Research Article
Evaluating the Systemic Importance of China’s Banks via Adjacency Information Entropy

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Received 6 March 2022; Revised 29 March 2022; Accepted 2 April 2022; Published 15 April 2022

Abstract
Information entropy can be utilized to assess the complexity of the Banking System and the uncertainty of association information between banks. Based on information entropy and the balance sheet data of 167 banks from 2011 to 2020, we proposed a centrality indicator based on Adjacency Information Entropy, then applied it to directed weighted and directed unweighted interbank networks to identify banks with systemically important status, and compared the results with those of traditional centrality indicators. The outcomes show that the results of centrality indicator based on Adjacency Information Entropy are more accurate than those of traditional centrality indicators in identifying banks with systemically important status in interbank networks. Six large state-owned commercial banks, nine joint-stock commercial banks, two policy banks, and two urban commercial banks with large assets are identified as systemically important banks based on the proposed centrality indicator, which is highly consistent with the list of systemically important banks published by the Chinese banking regulator. Among the systemically important banks, changes in systemic risk levels of joint-stock commercial banks and urban commercial banks are more susceptible to national policies than those of large state-owned commercial banks. The findings of this paper have certain reference significance for strengthening the supervision of banks with systemically important status in interbank networks and formulating targeted policies for regulating large commercial banks and small- and medium-sized commercial banks.

1. Introduction
One of the main lessons of regulators and academics from the 2008 subprime mortgage crisis is the need to impose stricter supervision on Systemically Important Financial Institutions (SIFIs) from a macroprudential dimension [1–4]. As China’s banking industry has long maintained its total assets at more than 90% of that of the financial sector and provides more than 60% of the new financing on the market, the occurrence of their risk events could result in significant negative externalities on financial stability and the smooth development of the real economy [5]. As such, for the need of systemic financial risk prevention, it is particularly important to focus on China’s banking institutions and identify banks with systemic importance status.

The existing main methods for identifying SIFIs can be grouped into four categories: the indicator method based on macrodata and microdata [6, 7], the modelling method based on public market data (CCA [8–10], MES [11, 12], SES [12], CoVaR [13–15], SRISK [16, 17], etc.), the network analysis method based on public market data [18–20], and the network analysis method based on balance sheet data [21, 22]. The indicator method is mostly used by regulators to rate financial institutions according to five aspects: scale, relevance, substitutability, complexity, and cross-border operations. There are data lags and difficulty in obtaining data with this method. The modelling method based on public market data uses the high-frequency characteristics of stock data to improve the foresight and accuracy of risk measurement. However, this method has high requirements in terms of the effectiveness of data, which is not necessarily applicable to developing countries, such as China, and it is incapable of describing the correlation among financial institutions [23]. The network analysis method based on
public market data mainly uses the data of financial market instruments, such as stocks, bonds, and CDS issued by financial institutions, to establish a model to measure the tail dependence among financial institutions and form an association network. However, this method also depends heavily on the effectiveness of the data [23]. The network analysis method based on asset-liability data mainly considers related risks among financial institutions due to interbank business or holding common assets. It mainly uses the financial network model to identify SIFIs, which better compensates for the poor effectiveness of financial market data in China and other developing countries and is more suitable in describing the risk contagion among financial institutions [23]. Thus, there has been an increasing interest in using the asset-liability-oriented network analysis method to investigate SIFIs in financial networks.

This study reviewed the existing literature on systematically important banks (SIBs) from the perspective of networks and finds that some studies simplified the interbank network into a directed unweighted structure [24] and some of them employed traditional central indicators to identify SIBs. However, compared with the list of SIBs published by People’s Bank of China (PBC) and China Banking and Insurance Regulatory Commission (CBIRC), the research results are mostly biased. Based on this finding, this paper attempts to accurately evaluate China's SIBs by introducing a new complex network topology metric without simplifying the characteristics of interbank networks.

Information entropy can be utilized to assess the complexity of the Banking System and the uncertainty of association information between banks [25]. The network formed by banks through lending and borrowing relationships and holding common assets is known as the interbank network. The structure of this network belongs to a complex network. Information entropy measures the information of nodes in the interbank network, such as the systemic importance of banks, by eliminating uncertainties in the network under the methods of probability statistics, systematic multidimensionality, and hierarchical correlation, starting from wholeness, ambiguity, and correlation. In existing studies, some scholars have researched the application of information entropy in measuring the centrality of network nodes [26–35]. Some studies show that entropy-based centrality indicators can fully use the information on neighbouring nodes, as well as be suitable for various types of networks [28, 29]. Inspired by this, this study constructed the adjacency information entropy centrality (AIEC) metric by introducing the concept of information entropy and evaluated the systemic importance of Chinese banks more accurately by applying it to interbank networks with a directed weighted structure.

The findings of this empirical study showed that the centrality indicator based on adjacency information entropy (AIE) improves the accuracy of identifying important nodes. Six large state-owned commercial banks (LSOCBs), nine joint-stock commercial banks (JSCBs), two policy banks (POBs), and two urban commercial banks (UCBs) with large assets are the SIBs identified in this paper based on AIEC, which is highly consistent with the list of SIBs published by PBC and CBIRC. Among the SIBs, JSCBs and UCBs are more sensitive to changes in national policies and changes in their systemic financial risk levels are more susceptible to national policies than those of LSOCBs.

The innovations of this study are as follows: (1) It breaks the limitation of assumptions, such as simplifying the interbank directed weighted structure into a directed unweighted one. (2) It proposes a centrality indicator using AIE, which not only takes into account the directed weighted characteristics of the interbank network and the correlation between banks and their direct neighbours but also fully considers the correlation between banks and their indirect neighbours, thereby improving the accuracy of identifying SIBs. (3) It significantly expands the number of assessable banks using balance sheet data, bypasses the restrictions posed by the small number of listed banks and the poor effectiveness of stock data, and provides a reference for regulators to more accurately evaluate the systemic risk status of small- and medium-sized banks.

This paper unfolds as follows: Section 2 introduces the study's research methods, detailing the construction model of the interbank network, the construction of centrality model based on AIE, and the data needed in the research. Section 3 elaborates and analyses the empirical results, mainly including the description of the interbank network and the comparison of identification results of SIBs based on centralities in the weighted and unweighted network. Section 4 concludes the study.

2. Materials and Methods

This study measures the systemic importance of banks in three steps. First, the interbank bilateral risk matrix is modelled using the Minimum Density (MD) method to obtain the interbank network. Second, a centrality index based on AIE is constructed. Third, the systemic importance of each bank in the interbank network is calculated through the centrality index constructed above.

2.1. Construction of the Interbank Network. The construction of an interbank network depends on the bilateral risk exposure among banks [36]. In reality, banks do not disclose specific interbank bilateral risk exposure, reporting only their aggregate risk exposure data [36]. The main method to obtain bilateral interbank risk exposure is to apply mathematics and computer technology to solve the problem of matrix optimization, such as using Maximum Entropy (ME) [37] and Minimum Density (MD) [36]. ME requires the risk exposure to be distributed as evenly as possible, resulting in some of the characteristics of interbank networks not being observed [36]. MD, on the other hand, takes into account the cost of establishing and maintaining interbank links, thereby allowing the constructed network to have the feature of disassortativity and sparsity that could be observed in real financial networks [36]. Thus, this study employs the MD method to construct the interbank network.

Assume that the bilateral risk exposure matrix is now composed of $N$ number of banks and the total assets and
total liabilities of interbank business of each bank are known, but the risk exposure of each bank to other banks is unknown. Suppose graph theory \( G = (E, X) \), where \( E \) represents the set of nodes and \( X \) represents the set matrix of the connected edges of the nodes. In the network formed by interbank business connections, the nodes represent the banks that are engaged in interbank business and the edges represent the volume of interbank business transactions. Since there are interbank businesses at both the bank’s asset and liability sides, this diagram is a directed loop diagram.

Sincethereareinterbankbusinessesatboththebank’sassetandliabilitysides,thistheoryisrepresentedthevolumeofinterbankbusinesstransactions.

In constructing the bilateral exposure matrix, this study assumes that \( c \) represents the fixed cost required to establish connections between banks. Then, the formula of the MD method is given by

\[
\text{min}_{X} c \sum_{i=1}^{N} \sum_{j=1}^{N} 1[x_{ij} > 0],
\]

\[
\sum_{j=1}^{N} x_{ij} = a_i, \quad \forall \, i = 1, 2, \ldots, N,
\]

\[
\sum_{i=1}^{N} x_{ij} = l_j, \quad \forall \, j = 1, 2, \ldots, N,
\]

\[
x_{ij} \geq 0, \quad \forall \, i, j.
\]

The integer function 1 in objective function (3) is 1, only when there is a loan relationship between banks \( i \) and \( j \), and is 0 in other cases.

By solving function (3), this study constructed a directed weighted interbank network; if the weight is assigned the value 1, we then obtain a directed unweighted network.

2.2. Centrality Index Based on Adjacency Information Entropy. The calculation of node \( i \)’s traditional centrality only considers nodes directly connected to it and does not consider the nodes indirectly connected to it [29]. In view of this, this study introduces information entropy into node importance calculation to more accurately identify the systemic importance of banking institutions [29].

In the study named “A Mathematical Theory of Communication,” Shannon proposed information entropy [38], using the following formula:

\[
H_i = - \sum_{j \in \Gamma_i} p_i \log p_i,
\]

where \( H_i \) represents the information entropy of node \( i \) and \( p_i \) represents the probability function of node \( i \).

To define the formula of \( p_j \), first, this paper introduces the adjacency degree to reflect the influence of nodes on their nearby nodes, which is defined as follows:

\[
Q_i = \sum_{w \in \Gamma_i} k_{wi},
\]

where \( k_{wi} \) is the degree value of node \( i \) and \( \Gamma_i \) is node \( i \)’s set of neighboring nodes.

Then, the mathematical formula of the probability function \( p_i \) can then be expressed as follows:

\[
p_i = \frac{k_i}{Q_i}, \quad j \in \Gamma_i,
\]

where \( p_j \) is used to describe the possibility of different nodes being selected in their neighboring nodes in this study.

Finally, the adjacency information entropy centrality \( H_i \) can be calculated.

2.2.1. Adjacency Information Entropy Centrality in the Directed Unweighted Interbank Network. In directed unweighted networks, nodes’ adjacency information entropy is calculated as follows:

First, we calculate the degree value of bank \( i \):

\[
k_i = \lambda k_i^\text{in} + (1 - \lambda) k_i^\text{out},
\]

where \( \lambda \) is the influence coefficient of node importance and \( \lambda = 0.65 \), assuming that the influence of node in-degree is greater than that of node out-degree. \( k_i^\text{in} \) is the in-degree value of node \( i \), \( k_i^\text{out} \) is the out-degree value of node \( i \), and \( k_i \) is the comprehensive degree value of node \( i \).

The comprehensive adjacency value of node \( j \) is calculated by

\[
Q_j = \lambda \sum_{w \in \Gamma_j} k_{wj} + (1 - \lambda) \sum_{w \in \Gamma_j} k_{jw},
\]

where \( k_{wj} \) is the comprehensive degree value of neighboring node \( w \) pointing to node \( j \), \( k_{wj} \) is the comprehensive degree value of neighboring node \( w \) pointing to node \( j \), and \( Q_j \) is the comprehensive adjacency degree value.

The mathematical formulas of the probability function and node adjacency information entropy are as follows:
\[ p_i = \frac{k_i}{Q_j}, \]
\[ H_i = \sum_{j \in \Gamma_i} \left[ -p_i \log p_i \right]. \] (9)

2.2. Adjacency Information Entropy Centrality in the Directed Weighted Interbank Network. In the directed weighted interbank network, the in-degree of bank \( i \) is defined as follows:
\[ s_{in}^i = \sum_{j \in \Gamma_i} \omega_{ji}. \] (10)
The out-degree of bank \( i \) is
\[ s_{out}^i = \sum_{j \in \Gamma_i} \omega_{ij}. \] (11)
The node degree value of bank \( i \) is
\[ s_i = \lambda s_{in}^i + (1 - \lambda) s_{out}^i. \] (12)
The adjacency degree of the nodes is defined as follows:
\[ Q_j = \lambda \sum_{i \in \Gamma_j} s_{in}^i + (1 - \lambda) \sum_{i \in \Gamma_j} s_{out}^i. \] (13)
The probability function \( p_i \) is
\[ p_i = \frac{s_i}{Q_j}. \] (14)
The adjacency information entropy centrality \( H_i \) of node \( i \) is
\[ H_i = \sum_{j \in \Gamma_i} \left[ -(p_i \log p_i) \right]. \] (15)

2.3. Data. This study selected sample data from 2011 to 2020, a total of 10 years. The sample includes 167 banks with assets of more than 100 billion yuan, for each in 2020, of which 6 are LSOCBs, 12 JSCBs, 3 policy banks (POBs), 94 UCBS, 39 rural commercial banks (RCBs), 2 private banks (PRBs), and 11 foreign banks (FBs). The total assets of these banks account for 87.18% of that of the banking sector in 2020, thereby constituting a good representation. All asset-liability data used are from the Wind database. Referring to the research of Fang Yi and Fan et al., the data from interbank due market, interbank lending and borrowing market, and interbank repurchase market are selected based on the actual interbank business. They are due from banks and other financial institutions (DFBOFI), due to banks and other financial institutions (DTBOFI), interbank lending (IBL), interbank borrowing (IBB), reverse repurchase agreements (RRAs), repurchase agreements (RAs), in which DFBOFI, IBL, and RRAs are bank interbusiness assets, whereas DTBOFI, IBB, and RAs are bank interbusiness liabilities.

As Table 1 displays, the business scale of different types of banks in the interbank business market varies greatly. In view of this, this study uses the MD method to estimate the data of the interbank due market, lending and borrowing market, and repurchase market separately and aggregate them to obtain the interbank bilateral exposure data. Thus, the bilateral exposure data obtained can comprehensively reflect the characteristics of interbank business transactions in China. Table 1 also reveals that the sum of DFBOFI, IBL, and RRA of each type of commercial banks is higher than the sum of DTBOFI, IBB, and RRAs of them, which indicates that the impact of banks’ capital inflows on banks’ risk is greater than the impact of capital outflows on them. Therefore, there is some justification for the assumption that \( \lambda = 0.65 \).

Table 2 shows the 19 systemically important domestic banks as assessed and identified by PBC and CBIRC based on the 2020 data. Of these 19 systemically important domestic banks, 6 are LSOCBs, 9 JSCBs, and 4 UCBS. The banks are classified into five groups in the descending order of systemic importance. Group 1 consists of eight banks: Ping An Bank (SPABANK), Everbright Bank (CEB), Huaxia Bank (HXBANK), Guangdong Development Bank (GDB), Bank of Ningbo (NBBANK), Bank of Shanghai (SHBANK), Bank of Jiangsu (JSBANK), and Bank of Beijing (BJBANK). Group 2 consists of four banks: Shanghai Pudong Development Bank (SPDB), CITIC Bank (CITIC), Minsheng Bank (MCMB), and Postal Savings Bank (PSBC). Group 3 consists of three banks: Bank of Communications (BoCom), China Merchants Bank (CMB), and Industrial Bank (CIB). Group 4 consists of four banks: Industrial and Commercial Bank of China (ICBC), Bank of China (BOC), China Construction Bank (CCB), and Agricultural Bank of China (ABC). No bank is classified under Group 5. Please refer to appendix in the Supplementary Materials (available here) for more name abbreviations of 167 banks.

The data in Table 2 are used to assess the accuracy of the ranking of China’s SIBs identified based on AEIC.

3. Results and Discussion

3.1. Description of the Interbank Network. In this study, the network constructed based on the MD method features sparse characteristics. (1) Density represents the ratio between the actual bilateral connections and the maximum possible connections in the interbank network. The density value, 0.0344, indicates that the connection number between nodes is very small, which is confirmed by the number of bilateral connections between banks. The number of bilateral connections, 964, in the constructed interbank network is far lower than that in the fully connected network. (2) The relationship between the median and mean of node degree can reflect the distribution characteristics of network edges. The median value is far lower than the mean value, indicating that the degree of most of the nodes is small and the network features positive skewed distribution characteristics, which to a certain extent implies that fewer banks have more connections. (3) The clustering coefficient is used to describe the clustering degree of nodes. The clustering
coefficient, 0.5682, indicates that only some of the nodes in the network have two-way connections with each other. Some banks in the network may be the core and other banks the periphery. Table 3 shows that the interbank network in this study has sparse characteristics and may also have core-periphery structure characteristics.

Figure 1 represents the spatial distribution of the bilateral connections of the interbank network. The points in Figure 1 represent the business relationship between banks, and the serial number of banks is obtained from 1 to 167 according to the asset scale. The more the points corresponding to a bank in the spatial distribution map, the more active that bank is. The distribution of the points in Figure 1 shows that China’s interbank network evidently has the characteristics of a “core-periphery” structure. (1) The top 20 banks by asset size are very active in interbank business. These banks conduct business with each other and also form business contacts with banks with assets ranking below the top 20. These banks consist of three POBs (China Development Bank (CDB), Agricultural Development Bank of China (ADBC), and Export-Import Bank of China (EIBC)); six LSOCBs (ICBC, CCB, ABC, BOC, PSBC, and BoCom); nine JSCBs (CMB, SPDB, CIB, CITIC, CMBC, CEB, SPABANK, HXBANK, and GDB); and two UCBs (BJBANK and SHBANK). (2) The banks ranking below the top 20 by assets have very few interbank business connections. The spatial distribution of business connections shows that these banks are mainly engaged in business with the top 20 banks by asset size. These banks mainly consist of UCBs, RCBS, PRBS, and FBs. Thus, it can be concluded that the interbank network has the form of “core-periphery,” with small banks tending to establish business relationships with large banks.

Figure 2 shows the bilogarithmic plots of the out-degree and in-degree of the interbank network nodes. As shown in Figure 2, the distribution of the out- and in-degree of the interbank network nodes does not follow the scale-free distribution characteristics of the BA network, nor does it match the binomial distribution of the ER network. The scale-free network has a pile of low-degree nodes and a small number of high-degree nodes. A binomial distribution network has a heap of medium-degree nodes and a small number of low-degree and high-degree nodes. The number of low- and high-degree nodes of the sample network is similar to that of the scale-free network, and the distribution in the medium degree is similar to that of the ER network. Although the sample network is neither a scale-free network nor an ER network, it presents a hierarchical structure. Combining with the spatial distribution map, it can be deduced that this is because the core banks not only have business dealings with each other but also function as financial intermediaries, which means that they have business connections with peripheral banks. This conclusion is in line with the pattern of the financial system with PBC as the center, LSOCBs as the main body, and a variety of financial institutions coexisting after more than 40 years of Reform and Opening. Among various types of banks, the total assets or liabilities of LSOCBs account for more than 40% of those of banking financial institutions and the total assets or liabilities of LSOCBs and JSCBs account for more than 57% of those of banking financial institutions. Therefore, the sample network is suitable for identifying SIBs.

Based on the analysis of the interbank network in 2020, this study provides a comprehensive analysis of the characteristics of the interbank network in the chosen sample period. Table 4 and Figure 3 show the characteristics of the interbank network on a yearly basis. (1) The average number of active banks in the interbank network per year during the sample period is 163; the average number of business connections between banks is 911, and the average network density per year is 0.0347. The data show that a considerable number of banks do not conduct bilateral business in a year, which reflects that China’s interbank network is quite sparse. (2) The number of active banks in the interbank network gradually increased during the sample period, and the total interbank business connections, average bank business connections, and network density exhibit a similar movement trend. From 2011 to 2012, the three indicators declined; from 2012 to 2017, all three indicators gradually
increased and reached their peak; and the three indicators showed a decreasing trend from 2017 onward. (3) The total number and the average number of interbank business connections reflect the overall strength of correlation of the interbank network. Fluctuations in network density can reflect changes in systemic risk in the banking sector. From 2009 to 2013, China’s interbank business has experienced rapid development against the background of a relaxed liquidity environment and restricted credit scale. Banks took the initiative of transferring assets out of the balance sheet, the interbank correlation gradually strengthened, and the systemic risk increased to a certain extent. In 2014, to regulate the development of interbank businesses and prevent systemic risks, the China Banking Regulatory Commission (CBRC) issued Circular No. 127 “Notice on Regulating the Interbank Business of Financial Institutions,” which imposed strict restrictions on the transactions of nonstandard assets between banks, thereby slightly weakening interbank correlation. From 2014 to 2016, active debt became a new way for rapidly developing interbank business. The banks’ leverage ratio increased, the term mismatch intensified, and the overall correlation was further strengthened, which also resulted in high liquidity risk and contributed to the diversion of funds from real to virtual economy. In 2017, to prevent and resolve systemic risks and deleverage, PBC established a dual-pillar policy framework named “Monetary Policy and Macroprudential Policy.” The financial sector entered a period of strong supervision, and on-balance-sheet nonstandard assets and interbank negotiable certificates of deposit (IBNCD) became key objects of suppression. Since then, the development of interbank business in China entered a period of risk slow-release, with the overall correlation of the interbank network showing a downward trend and systemic risks continuing to ease.

3.2. Identification of Systemically Important Banks Based on Centrality Indicators. To describe the structure of China’s interbank network more accurately and to precisely identify the banks with systemic importance in the network, this study used adjacency information entropy centrality (AIEC) to rank banks according to their systemic importance in the network. This study also adopted traditional centrality indicators as the control group to verify the superiority of AIEC. The traditional centrality indicators include degree centrality (DC), closeness centrality (CC), betweenness centrality (BC), and eigenvector centrality (EC).

3.2.1. Comparison of Centrality Indicators Based on the Directed Unweighted Interbank Network. Some previous studies that use centrality indicators to identify SIBs simplify the interbank network into an unweighted network. First, the present study follows the ideas of previous scholars and measures the value of each centrality indicator on the directed unweighted interbank network, to explore the ranking of banks’ systemic importance. Table 5 lists the ranking of the top 20 banks by the centrality indicator. The Central Bank’s report reveals that, of China’s 19 SIBs, 15 are LSOCBs and JSCBs and only 4 are UCBs (SHBANK, BJ BANK, JSBANK, and NBBANK). However, the top 20 banks identified by per indicator
include UCBs, RCBs, and FBs that are not listed by PBC. It is obvious that this is factually unreasonable and contrary to the perception of “too big to fail.” DC, CC, and AIEC identify Ordos Bank as the bank with the highest degree of systemic importance; Citibank (China) is identified as a bank with systemic importance by all five indicators; and Ningbo Cixi Rural Commercial Bank (CIXIBANK) is identified as one of SIBs by DC, EC, and AIEC. It can be seen that applying the various centrality indicators to directed unweighted interbank networks is debatable.

The conclusions in this section differ from those in previous studies, possibly due to the small number of sample banks used in previous studies or the lack of an authoritative control group, leading to discrepancies between the results obtained using centrality indicators and the actual situation in reality [39, 40]. For example, Tang et al. collected the asset-liability data of 16 listed banks to construct the interbank network and Yang and Hu collected the asset-liability data of 30 banks to estimate China’s interbank matrix [39]. Ma et al. collected the data of 19 banks to calculate the network structure of China’s interbank system [40]. Fan et al. built China’s interbank network using asset-liability data of 32 listed banks. Qi and Xu used the data of 246 financial institutions to simulate the financial network. All these scholars measured the systemic importance of financial institutions using traditional centrality indicators, leading them to assign a high degree of systemic importance to some rural and urban commercial banks. Fan and Zhang used the data of 256 banks to build the interbank lending network and established a ranking of SIBs from the perspective of BC and CC, leading them to also identify some of RCBs and UCBs as systemically important banks [22].

3.2.2. Comparison of Centrality Indicators Based on the Directed Weighted Interbank Network. When banks are measured and ranked according to their systemic importance by applying centrality indicators to the directed unweighted interbank network, the conclusion showed that the unweighted network fails to accurately reveal the ranking of
the banks’ systemic importance. Therefore, this section did not simplify the structure of the directed weighted interbank network to an unweighted one and used indicators, including BC, CC, EC, and AIEC, to identify SIBs. Generally, DC is applied to nodes’ importance measurement in the directed unweighted network; for the directed weighted network, there is no standardized formula for DC in the previous literature. Therefore, DC is excluded.

Table 6 shows the ranking of the top 20 banks identified via centrality indicators based on the directed weighted interbank network. The results identified using CC and BC show that the accuracy of identification using the two indicators is questionable. The two indicators, CC and BC, identified some of RCBs and UCBs as banks with a high degree of systemic importance. Such results are contrary to the notion of “too big to fail” and diverge from the list of SIBs issued by PBC. Thus, caution is advised when applying BC and CC to identify SIBs. Both EC and AIEC better identified the degree of banks’ systemic importance. The SIBs identified by EC and AIEC are POBs, LSOCBs, JSCBs, and two UCBs with relatively large assets. This not only follows the notion of “too big to fail” but is also consistent with the ranking of SIBs issued by PBC. In ranking SIBs, AIEC is slightly superior to EC in terms of accuracy. The ranking of CMB, BoCom, and PSBC identified by AIEC is closer to the result of grouping published by PBC. This may stem from the possibility that, compared with EC, which only considers the importance of directly connected nodes, AIEC considers the importance of direct neighbours, as well as that of the indirect ones.

### Table 5: Top 20 banks by importance based on centrality (2020).

<table>
<thead>
<tr>
<th>Ranking</th>
<th>DC Score</th>
<th>Bank</th>
<th>CC Score</th>
<th>Bank</th>
<th>BC Score</th>
<th>Bank</th>
<th>EC Score</th>
<th>Bank</th>
<th>AIEC Score</th>
<th>Bank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7365</td>
<td>Ordos Bank</td>
<td>1.2413</td>
<td>Ordos Bank</td>
<td>0.1174</td>
<td>ICBC</td>
<td>0.4268</td>
<td>Citibank</td>
<td>0.3474</td>
<td>Ordos Bank</td>
</tr>
<tr>
<td>2</td>
<td>0.5988</td>
<td>ICBC</td>
<td>1.1514</td>
<td>ICBC</td>
<td>0.0793</td>
<td>ABC</td>
<td>0.2089</td>
<td>ICBC</td>
<td>0.3468</td>
<td>ICBC</td>
</tr>
<tr>
<td>3</td>
<td>0.5808</td>
<td>Citibank</td>
<td>1.1010</td>
<td>ABC</td>
<td>0.0722</td>
<td>CCB</td>
<td>0.1595</td>
<td>BoCom</td>
<td>0.3406</td>
<td>Citibank</td>
</tr>
<tr>
<td>4</td>
<td>0.5150</td>
<td>ABC</td>
<td>1.0915</td>
<td>CCB</td>
<td>0.0598</td>
<td>BOC</td>
<td>0.1574</td>
<td>CDB</td>
<td>0.3208</td>
<td>CCB</td>
</tr>
<tr>
<td>5</td>
<td>0.4850</td>
<td>CCB</td>
<td>1.0641</td>
<td>BOC</td>
<td>0.0514</td>
<td>CDB</td>
<td>0.1568</td>
<td>BOC</td>
<td>0.3145</td>
<td>BOC</td>
</tr>
<tr>
<td>6</td>
<td>0.4252</td>
<td>BOC</td>
<td>1.0608</td>
<td>CDB</td>
<td>0.0322</td>
<td>BoCom</td>
<td>0.1481</td>
<td>CCB</td>
<td>0.3128</td>
<td>ABC</td>
</tr>
<tr>
<td>7</td>
<td>0.3653</td>
<td>DCD</td>
<td>1.0406</td>
<td>Citibank</td>
<td>0.0242</td>
<td>Ordos Bank</td>
<td>0.1447</td>
<td>CIXIBANK</td>
<td>0.2796</td>
<td>CDB</td>
</tr>
<tr>
<td>8</td>
<td>0.2635</td>
<td>BoCom</td>
<td>1.0311</td>
<td>BoCom</td>
<td>0.0215</td>
<td>SPDB</td>
<td>0.1441</td>
<td>CIB</td>
<td>0.2555</td>
<td>CITIC</td>
</tr>
<tr>
<td>9</td>
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<td>CIB</td>
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3.3. Comparison of the Results of Adjacency Information Entropy Centrality Based on Various Influence Coefficients. In the research above, \( \lambda = 0.65 \), which means that this paper assumes the impact of a bank’s in-degree value on its systemic importance is greater than that of the out-degree value on its systemic importance. Without changing this assumption, this study explored the influence of different values of \( \lambda \) on the identification results. Taking \( \lambda = 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, \) and 0.8, the identification results of AIEC as applied on the directed weighted interbank network are calculated. Table 7 compares the identification results of the systemic importance of banks with different values of \( \lambda \). The analysis in Table 7 showed that different values of \( \lambda \) have a very weak effect on variance in identifying SIBs, indicating that the centrality indicator constructed in this study has greater adaptability. Compared with the list of SIBs published by PBC, the identification result is more accurate, when \( \lambda \) takes the value 0.65.

3.4. Changes in Systemically Important Banks. Based on the section above, which measured the systemic importance of banks using the 2020 AIEC, this section analysed the changes in ranking of SIBs during the sample period. Table 8 shows the centrality ranking of SIBs in China based on the 2020 AIEC over the sample period. Overall, regardless of the state of the financial market, the 19 SIBs identified based on the 2020 AIEC are consistently in the top 20 of the overall bank ranking, with these banks being POBs, LSOCBs, JSCBs, and two UCBs (BJBANK and SHBANK) with relatively large asset size. Among them, ICBC, BOC, CCB, and CDB are always in the top five. ABC, CIB, CITIC, SPDB, BoCom, and CMBC are always in the top 10. CMB, EIBC, and CEB are always in the 11th to 15th place. BJBANK, GDB, SPABANK, and HXBNK are always in the 16th to 20th place. It is noteworthy that ICBC, BOC, CCB, and ABC frequently appear in the top five of the ranking by systemic importance. Furthermore, the top three banks, ICBC, BOC, and CCB, always rank higher than ABC, which
is consistent with both the notion of "too big to fail" and the grouping of Chinese banks on the List of Global Systemically Important Banks (G-SIBs). However, as one of the six LSOCBs, PSBC does not rank as high as other five banks by systemic importance. B+_his is perhaps due to the unique "agency+self-management" model of PSBC, which gives it a very low funding cost and therefore a lower incentive to obtain funds and profits through interbank business than the other five banks. The systemic importance of BoCom has gradually declined since 2017, which may be attributed to the bank’s efforts at reducing the scale of its interbank assets from year to year. Among JSCBs, it is noteworthy that CIB, SPDB, and CMBC are frequently higher in systemic importance than other banks of the same type. An analysis to their annual reports shows that this is because CIB and SPDB rely on interbank funding support for a large part of their funding sources and CMBC has experienced a period of high growth in nonstandard investments. As a result, these three JSCBs have had a higher systemic risk than their peer banks for a long time. Among the POBs, CDB’s systemic importance has undergone a rapid rise during the sample period. Based on public market information, this is because CDB is currently one of the most important domestic money market participants and is the main capital finance provider in the market, with deep involvement in the interbank business. Among UCBs, BJ/BANK and SHBANK are the only two systemically important urban banks identified in this study. This is because the series of stimulus policies launched in response to the 2015 "stock market crash" during the sample period led to a rapid increase in the scale of interbank business. Moreover, a continued increase in the proportion of the interbank liabilities of the two banks, overlaid with the expansion of their asset scale, made them more important in the interbank network.

Systemic financial risk is the risk that the failure of one or a few important financial institutions will cause the failure of other financial institutions through the interconnectedness of the financial institutions and, in turn, have a substantial negative effect on real economy. Based on this, the higher the systemic importance of a financial institution, the more likely it is to directly trigger systemic risk. Therefore, this section indirectly analyses the changes in the level of systemic financial risk of SIBs over the sample period by analyzing the changes in the systemic importance of those. As Table 9 shows, the level of systemic financial risk of all types

is consistent with both the notion of "too big to fail" and the grouping of Chinese banks on the List of Global Systemically Important Banks (G-SIBs). However, as one of the six LSOCBs, PSBC does not rank as high as other five banks by systemic importance. This is perhaps due to the unique "agency+self-management" model of PSBC, which gives it a very low funding cost and therefore a lower incentive to obtain funds and profits through interbank business than the other five banks. The systemic importance of BoCom has gradually declined since 2017, which may be attributed to the bank’s efforts at reducing the scale of its interbank assets from year to year. Among JSCBs, it is noteworthy that CIB, SPDB, and CMBC are frequently higher in systemic importance than other banks of the same type. An analysis to their annual reports shows that this is because CIB and SPDB rely on interbank funding support for a large part of their funding sources and CMBC has experienced a period of high growth in nonstandard investments. As a result, these three JSCBs have had a higher systemic risk than their peer banks for a long time. Among the POBs, CDB’s systemic importance has undergone a rapid rise during the sample period. Based on public market information, this is because CDB is currently one of the most important domestic money market participants and is the main capital finance provider in the market, with deep involvement in the interbank business. Among UCBs, BJ/BANK and SHBANK are the only two systemically important urban banks identified in this study. This is because the series of stimulus policies launched in response to the 2015 "stock market crash" during the sample period led to a rapid increase in the scale of interbank business. Moreover, a continued increase in the proportion of the interbank liabilities of the two banks, overlaid with the expansion of their asset scale, made them more important in the interbank network.

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of SIBs in China exhibits a “three-stage” trend: first a decrease, followed by an increase, and lastly another decrease. (1) From 2011 to 2012, the level of systemic financial risk of all types of SIBs showed a downward trend, with the risk of JSCBs and UCBs showing the most prominent decrease. In April 2011, CBRC issued guidelines on new regulatory standards for the banking industry. Based on Basel III, CBRC raised the regulatory standards on the basis of a comprehensive evaluation of the effectiveness of the current prudential regulatory system and established a more forward-looking, integrated prudential supervision system, which was implemented on January 1, 2012. This may help explain the decline in the level of systemic financial risk of various types of SIBs in China in 2012. (2) From 2012 to 2017, the level of systemic financial risk of all types of SIBs generally increased, with JSCBs and UCBs exhibiting the most prominent increase. From 2012 to 2017, the interbank business of China’s banking industry grew rapidly, with an average compound annual growth rate of over 25.3%. This development of interbank business greatly deepened interbank correlation, which pushed the risk exposure to also expand and the level of systemic financial risk to rise. (3) From 2017 to 2020, the level of systemic financial risk for all types of SIBs generally declined, with JSCBs and UCBs exhibiting the most widespread decline in the level of systemic financial risk. At the end of 2016, after it was proposed at the Central Economic Working Conference to “put the prevention and control of financial risks in a more important position, and resolve to dispose of a number of risk points,” the scale of interbank assets was reduced in an orderly manner from a peak of nearly 60 trillion yuan to 53.4 trillion yuan until the end of July 2019. The PBC’s report showed that after the governance, China’s systemic financial risk slightly decreased during the period 2017–2020.

### Table 8: Changes in systemically important banks during the sample period.

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### Table 9: Increase in the systemic risk of various types of systemically important banks.

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<th>Bank type</th>
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It is worth noting that when the financial market is at different stages, the level of systemic financial risk of JSCBs and UCBs is more vulnerable to changes in national policies compared with that of LSOCBs, which, with stable operation, wide business scope, and superior deposit collection capacity, have wide sources of liabilities, stable structure, and low dependence on interbank liabilities. Compared with LSOCBs, JSCBs and UCBs have more difficulty in absorbing deposits, leading to lower proportion of deposits. In this case, JSCBs and UCBs vigorously increase the proportion of their interbank liabilities to maintain sufficient liquidity and gradually form the operating characteristics of low-speed, steady balance sheet expansion, high leverage and risk appetite, high debt cost, and low interest margin, so they are more vulnerable to changes in national policies.

### 4. Conclusions

The Global Financial Crisis of 2008 seriously impacted the world financial system, and the aftermath of the crisis still affects the financial stability of countries around the world. A lesson from the crisis is the need to strengthen the regulation
of financial institutions with systemic importance. In this context, this study reviewed the existing literature and used information entropy to construct centrality indicator to identify SIBs in the China Banking System. The proposed indicator makes fully use of the impact of banks’ direct and indirect neighbours on them, as well as the size and direction of capital flow between them.

In this study, we draw the following main conclusions.

First, China’s interbank network shows sparse characteristics, as well as an obvious “core-periphery” structure. The top 20 banks by asset size are very active in the interbank network and have the largest number of interbank connections.

Second, the centrality indicator based on adjacency information entropy improves the accuracy of identifying SIBs. Regardless of the state of China’s financial market, the centrality indicator based on adjacency information entropy always identifies the six LSOCBs, nine JSCBs, two POBs (ADB and EIBC), and two UCBs (BJBANK and SHBANK) as the systemically important banks. This list or ranking of SIBs is more in line with that published by PBC and is also consistent with the perception of “too big to fail.”

Third, on the whole, regardless of the state of China’s financial market, ICBC, BOC, CDB, and CCB are always the four most SIBs in China’s banking network and ABC is always in the top ten in terms of systemic importance. Compared with LSOCBs, JSCBs and UCBs are more sensitive to changes in national policies, and changes in their systemic financial risk levels are more susceptible to national policies.

This paper has the following implications: (1) Although systemic financial risks have been mitigated since the strong financial regulation, they are still at a high level and therefore strong regulation of the financial system still needs to be strengthened. (2) Differentiated policies should be designated to regulate each type of financial institution in response to the difference in the degree of response to regulatory policies.

By the way, we admit that the proposed method has limitations. Although the centrality algorithm combined with information entropy improves the accuracy of SIBs identification, it is still based on local information. How to incorporate a wider range of information into the calculation is a direction worth studying in the future.

Data Availability

The data are available from the corresponding author upon request.

Conflicts of Interest

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

Supplementary Materials

The complete list of the abbreviation of banks’ name is shown in the document named “abbreviation of bank name.” The first column is the name of banks, and the second is the abbreviation of bank names. (Supplementary Materials)

References


