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Research Article

Co-Loan Network of Chinese Banking System Based on Listed Companies' Loan Data

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Based on the loan data of Chinese listed companies from 2008 to 2016, this paper constructs a co-loan network of the Chinese banking system and analyzes the topological structures and corresponding evolvement characteristics from the perspective of complex network. Through the empirical studies, we find that the co-loan network always displays a core-periphery structure; for example, ten banks including four state banks and six large commercial banks are always in the core region of the Chinese banking system for nine consecutive years. Furthermore, the co-loan network is a small-world network lasting for nine years.

1. Introduction

Banking is not only a significant part of the modern financial system, but also an indispensable financial intermediary for the healthy operation of the entire economic system. Banking is highly interdependent due to all sorts of connections and forms a huge banking network. Interconnection between banks not only brings many economic benefits, but also provides channels for risk transmission. The collapse of small and medium banks in the United States triggered by the subprime crisis in 2007 is a typical example. Therefore, it is important to study the structural characteristics of banking networks to maintain the stability of banking systems.

In reality, there are two main ways to construct the banking network. One way constructs the network directly by interbank balance sheets or payments. There is growing literature on network structures of real banking systems in different countries. For instance, Boss et al. [1] discover that the Austrian banking network of debt relationships shows a small-world property and a community structure, and the degree distribution displays two different power-law exponents. Inaoka et al. [2] prove that the Japanese interbank network of monetary transactions is a scale-free network described by a power-law degree distribution. De Masi et al. [3] find that the Italian interbank network composed of different banks exchanging on a daily basis loans and debts of liquidity shows a community structure. Soramäki et al. [4] suggest that the American interbank payment network is compact despite low connectivity, and the degree distribution is scale-free over a substantial range. Blasques et al. [5] argue that the interbank lending network in Netherlands can be characterized as a structure with multiple monetary centers, which also exists in Germany (2004), Hungary (2006), Belgium (2007), and Finland (2009). Furthermore, the interbank network also presents the characteristic of dynamic evolution in Brazil (2008) and Mexico (2014).

The other way constructs the network indirectly by cross-holding or co-holding relationships of assets or liabilities. For example, Bubna et al. [6] discover that the co-lending network of the American banking system shows a community structure and a centrality structure. Gong et al. [7] find that the co-lending network of the Chinese banking system shows a small-world property and a core-periphery structure. Elliott et al. [8] analyze the European debt cross-holding network, which exhibits realistic structural features such as core-periphery and segregation structure. In addition, there are other significant studies in this area; see Hernandez et al. [9], Gathergood and Weber [10], Burdick et al. [11], Lux [12], and so forth.

In addition to the empirical researches, scholars also carry out simulation studies to explain the formation mechanism of banking networks. For instance, Li et al. [13] put forward

Table 1: Initial data statistics.

	2008	2009	2010	2011	2012	2013	2014	2015	2016
Number of banks	74	100	108	113	145	171	209	236	283
Number of firms	344	386	374	380	684	936	1071	1175	1199
Number of loans	788	951	957	988	1828	3285	4503	5330	6024

an interbank network based on interbank credit lending relationships and it generates some network features including a low clustering coefficient, a relatively short average path length, a community structure, and a two-power-law distribution of degree. Fricke et al. [14] construct a scare-free network of the banking system based on the balance sheets and Monte-Carlo simulations. Lux [15] presents a dynamic model of interbank credit relationships, which forms a core-periphery structure. Furthermore, there are other simulation studies on the banking network; see Georg [16], Craig and Von Peter [17], Anand et al. [18], González-Avella et al. [19], and so forth.

As for the Chinese banking system, it is clumsy to obtain actual data of interbank transactions. Consequently, we consider building the co-loan network indirectly to study the network structures of the Chinese banking system. Gong et al. [7] carry out a similar study covering 126 banks, 766 firms, and 1787 links for two years (2000 and 2009). However, the network in this paper consists of 373 banks, 1994 firms, and 12747 links for nine consecutive years. Compared with the existing researches, this paper collects more sample data and explores the evolvement characteristics of the banking network, which can better reflect the structural characteristics of the Chinese banking system.

The remainder of this paper is organized as follows: After this introduction, Section 2 describes the data analysis, including data preprocessing and network construction. Section 3 presents the main empirical results of the Chinese banking system, and Section 4 provides a conclusion.

2. Data Analysis

2.1. Data Preprocessing. The initial data used in this paper is the loan data of Chinese listed companies from 2008 to 2016, provided by the Tai'an database of China (CSMAR Solution). The data include listed company code, issuing bank, and loan amount. We consider all types of loans in this paper. The initial data are preprocessed as follows: (1) The transaction data without a clear loan amount are excluded. (2) If one company borrows multiple times from the same bank in the same year, the multiple loan relationships are merged into a single loan relationship. The results of initial data processing are shown in Table 1.

2.2. Network Construction. Based on the initial data of nodes (banks and firms) and edges (loans), we can construct the co-loan network. The co-loan network consists of N nodes and M edges (links), where the node represents the bank and the edge denotes the co-loan relationship between two banks. The co-loan network can be represented as a square matrix of dimension $N \times N$ (data matrix, denoted by D). The matrix elements d_{ij} consist of 0 and 1, where $i, j = 1, 2, \ldots, N$. If d_{ij} equals 1, this means that bank i and bank j provide loans to the same firm. Otherwise, d_{ij} equals 0. Obviously, the matrix D is a symmetric matrix and it is calculated by MATLAB. Figure 1 illustrates the co-loan network structure of the Chinese banking system in 2016, where the node size represents the degree of centrality.

3. Empirical Results

3.1. Loan Scale. The co-loan network is constructed based on the lending relationships between banks and firms. Therefore, it is necessary to analyze the loan scale in the first place. Figure 2 illustrates changes in the total number and total amount of loans from 2008 to 2016. Both the total number and total amount of loans remained stable from 2008 to 2011 but have begun to proliferate since 2012. Overall, Figure 2 shows the phenomenon that the loan scale of Chinese financial market has increased dramatically in the recent 5 years. Figure 3 displays the complementary cumulative distribution functions (CCDF) of the loan scale from 2008 to 2016. Through fitting analysis, we can find that the tail of the loan scale distribution always exhibits linear decay in log-scale, suggesting a Pareto tail, where the tail exponent is always between 2 and 3 in the consecutive nine years. A similar phenomenon also appears in Bargigli et al.'s [20] study on the Japanese financial market.

3.2. Degree Distribution. Degree distribution is one of the most important network topologies. The degree of a node is the number of connections it has to other nodes, and the degree distribution is the probability distribution of these degrees over the whole network. In the banking network, the degree k_i of bank i is defined as the number of other banks connected to bank i. The larger the degree is, the more significant role the bank plays. The degree distribution can be well expressed as a power-law distribution, which is given as $P(k) \propto k^{-\gamma}$, where γ represents the power-law exponent. For the analysis of the degree distribution, a common approach is to plot the complementary cumulative distribution function $P(k)$, which represents the fraction of nodes with degrees greater than or equal to k in the entire network.

Figure 4 demonstrates the complementary cumulative distribution functions (CCDF) of the degrees from 2008 to 2016. In the consecutive nine years we always find two regions which can be fitted by a power-law. Accordingly, we fit one regression line to the small degree distribution and the other to the obvious Pareto tail in every year. For the left part of the distribution, we find that these exponents are small and less than 2, which leads to a strong hierarchical structure, and a smaller exponent means a more obvious hierarchical

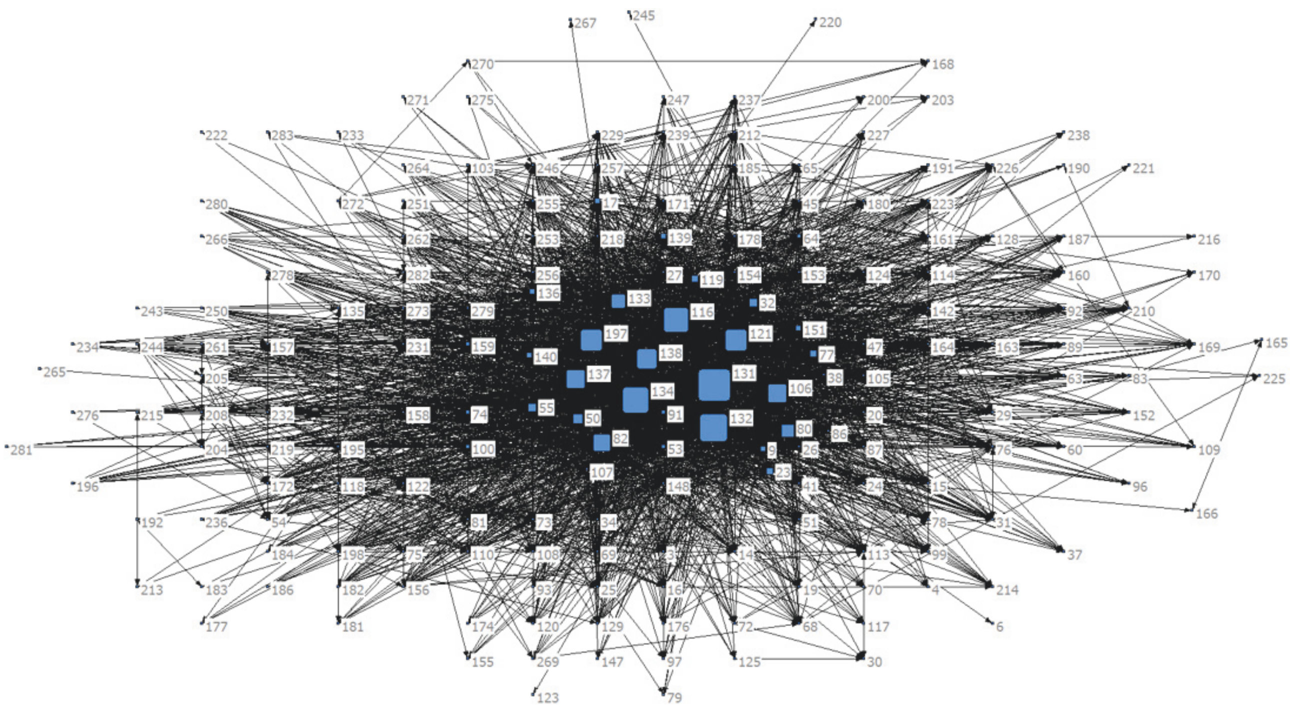


Figure 1: Co-loan network structure in 2016.

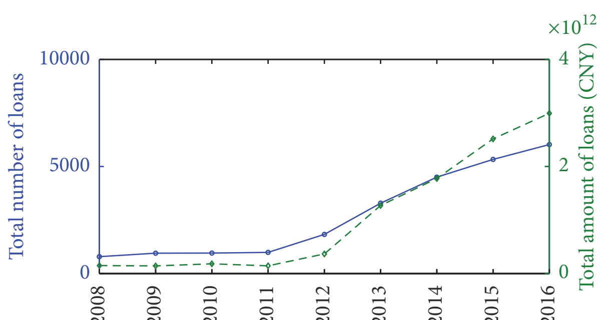


Figure 2: Total number and total amount of loans.

structure. An analogous result also emerges in Boss et al.'s [1] research of the Austrian banking network.

3.3. Network Centrality. Indicators of centrality identify the most important vertices within a network. Through centrality analysis, we aim to confirm the most influential banks in the co-loan network of the Chinese banking system. Betweenness centrality is devised as a general measure of network centrality: it represents the extent to which nodes stand between each other. In a banking network, a node with higher betweenness centrality will have more control over the network, because more information will pass through that node. The betweenness centrality of a node i is given by the following expression:

$$B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}, \tag{1}$$

where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(i)$ is the number of those paths that pass through i.

Figure 5 illustrates the network structures of Chinese banking co-loan relationships from 2008 to 2016. The node size represents the scale of betweenness centrality. Obviously, in each figure we find the same phenomenon that few large nodes lie in the core region of the network while most small nodes lie in the periphery region of the network, which displays a clear core-periphery structure. Which banks do these core nodes represent? This problem needs to be solved urgently. We calculate the frequency with which each bank appears in the annual top ten of the betweenness centrality. The result is shown in Figure 6. We can find that there are ten banks frequently playing the core role in the banking network for nine consecutive years. These core banks include four state banks, in order, ICBC, ABC, BOC, CCB, and six large commercial banks, in order, BOCOM, CMB, CITIC, SPDB, CMBC, CIB. This indicates that state banks and large commercial banks are always in the core region of the Chinese banking system. In fact, the core-periphery structure also exists in many other countries, such as Austria (2004), Germany (2004), Hungary (2006), Belgium (2007), Finland (2009), America (2009), and Netherlands (2015).

3.4. Clustering Coefficient and Average Path Length. In addition, clustering coefficient and average path length are significant indicators of network correlation. For one thing, the clustering coefficient is a measure of the extent to which nodes in a network tend to cluster together. The clustering coefficient C_i of node i is defined as the number of triangles

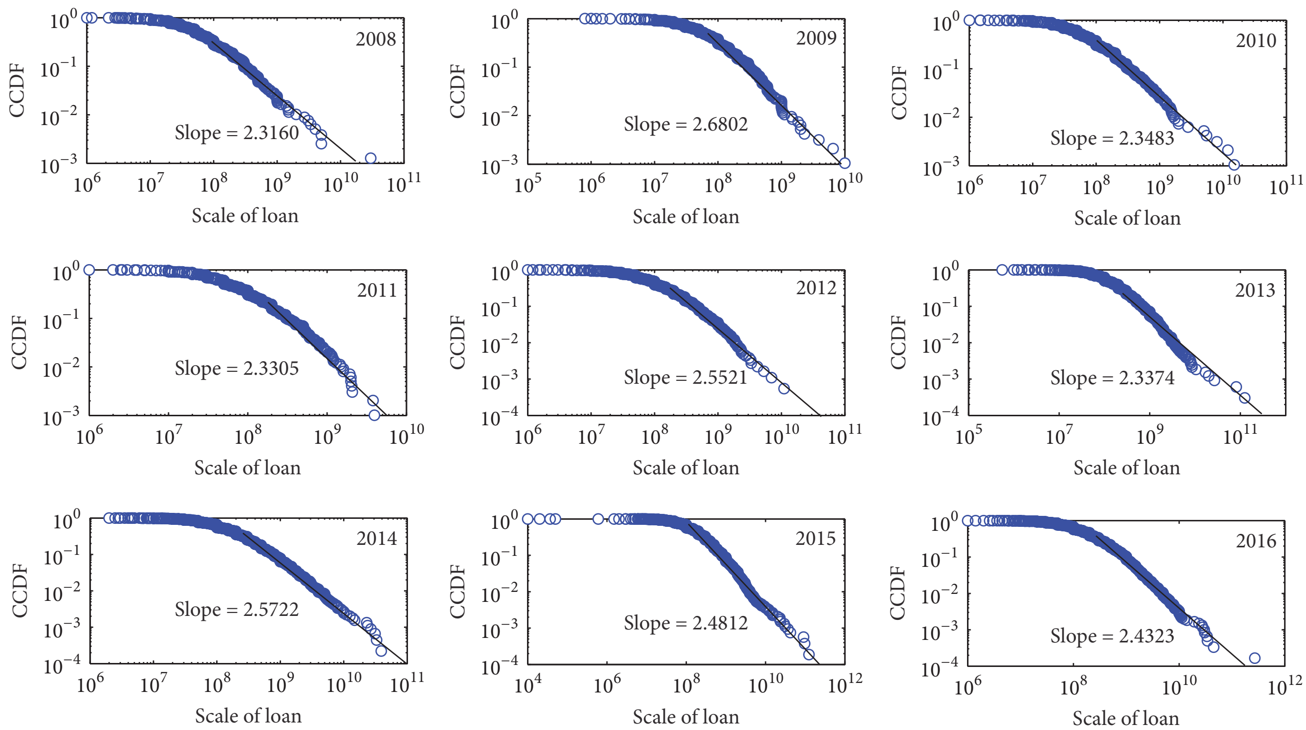


Figure 3: Complementary cumulative distribution functions of the loan scale.

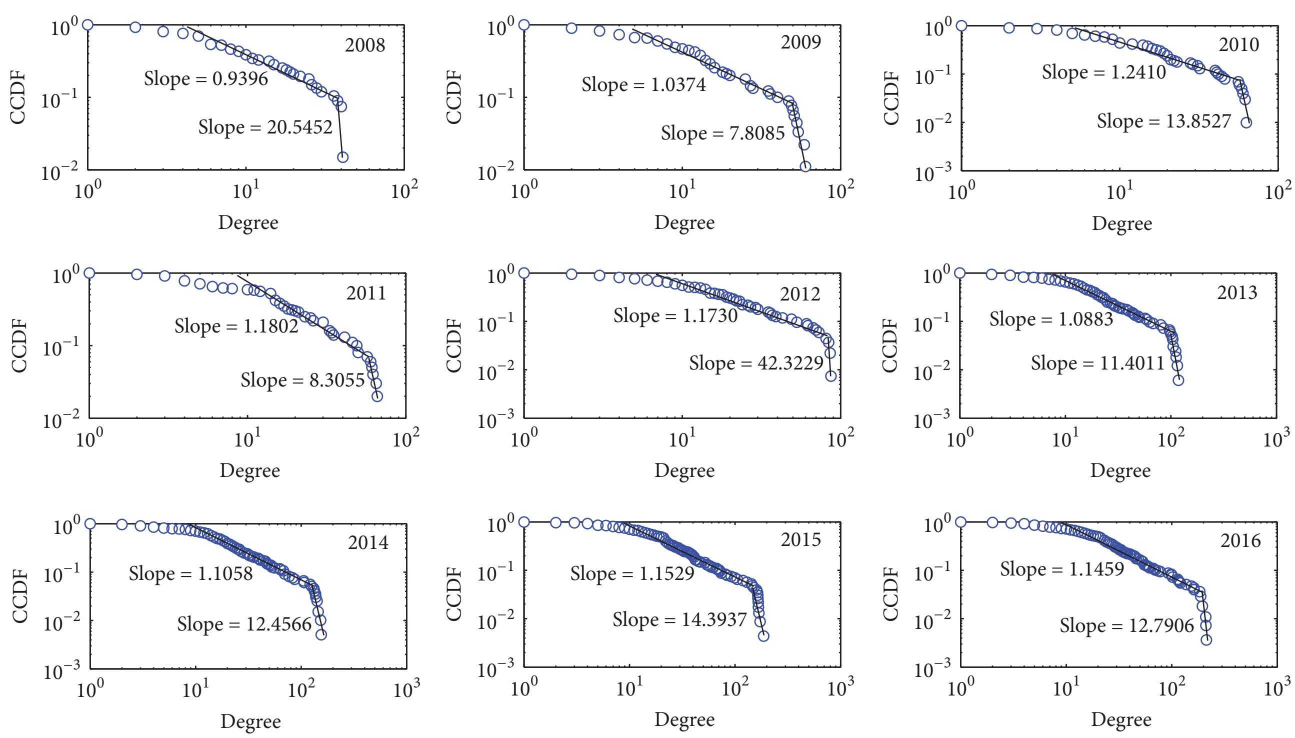
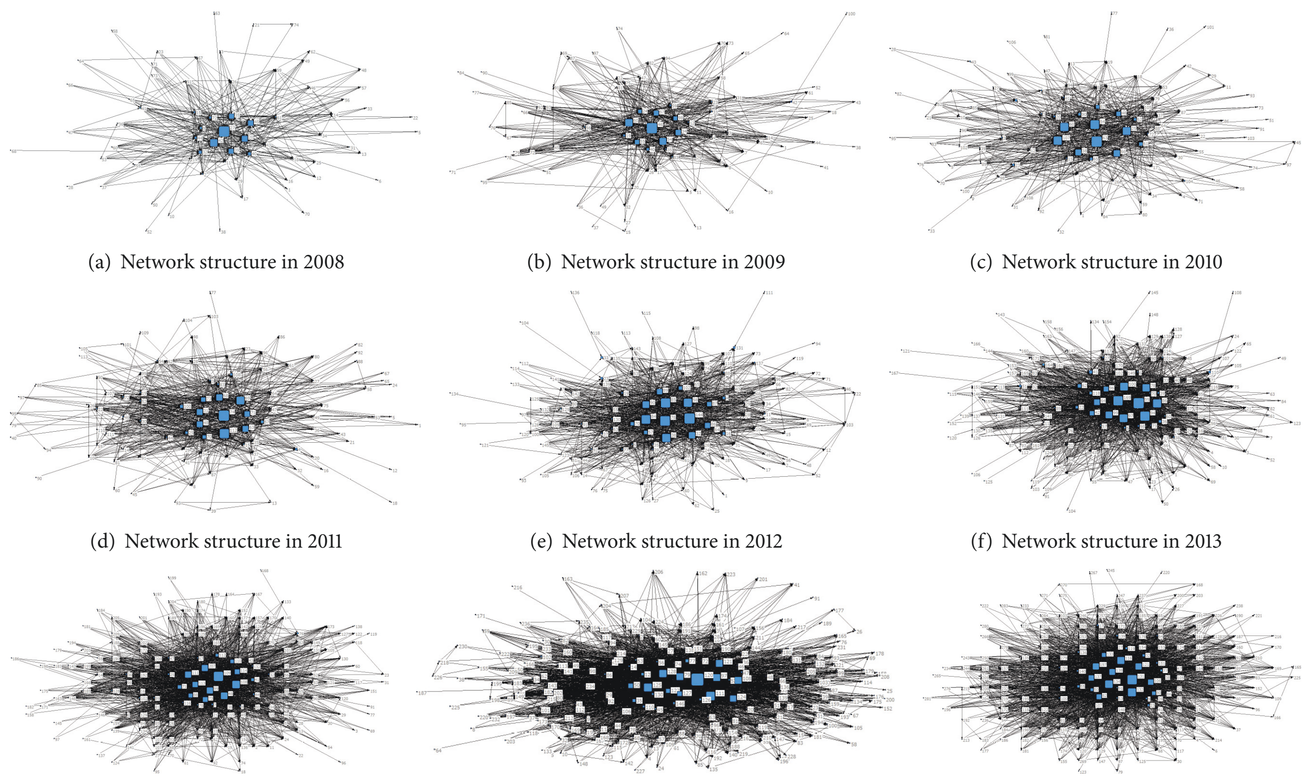


Figure 4: Complementary cumulative distribution functions of the degrees.



(a) Network structure in 2008 (b) Network structure in 2009 (c) Network structure in 2010

(d) Network structure in 2011 (e) Network structure in 2012 (f) Network structure in 2013

(g) Network structure in 2014 (h) Network structure in 2015 (i) Network structure in 2016

Figure 5: Network structures of banking co-loan relationships.

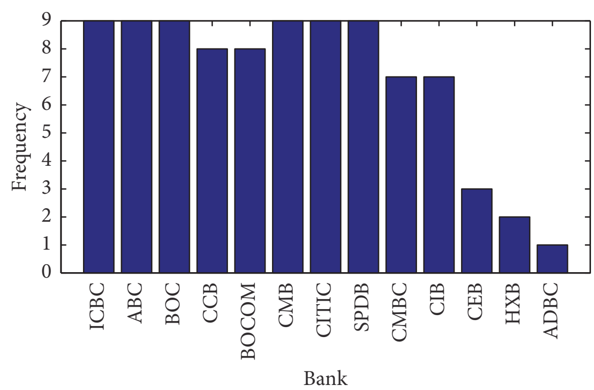


Figure 6: The banks' frequency statistics of top-ten betweenness centrality.

containing node i, normalized by the maximum possible number of such triangles. The specific formula is shown below:

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

where E_i is the number of triangles around node i and k_i is the degree of node i. The clustering coefficient C of the whole network is defined as the average of the clustering coefficients of all nodes, as follows: $C = (1/N)\sum_{i=1}^{N} C_i$, where $0 \le C \le 1$. In the co-loan network, the clustering coefficient of bank i measures the probability of holding the co-loan relationships between the banks that own co-loan relationships with bank i.

For another thing, the average path length is a measure of the efficiency of information or mass transport on a network. The average path length L is defined as the average number of steps along the shortest paths for all possible pairs of network nodes and determined by the following formula:

$$L = \frac{1}{(1/2)N(N-1)}\sum_{i \ge j} d_{ij}, \tag{3}$$

where d_{ij} is the minimal number of links connecting node i and node j. In the co-loan network, a shorter average path length indicates a closer co-loan relationship between two banks.

Figure 7 displays the clustering coefficient and the average path length of the co-loan network from 2008 to 2016. In the consecutive nine years, the clustering coefficient is always between 0.8 and 0.9. Simultaneously, the average path length is in the interval (1.9–2.1). Considering the node scale of the co-loan network in the Chinese banking system, we produce the conclusive result that the co-loan network has a higher clustering coefficient along with a shorter average path length, which leads to a small-world network lasting for nine years. Due to the existence of the core-periphery structure, the new nodes are connected preferentially to the

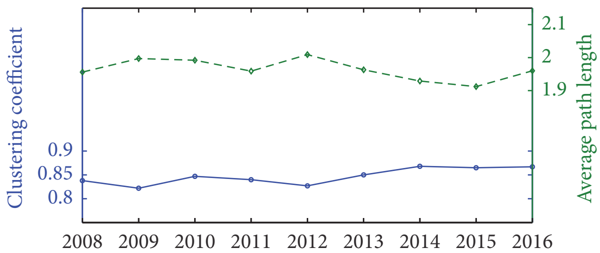


Figure 7: Clustering coefficient and average path length.

nodes in the core regions. Therefore, the clustering coefficient and the average path length of the co-loan network can still remain stable despite the significant increase in the number of banks since 2012. The small-world property suggests that although most small banks have less direct contact, they can establish indirect associations through fewer other banks. This implicit association is more worthy of our attentions.

4. Conclusion

Banking network structures are significant to the stability of banking systems. Taking the bank loans of Chinese listed companies as the basic relationship, this paper builds a co-loan network to research the topological structures and corresponding evolvement characteristics of the Chinese banking system from 2008 to 2016. As it turns out, the scale of bank loans of Chinese listed companies remained stable from 2008 to 2011 but has begun to proliferate since 2012. In addition, the co-loan network of the Chinese banking system always displays the features of core-periphery and small-world for nine consecutive years. Furthermore, there are ten banks including four state banks and six large commercial banks always in the core region of the Chinese banking system. These core banks have increasing common loan clients, which not only intensifies competition between banks but also strengthens the information sharing and risk exposure between banks. Therefore, we need to strengthen the supervision of these core banks to guard against systemic risks.

In this paper, our research is limited to some basic network structure features. In the future we will consider more network properties such as the robustness for the study of banking system. In addition, we only consider one kind of banking relationships, namely, the co-loan relationship. However, the real-world financial system covers multiple financial agents and multiple relationships. Therefore, in the future we will take different types of links between multiple financial agents into consideration to construct more complex financial networks as close to the real world as possible.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Acknowledgments

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