution curve of the multilayer network's clustering coefficient from 2011 to 2020. As shown in Fig. 3, the mean value of the clustering coefficient throughout the entire evolution process is 10.255 2 and fluctuates in the range of 5-20. The average clustering coefficient of the random network at the same scale is 1.463 8, which explains why the banking multilayer network constructed in this study has a high clustering coefficient. This demonstrates that the whole multilayer network of the banking system has maintained a high level of aggregation throughout its evolution. It also shows the close relationship between bank businesses.

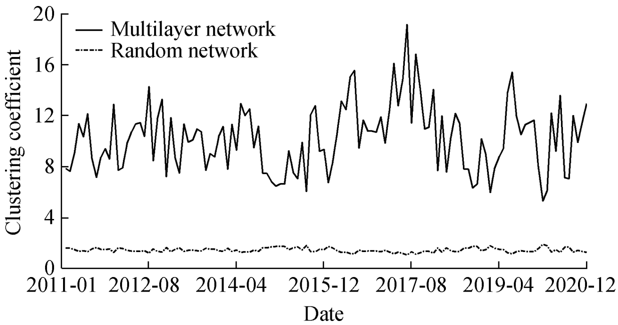

Fig. 3 Clustering coefficient of banking multilayer network

2.5 Average path length of multilayer network

The average path length of the bank-firm multilayer network represents the distance between any two nodes in the bank-firm system. Referring to Boccaletti et al. [26], we expressed the average path length of a multilayer network $\boldsymbol{W}$ as

$$L(\boldsymbol{W}) = \frac{1}{N(N-1)} \sum_{\substack{u, v \in X_M \\ u \neq v}} d_{uv} \tag{10}$$

where N denotes the number of nodes in the network, and d_{uv} is the shortest path connecting u and v.

Fig. 4 illustrates the evolution curve of the multilayer network's average path length from 2011 to 2020. It also demonstrates that the mean path length throughout the entire evolution process is only 0.388 6. Moreover, the distance between any two nodes in the entire 16-node banking system is approximately 0.4. Meanwhile, the average path length fluctuates smoothly between 0.25 and 0.5. The average path length of random networks of the same size is 0.882 2, indicating that the average path length of the banking multilayer network constructed in this paper is short. In a similar vein, Berndsen et al. [19] found that the average path length of the multilayer network is minimal in an empirical study of the Colombia multilayer financial network. Based on the clustering coefficient and average path length, the banking multilayer network constructed in this paper appears to exhibit small-world characteristics.

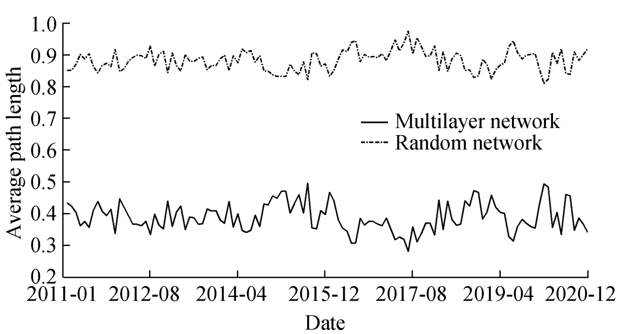

Fig. 4 Average path length of banking multilayer network

2.6 Participation coefficient of multilayer network

The participation coefficient of the bank multilayer network can be used to describe the participation degree of bank nodes in each layer network. Referring to the research of Battiston et al. [28], we express the multilayer participation coefficient P_i of the multilayer network $\boldsymbol{W}$ in the following equation.

$$P_i = \frac{M}{M-1}\left[1 - \sum_{\alpha=1}^{M} \left(\frac{k_i^{[\alpha]}}{o_i}\right)^2\right] \tag{11}$$

Moreover, the participation coefficient of the whole multilayer network $\boldsymbol{W}$ is the average value of all nodes' multilayer participation coefficient.

Fig. 5 illustrates the multilayer participation coefficient of the banking multilayer network node in the 120th month. The abscissa and ordinate represent the bank numbers and the nodes' multilayer participation coefficient, respectively. In addition, numbers 1-5, 6-13, and 14-16 denote large state-owned banks, national joint-stock banks, and regional banks, respectively. According to statistical analysis, all bank nodes' average multilevel participation coefficient is 0.997, and they are all above 0.994. Fig. 5 demonstrates that each bank node in the banking multilayer network has a higher multilayer participation coefficient. This indicates that all bank nodes have increased activity across all layers in the banking multilayer network.

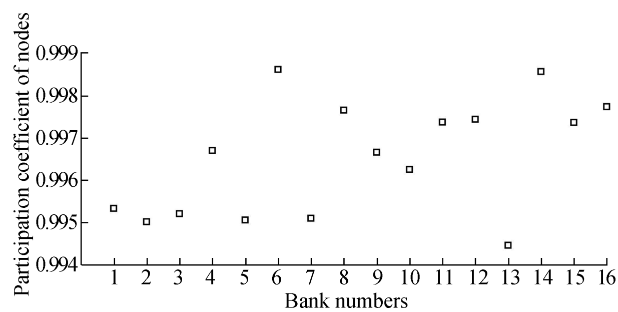

Fig. 5 Participation coefficient of nodes in banking multilayer network

To further characterize the activity of the banking multilayer network throughout the entire evolution process, we show in Fig. 6 the evolution curve of the bank multilayer network's participation coefficient from 2011 to 2020. Fig. 6 depicts the average value of all bank nodes for the multilayer network participation coefficient of the banking system. It also indicates that the average multilayer participation coefficient in the evolution of the entire banking system is significantly greater than 0.985. This demonstrates that all bank nodes have the potential to influence all layers in the multilayer network.

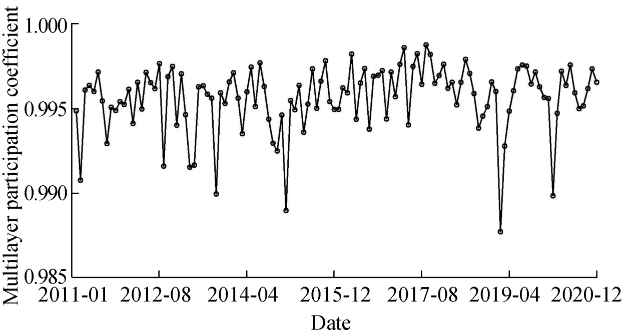

Fig. 6 Participation coefficient of banking multilayer network

3 Conclusions

1) The correlation between large state-owned banks is high, whereas that between regional banks is low. The Pearson layer network demonstrates a greater correlation. In banking multilayer networks, the large state-owned banks have relatively high node degrees, whereas the national joint-stock banks and regional banks have relatively low node degrees. This indicates that the large state-owned banks are more active within the banking system.

2) The interlayer correlation of the multilayer banking network exhibits a degree of volatility. A higher interlayer degree correlation exists between the Spearman and Kendall layers. This study presents a multilayer banking network with a high clustering coefficient and a short average path length, exhibiting apparent small-world characteristics. All bank nodes in the bank multilayer network exhibit a higher multilayer participation coefficient, indicating that all bank nodes have the potential to influence all network layers.

3) From the perspective of multilayer network theory, this study investigates in depth the evolution characteristics of the multilayer relevance of banking system. For deconstructing the interbank dependency structure between linear and nonlinear correlations, this study is of great reference value. This paper's findings not only advance the research of multilayer network theory in the banking system but also have practical implications for preserving interbank market stability.

References

[1] Li S W, Xie Y W, Yang K, et al. Impact of multiplex network structures of banks on systemic risk[J]. *Journal of Southeast University (Philosophy and Social Science)*, 2019, **21**(4): 77 − 84, 147. DOI: 10. 13916/j. cnki. issn1671-511x. 2019. 04. 009. (in Chinese)

[2] Maghyereh A I, Yamani E. Does bank income diversification affect systemic risk: New evidence from dual banking systems[J]. *Finance Research Letters*, 2022, **47**: 102814. DOI: 10. 1016/j. frl. 2022. 102814.

[3] Inaoka H, Takayasu H, Shimizu T, et al. Self-similarity of banking network[J]. *Physica A: Statistical Mechanics and Its Applications*, 2004, **339**(3/4): 621 − 634. DOI: 10. 1016/j. physa. 2004. 03. 011.

[4] Silva T C, de Souza S R S, Tabak B M. Network structure analysis of the Brazilian interbank market[J]. *Emerging Markets Review*, 2016, **26**: 130 − 152. DOI: 10. 1016/j. ememar. 2015. 12. 004.

[5] Leonidov A V, Rumyantsev E L. Default contagion risks in Russian interbank market[J]. *Physica A: Statistical Mechanics and Its Applications*, 2016, **451**: 36 − 48. DOI: 10. 1016/j. physa. 2015. 12. 130.

[6] Soramäki K, Bech M L, Arnold J, et al. The topology of interbank payment flows[J]. *Physica A: Statistical Mechanics and Its Applications*, 2007, **379**(1): 317 − 333. DOI: 10. 1016/j. physa. 2006. 11. 093.

[7] Becher C, Millard S, Soramäki K. The network topology of CHAPS sterling[J]. *SSRN Electronic Journal*, 2008. DOI: 10. 2139/ssrn. 1319277.

[8] Boss M, Elsinger H, Summer M, et al. Network topology of the interbank market[J]. *Quantitative Finance*, 2004, **4**(6): 677 − 684. DOI: 10. 1080/14697680400020325.

[9] León C, Machado C, Sarmiento M. Identifying central bank liquidity super-spreaders in interbank funds networks[J]. *Journal of Financial Stability*, 2018, **35**: 75 − 92. DOI: 10. 1016/j. jfs. 2016. 10. 008.

[10] Craig B, von Peter G. Interbank tiering and money center banks[J]. *Journal of Financial Intermediation*, 2014, **23**(3): 322 − 347. DOI: 10. 1016/j. jfi. 2014. 02. 003.

[11] Silva T C, de Souza S R S, Tabak B M. Network structure analysis of the Brazilian interbank market[J]. *Emerging Markets Review*, 2016, **26**: 130 − 152. DOI: 10. 1016/j. ememar. 2015. 12. 004.

[12] in't Veld D, van Lelyveld I. Finding the core: Network structure in interbank markets[J]. *Journal of Banking & Finance*, 2014, **49**: 27 − 40. DOI: 10. 1016/j. jbankfin. 2014. 08. 006.

[13] Iori G, De Masi G, Precup O V, et al. A network analysis of the Italian overnight money market[J]. *Journal of Economic Dynamics and Control*, 2008, **32**(1): 259 − 278. DOI: 10. 1016/j. jedc. 2007. 01. 032.

[14] Martinez-Jaramillo S, Alexandrova-Kabadjova B, Bravo-Benitez B, et al. An empirical study of the Mexican banking system's network and its implications for systemic risk[J]. *Journal of Economic Dynamics and Control*, 2014, **40**: 242 − 265. DOI: 10. 1016/j. jedc. 2014. 01. 009.

[15] Langfield S, Liu Z J, Ota T. Mapping the UK interbank system[J]. *Journal of Banking & Finance*, 2014, **45**: 288 − 303. DOI: 10. 1016/j. jbankfin. 2014. 03. 031.

[16] Poledna S, Molina-Borboa J L, Martínez-Jaramillo S, et al. The multi-layer network nature of systemic risk and its implications for the costs of financial crises[J]. *Journal of Financial Stability*, 2015, **20**: 70 − 81. DOI: 10. 1016/j. jfs. 2015. 08. 001.

[17] Bargigli L, di Iasio G, Infante L, et al. Interbank markets and multiplex networks: Centrality measures and statistical null models [M]// *Interconnected Networks*. Cham, Switzerland: Springer, 2016: 179 − 194.

[18] Aldasoro I, Alves I. Multiplex interbank networks and systemic importance: An application to European data[J]. *Journal of Financial Stability*, 2018, **35**: 17 – 37. DOI: 10.1016/j.jfs.2016.12.008.

[19] Berndsen R J, León C, Renneboog L. Financial stability in networks of financial institutions and market infrastructures[J]. *Journal of Financial Stability*, 2018, **35**: 120 – 135. DOI: 10.1016/j.jfs.2016.12.007.

[20] Hüser A C, Hałaj G, Kok C, et al. The systemic implications of bail-in: A multi-layered network approach[J]. *Journal of Financial Stability*, 2018, **38**: 81 – 97. DOI: 10.1016/j.jfs.2017.12.001.

[21] Li L A, Ma Q T, He J M, et al. Co-loan network of Chinese banking system based on listed companies' loan data [J]. *Discrete Dynamics in Nature and Society*, 2018, **2018**: 1 – 7. DOI: 10.1155/2018/9565896.

[22] Musmeci N, Nicosia V, Aste T, et al. The multiplex dependency structure of financial markets[J]. *Complexity*, 2017, **2017**: 1 – 13. DOI: 10.1155/2017/9586064.

[23] Liu Y Q, Mu Y, Chen K Y, et al. Daily activity feature selection in smart homes based on Pearson correlation coefficient[J]. *Neural Processing Letters*, 2020, **51**(2): 1771 – 1787. DOI: 10.1007/s11063-019-10185-8.

[24] Liu Q, Li C, Wanga V, et al. Covariate-adjusted Spearman's rank correlation with probability-scale residuals[J]. *Biometrics*, 2018, **74**(2): 595 – 605. DOI: 10.1111/biom.12812.

[25] Valencia D, Lillo R E, Romo J. A Kendall correlation coefficient between functional data[J]. *Advances in Data Analysis and Classification*, 2019, **13**(4): 1083 – 1103. DOI: 10.1007/s11634-019-00360-z.

[26] Boccaletti S, Bianconi G, Criado R, et al. The structure and dynamics of multilayer networks[J]. *Physics Reports*, 2014, **544**(1): 1 – 122. DOI: 10.1016/j.physrep.2014.07.001.

[27] Battiston F, Nicosia V, Latora V. Structural measures for multiplex networks[J]. *Physical Review E*, 2014, **89**(3): 032804. DOI: 10.1103/physreve.89.032804.

[28] Battiston F, Nicosia V, Latora V. The new challenges of multiplex networks: Measures and models[J]. *The European Physical Journal Special Topics*, 2017, **226**(3): 401 – 416. DOI: 10.1140/epjst/e2016-60274-8.

银行系统多层网络模型及其演化

姜 乔[1]　刘晓星[1,2]　马钱挺[2,3]

([1]东南大学网络空间安全学院，南京 211189)
([2]东南大学经济管理学院，南京 211189)
([3]南京农业大学金融学院，南京 210095)

摘要：基于股票收益率间 Pearson 相关性、Spearman 相关性和 Kendall 相关性，构建了银行系统多层网络模型，其中 3 种相关性分别对应于多层网络中 Pearson 层、Spearman 层和 Kendall 层. 根据 2011—2020 年期间中国上市银行数据，实证分析了银行系统多层网络结构的演化特征. 结果表明：大型国有银行在整个银行系统中表现出更高的活跃度；银行间多层网络的层间度相关性呈现一定的波动性，其中 Spearman 层和 Kendall 层的相关性更高；构建的银行多层网络表现出明显的小世界特征；所有的银行节点在多层网络中的每一层中都发挥作用. 研究结论揭示了银行收益率波动不同关联性之间的相依结构，对于维护银行系统稳定具有一定的理论参考价值.

关键词：多层网络模型；银行系统；网络演化特征；小世界特征；相依结构

中图分类号：F830