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Research article

Research on systemic risk of China's bank-asset bipartite network

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A R T I C L E I N F O

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A B S T R A C T

Systemic risk caused by banks due to common asset holdings serve as a significant contagion channel. In this study, we use empirical data from Chinese banks to construct a bank-asset bipartite network, employ the DebtRank algorithm for risk measurement, and incorporate asset price correlation into the DebtRank algorithm. Then we show the changes of the systemic risk in the Chinese banking system from 2018 to 2021. Furthermore, we analyze the systemic risk triggered by different types of banks and different industry assets and quantify the impact of each asset under different stress scenarios. We also conduct a validity analysis of asset price correlation, finding that the systemic risk considering asset price correlation is higher than that without considering asset price correlation. This study of financial systemic risk under the bank-asset bipartite network provides a new perspective for the regulation of systemic risk and is of significant importance for the prevention of systemic risk.

1. Introduction

The occurrence of systemic risk can trigger significant losses to economy. Systemic risk can be understood as a multi-channel risk contagion phenomenon, with each channel associated with different categories of risks [1–3]. At present, the research on systemic risk in the banking system mainly focuses on two channels: one is the direct contagion channel of counterparties in interbank lending transactions, and the other is the indirect contagion channel through common asset holdings of banks, which is a contagion form in a bank-asset bipartite network. Since the 2007–2009 financial crisis, an increasing number of scholars have turned their attention to systemic risk. The 2007–2009 financial crisis was sparked by the collapse of Lehman Brothers, but the bankruptcy of all banks was not due to direct debt relations with Lehman Brothers, but rather because they held a large amount of common bad assets. It was found that the indirect contagion channel of common asset holdings could amplify the contagion of risk significantly, thus triggering more severe systemic risk than direct debt relations [4,5]. Consequently, in recent years, scholars have begun to pay more attention to systemic financial risk contagion through bank-asset bipartite networks.

Since Allen and Gale [6] first employed the method of networks to study risk contagion among banks, an increasing number of scholars have begun to use the approach of networks to explore systemic risk within the interbank lending network. This includes the reconstruction of networks [7–10], the impact of different network structural features on risk [11–13], and the calculation of risk within the interbank lending network [14–17]. As research has further advanced, the methodology of networks has also been applied to the bipartite network of common asset holdings. Cifuentes et al. [18] were the first to propose the model of bipartite network, in which they explored the indirect contagion stemming from asset devaluation sales. The author demonstrated that liquidity requirements might be more effective than capital buffers in some scenarios, particularly in terms of the impacts of asset price shocks.

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Building on the work of Cifuentes et al. [18], Chen et al. [19] constructed a model of bank-asset portfolios, analyzed the role of common asset holdings during the contagion process, and discussed how adjusting asset portfolios can influence price. Glasserman and Young [5] found that once a bank in a financial network sells off assets, it will lead to a decline in the market value of the assets valued at market prices, thereby deteriorating its balance sheet. The result could be a decrease in the value of the entire system, generating risks that cannot be triggered solely by considering direct contagion channels between interbank transaction counterparts. Adrian and Shin [20] demonstrated that within an accounting framework where assets are valued at market prices, changes in asset prices are immediately reflected as changes in net asset values, triggering indirect risk contagion. Caccioli et al. [21] developed a network approach to study financial indirect contagion caused by overlapping portfolios, confirming the significant role of indirect channels in financial contagion. Guo et al. [22] defined the weak associations formed among financial institutions' common asset holdings through the use of a threshold method. They used this definition to construct a network, discovering that this network structure exhibits scale-free characteristics. Braverman and Minca [23] quantified the interrelationships between financial institutions caused by common asset holdings, proposed a network model, and applied this model to the holdings of common funds and stocks. The study showed that the action of fire sales of assets reduces the value of other financial institutions holding the same assets. Barucca et al. [24] carried out research on the mutual associations between different types of financial institutions through common asset holdings, confirming the existence of contagion channels among financial institutions due to price changes. Our work on network models is similar to that of these scholars, as we study systemic risk through the construction of a bank-asset bipartite network model. However, most current research primarily involves simulation studies, with empirical analysis largely unaddressed. This paper conducts an empirical study using a large amount of empirical data. The results of the study have a certain degree of reliability and serve as a supplement to previous work.

In the study of systemic risk, network-based risk measurement methods are a major focus of scholars, In this context several network-based measures have been proposed recently. The most commonly used methods are represented by Greenwood et al. [25] and Battiston et al. [26]. Greenwood et al. [25] proposed a deleveraging model and used data from European banks to study the contagion mechanism of asset devaluation sales, designing an indicator to measure the systemic risk. Some scholars have utilized the model proposed by Greenwood et al. [25] to study systemic risk in financial institution investment portfolio networks, measuring the systemic importance and indirect vulnerability of individual institutions [27–29]. Additionally, inspired by the Page Rank algorithm, Battiston et al. [26] proposed the DebtRank algorithm for measuring risk in financial networks. They utilized this algorithm to quantify the systemic importance of each institution within the financial network and calculated the losses caused by each institution to the system. Afterwards, many scholars have expanded the DebtRank algorithm for studying systemic risk within financial networks [30–33]. Among them, Poledna et al. [30] extended the DebtRank algorithm to networks of common asset holdings, quantifying the systemic risk brought about by indirect interconnectivity between financial institutions based on Mexico's securities portfolio data, thereby confirming the importance of indirect contagion. In terms of risk measurement, following the approach of Poledna et al. [30], we apply the DebtRank algorithm to measure risk within the bank-asset bipartite network.

Despite the abundance of literature on systemic risk in the financial bipartite network, few studies consider the correlation among assets. Some research indicates that fluctuations in different assets in actual financial markets have certain correlations. For instance,

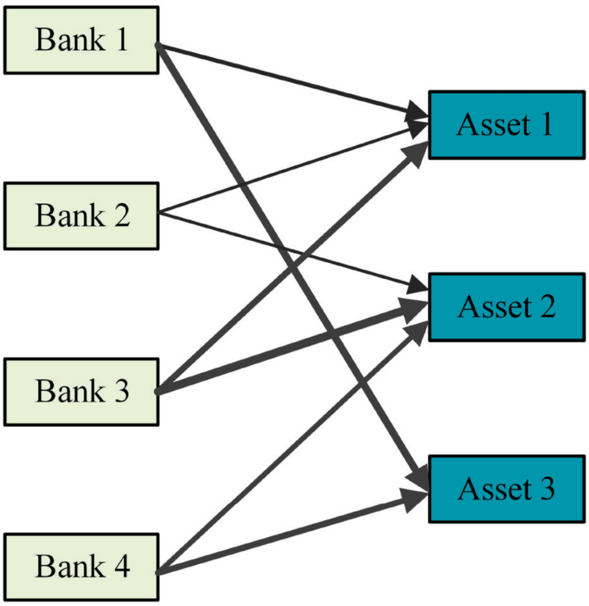


Fig. 1. A typical bank-asset bipartite network. The nodes on the left represent banks, while the nodes on the right signify assets. Links between a bank and an asset exist if the bank holds the asset in its portfolio. Links are weighted, with the thickness indicating the amount of assets held - the thicker the edge, the more assets are held.

Cont and Wagalath [34,35] proposed a multi-period model based on financial markets with multiple assets, demonstrating that mechanisms such as asset liquidation, markdown sales, and short selling could trigger inherent correlations among asset returns. In actual banking systems, there is undeniably a certain degree of correlation between different assets held by banks, mainly reflected in the correlation of asset prices. However, there is very little research in this area. Furthermore, by reviewing the literature, we find that although the research on indirect contagion channel is plentiful, current studies are primarily focused on simulations, with empirical research being relatively scarce. And no scholars have incorporated asset correlation into the DebtRank model for the measurement of systemic risk. Therefore, in light of these research gaps, this paper uses the loans made by Chinese banks to different industries as the common assets held by the banks to construct a bank-asset bipartite network model. By incorporating asset correlation into the DebtRank algorithm that measures systemic risk, we conduct an empirical study on systemic risk in the bank-asset bipartite network. This paper is of practical significance for empirical research on systemic risk under the bank-asset bipartite network. The research results are reliable and add some novel conclusions to the field, providing important reference value for the regulation of financial system stability and playing a significant role in preventing financial systemic risk.

This paper is organized as follows: In section 2 we elucidate the process of fire sale and financial risk propagation, and then calculate the systemic risk in bipartite network. In Section 3, we describe the data set used for this study and visualize the bipartite network of the Chinese banking system. In Section 4, we present the results and related discussions. Finally, in Section 5, we summarize the main conclusions.

2. The model

2.1. Network of common asset holdings

The network of common asset holdings constructed in this paper is a financial bipartite network composed of bank and asset nodes. If bank i invests in asset k, there is a weighted edge between i and k, with the arrow pointing from the bank to the asset, as shown in Fig. 1.

Assuming there are N banks and M assets within the banking system, the bipartite network can be represented by the $N\times M$ matrix LA in Eq. (1) :

$$\mathrm{LA} = \begin{array}{c} \begin{bmatrix} LA_{11} & \cdots & LA_{1k} & \cdots & LA_{1M} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ LA_{i1} & \cdots & LA_{ik} & \cdots & LA_{iM} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ LA_{N1} & \cdots & LA_{Nk} & \cdots & LA_{NM} \end{bmatrix} \\ {\scriptstyle TA_1 \cdots TA_k \cdots TA_M} \end{array} \begin{array}{c} LA_1 \\ \vdots \\ LA_i \\ \vdots \\ LA_N \\ \end{array} . , \tag{1}$$

where LA_{ik} represents the amount of the investment in monetary units from bank i to asset k, $LA_i = \sum_{k=1}^{M} LA_{ik}$ represents the total amount of investment from bank i to all assets, and $TA_k = \sum_{i=1}^{N} LA_{ik}$ represents the total value of asset k.

Although there are no direct links between banks, bank i can, in fact, have an indirect risk exposure to bank j, assuming both bank i and bank j hold the same asset. If bank j sells the commonly held asset k, we can say the asset k undergoes a fire sale, then within a mark-to-market accounting framework, the price of asset k, denoted as p_k, would drop due to the fire sale, and the value of bank i's portfolio would decrease correspondingly.

2.2. The process of fire sale based on the common asset holdings

In the bipartite network of common asset holdings, an external shock leading to a net worth loss in bank i results in an increase in the leverage ratio. The external shock in this study refers to the loss of other assets of the bank (excluding industry loan assets). For simplification, it is directly manifested as a reduction in i's equity, and the lost part of the assets in this study does not participate in the liquidation. To restore the original leverage level, bank i will sell off its industry loan assets. Under the framework of asset valuation at market value, the selling behavior will lead to a decline in asset prices. The decline in asset prices will also affect the prices of related assets, so other banks will be affected by the shock of the asset price decline. In order to restore the leverage ratio, other banks will trigger a new round of selling, forming a vicious cycle of risk contagion.

According to the research on risk contagion of commonly held assets by Greenwood et al. [25], we make the following two assumptions:.

(1) Banks restore their leverage ratio via industry loan asset fire sales. In this paper, we define leverage ratio as the ratio of a bank's total assets to its equity.
(2) Banks do not have a preference for the type of assets sold, i.e., banks sell assets in proportion to their holdings.

In this paper, the common asset holdings are bank loans in different industries. We assume that the total assets of bank i are composed of industry loans LA_i and other assets OA_i. The other assets OA_i do not change over time. At time t, the total assets of bank i, denoted as A_i^t, as shown in Eq. (2):

$$A_i{}^t = LA_i{}^t + OA_i. \tag{2}$$

The asset-liability relationship of bank i is as follows:

$$A_i{}^t = L_i + E_i{}^t. \tag{3}$$

In Eq. (3), L_i and E_i^t represent the total liabilities and equity of bank i at time t, respectively. with the total liabilities being independent of time referring to Caccioli et al. [21]. The leverage ratio of the bank at time t is defined as the ratio of total assets to equity as shown in Eq. (4).

$$l_i^t = \frac{A_i{}^t}{E_i^t}. \tag{4}$$

The process of a bank's asset sale for deleveraging is deduced as follows: When bank i suffers an external shock, the loss is reflected in the decrease in equity E_i^t on the bank's balance sheet. Consequently, the equity of the bank at time $t+1$ is as follows:

$$E_i^{t+1} = E_i^t - \varphi. \tag{5}$$

In Eq. (5), φ represents the external shock experienced by bank i, which is manifested as a reduction in i's equity. A decrease in equity will lead to an increase in leverage. Thus, the leverage ratio of bank i at time $t+1$ becomes l_i^{t+1} according to Eq. (6):

$$l_i^{t+1} = \frac{A_i^{t+1}}{E_i^{t+1}} = \frac{LA_i{}^t + OA_i - \varphi}{E_i^t - \varphi}. \tag{6}$$

In order to restore the initial leverage level ($l_i^{t+1} = l_i^t$), the bank will sell off its assets. In this paper, the fire sale assets being sold off are industrial loans. During the asset sales process, the bank's equity remains unchanged. Assuming that the total amount of assets that bank i needs to sell at time $t+1$ is σ_i^{t+1}, which can be calculated in Eq. (7):

$$l_i^{t+1} = \frac{A_i^{t+1} - \sigma_i^{t+1}}{E_i^{t+1}} = l_i^t \Rightarrow \sigma_i^{t+1} = A_i^{t+1} - l_i^t \cdot E_i^{t+1} = \varphi\left(l_i^t - 1\right). \tag{7}$$

As shown in Eq. (8), the total amount of assets sold by bank i cannot be greater than the equity of bank i:

$$\sigma_i = \min\left\{\sum_t \sigma_i(t), E_i\right\}. \tag{8}$$

When a certain type of asset of a bank is completely sold off, the remaining assets of the bank continue to be sold proportionally. In the event of a bank default, at the next moment, the bank will sell off all remaining held assets.

2.3. Quantification of the systemic risk in bipartite networks

In the bipartite network of common asset holdings, bank i may experience an equity loss due to an exogenous shock, to return its leverage ratio, bank i will sell off assets (the assets sold by the banks are industry loan assets in this paper). Under the mark-to-market accounting framework, the fire sale will cause the price of the assets in the bank's portfolio to drop. Given the correlation among assets, the decline in the price of one asset will also affect the prices of correlated assets. Therefore, other banks will be impacted by the decrease in asset prices. In order to restore their leverage ratios, these other banks will trigger a new round of asset sales, creating a vicious cycle of risk contagion.

(1) Definition of the impact matrix between Banks

If both bank i and bank j commonly hold asset k, then an indirect contagion can occur between i and j through asset k. The indirect risk exposure between i and j, via their common holding of asset k, can be calculated as follows:

$$V_{ij} = \sum_k \frac{p_k^t \cdot LA_{ik}^t \cdot LA_{jk}^t}{TA_k^t}. \tag{9}$$

In Eq. (9), LA_{ik}^t and LA_{jk}^t represent the value of asset k held by bank i and bank j at time t, respectively. TA_k^t denotes the total value of asset k, while p_k^t represents the price of asset k at time t, with the initial price at $p_k^0 = 1$. The value of asset k in bank i's portfolio, LA_{ik}^t, is calculated as $LA_{ik}^t = q_i^k \cdot p_k^t$, where q_i^k refers to the quantity of asset k held by bank i. A bank holds its portfolio as long as it is solvent so q_i^k is independent of time referring to Caccioli et al. [21]

Under the mark-to-market accounting framework, the act of a bank selling its assets will lead to a decrease in the price of the assets. If bank i sells asset k, it will result in the price of asset k to drop due to market influence. Therefore, we introduce the market impact function as shown in Eq. (10):

$$f\left(x_k^t\right) = e^{-\alpha \cdot x_k^t}, \tag{10}$$

where x_k^t represents the ratio of the quantity of asset k sold at time t to the total quantity of asset, α denotes the sensitivity of asset prices, i.e., the degree of price fluctuation of asset k due to its fire sale. Following the research of Caccioli et al. [21], we set $\alpha = 1.0536$, i.e., when 10% of asset k is sold, the price of asset k decreases by 10%; hence, the price of asset k at time t is p_k^t, as shown in Eq. (11)

$$p_k^t = p_k^{t-1} \cdot f\left(x_k^t\right). \tag{11}$$

Because there is a correlation between asset prices, the price of asset u will also be affected by asset k, therefore, the price of asset u is:

$$p_u^t = p_u^{t-1} - p_u^{t-1} \cdot r_{ku} \cdot \left(1 - f\left(x_k^t\right)\right), u \neq k. \tag{12}$$

In Eq. (12), r_{ku} is the correlation between assets k and u, and the impact matrix W_{ij} of bank i on bank j in the bipartite network can be calculated in Eq. (13):

$$W_{ij} = \frac{V_{ij}}{E_i^t} = \sum_k \frac{p_k^t \cdot LA_{ik}^t \cdot LA_{jk}^t}{E_i^t \cdot TA_k^t}. \tag{13}$$

(2) The dynamic propagation of bank stress levels

This paper adopts the DebtRank proposed by Bardoscia et al. [36] to characterize the risk contagion mechanism. Firstly, in Eq. (14), we introduce the stress level of bank i, denoted as the relative equity loss of bank i at time t:

$$h_i(t) = \frac{E_i^0 - E_i^t}{E_i^0}. \tag{14}$$

Then, by iterating the balance sheet identity, the dynamic evolution of the stress level of bank i at time $t+1$ can be derived in Eq. (15). It is the sum of its own stress level at the prior moment and the stress levels imposed on it by all related banks:

$$h_i(t+1) = \min\left\{1, h_i(t) + \sum_{j\in N} W_{ij}\Delta h_j(t)\right\}, \tag{15}$$

where $\Delta h_j(t)$ represents the stress increment of bank j at the moment t. When $t = 1$, set $\Delta h_j(0) = \Delta h_j(0)$, and for any $t > 1$, $\Delta h_j(t) = h_j(t) - h_j(t-1)$.

(3) Calculate the systemic risk

According to the DebtRank algorithm, the proportion of equity loss caused by bank i to the banking system (i.e., The risk value caused by bank i) is defined as the sum of the product of the stress level of bank nodes in the network and their economic value at convergence state T, minus the product of the initial stress level of the impacted bank node and its economic value. The risk value caused by bank i is calculated in Eq. (16):

$$DR_i = \sum_{j\in N} h_j(T)v_j - h_i(0)v_i, \tag{16}$$

where N is the set of all banks; the first term on the right side of the equation represents the sum of the product of the stress level of all banks and their economic value when the system reaches stability. $h_i(0)$ represents the stress level of the impacted bank i at the initial moment, and v_j represents the economic value of bank j in the banking system, which is calculated as the proportion of the sum of the industry assets of bank j to the total industry assets of all banks in the banking system. v_j is culculated in Eq. (17):

$$v_j = \frac{LA_j}{\sum_j LA_j}. \tag{17}$$

After calculating the DebtRank (DR) value of each bank, the systemic risk of the banking system can be obtained by taking the average of the DR values of all banks.

Based on the risk contagion model, we design a corresponding risk contagion dynamic evolution algorithm with specific steps as follows.

Step 1. Calculate the influence matrix of banks holding common assets.

Step 2. At $t = 1$, subject a certain bank to an exogenous shock, and calculate the stress level of the shocked bank and the number of assets sold by the shocked bank.

Step 3. Update the status of common assets held by each bank and the prices of all assets.

Step 4. Calculate the stress level of other affected banks based on the updated asset prices.

Step 5. Repeat Steps 1 to 4 until the system converges at time T.

Step 6. Calculate the DR of each bank.

3. Data

In this study, we collect data of 193 Chinese banks from the Wind database, with missing data supplement from the annual reports of each bank. we use the natural experiment of Covid-19 to validate the effectiveness of the model, thus selecting data from 2018 to 2021. The 193 banks we collected include 6 state-owned banks, 11 joint-stock banks, 84 city commercial banks, and 92 rural commercial banks. Given the large sample size, the data is highly representative. In accordance with the industry classification standard in China, 18 types of industries are selected as the common assets held by the banks, namely agriculture, mining, manufacturing, utility and gas, construction, wholesale and retail, transportation, information transmission, hotel and catering, finance, real estate, commercial leasing, scientific research and technology, water conservation and environment, education, health and social work, culture and sports, and general. The correlation among industry prices is approximated using the correlation of the Wind Securities Regulatory Commission's primary industry indices, which can be directly obtained from the Wind database.

Fig. 2 visualizes the bipartite network structure of common assets held by banks in 2021, comprising two types of nodes: banks and industries. The network consists of 193 bank nodes and 18 industry nodes, with a total of 2892 edges, indicating that 193 banks have made a total of 2892 credit transactions to 18 industries.

In terms of banks, the largest nodes are numbers 1, 2, 3, and 4, which represent Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, and Bank of China, respectively. This indicates that these four state-owned banks have the largest loan scale in the banking system. From the industry perspective, the largest nodes are letters C, L, G, and K, representing Manufacturing, Commercial Leasing, Transportation, and Real Estate respectively. These sectors constitute a significant proportion of assets in many banks and play pivotal roles in China's economy.

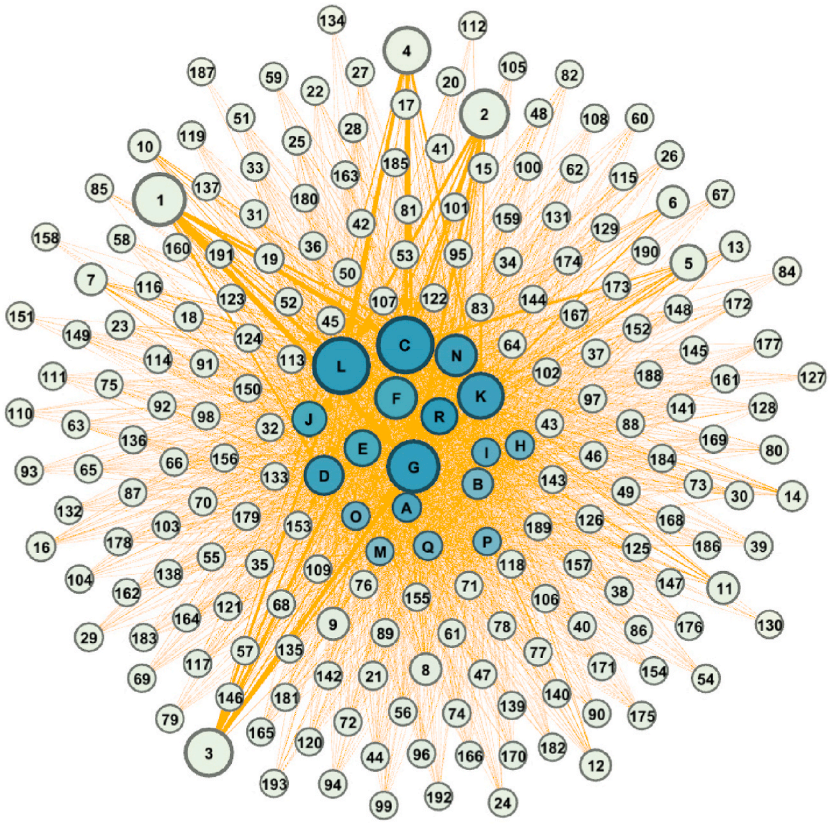


Fig. 2. Bipartite network structure of common assets held by banks in 2021. The numbers and letters in the circles respectively represent identifiers for banks and industries (the names corresponding to the identifiers can be found in Appendix A). The size of the circle is proportional to the scale of assets. If a bank invests in a particular industry, the nodes are connected by a weighted link, with the weight representing the investment amount in monetary units.

4. Results

4.1. Systemic risk under different shocks

We conduct a macroprudential stress test by applying localized shocks affecting either a single bank or a single asset. A single bank shock is characterized by the default of an individual bank, while a single asset shock is defined as a 10% reduction in the asset price. Subsequently, we compute the *DR* values for all banks. The systemic risk is defined as the average of the *DR* values across all banks.

Fig. 3 depicts the systemic risk of different years under the conditions of bank and asset shocks. The results from the graph indicate that under both types of shocks, the systemic risk of the banking system displayed a declining trend from 2018 to 2021. This suggests that financial systemic risk is generally well-controlled in China. Additionally, the results from Fig. 3 reveal that the systemic risk under asset shock is higher than that under bank shock. The extent of risk variation under asset shock is greater, implying a higher sensitivity of banks to changes in asset prices. When the price of an asset is affected, all banks investing the asset are impacted, leading them to divest their assets. The higher the interconnectivity of investment portfolios among banks, the greater the indirect impact of one bank's asset divestiture on other banks holding the same asset. Influenced by market demand, this can amplify the initial shock of price decline, and the longer the duration of the deleveraging spiral, the more severe the negative externality of asset prices. Against the backdrop of a complex economic environment, fluctuations in asset prices can easily plunge banks into trouble, and overlooking changes in asset prices can lead to an underestimation of systemic risk.

4.2. Analysis of systemic risk triggered by different types of banks

This paper further investigates the systemic risk triggered by different types of banks, categorizing them into four types: state-owned banks, joint-stock banks, city commercial banks, and rural commercial banks. As illustrated in Fig. 4(a), the systemic risk induced by the two types of large banks, namely state-owned and joint-stock banks, are significantly higher than those of the other two types of smaller banks. Large banks hold a larger scale of loans than small banks, thus the systemic risk effect triggered by large banks is more significant. If large banks are affected by shocks, it will cause turbulence in the entire banking system. This indicates that state-owned and joint-stock banks are the risk centers of China's banking system. The default of these two types of banks will have a significant negative impact on the country's banking system. Therefore, it is imperative to increase the regulatory intensity for these two types of banks.

Given the significant magnitude differences in systemic risk induced by different types of banks, we have separately illustrated the systemic risk triggered by joint-stock banks, city commercial banks, and rural commercial banks. This allows for a more intuitive display of the annual variations in systemic risk caused by these three types of banks, as shown in Fig. 4(b). The results from Fig. 4 further reveal that the systemic risk triggered by state-owned banks has been steadily declining year by year from 2018 to 2021. Although the systemic risks induced by the other three types of banks overall exhibit a downward trend, there was a certain degree of increase in each of them in 2020, indicating that joint-stock banks, city commercial banks, and rural commercial banks posed higher systemic risk values in that year. 2020 marked the onset of the COVID-19 pandemic, which caused turbulence in global financial markets and dramatic fluctuations in international financial asset prices, with varying degrees of declines in stock markets, bond markets, and foreign exchange markets. Multiple complex factors led to certain changes in the relationships among banks in China. Coupled with China's epidemic control measures and banks' slight adjustments to the loan structure of various industries, the systemic risk of banks increased in 2020. However, state-owned banks, with their stronger ability to withstand risks, were less impacted by the

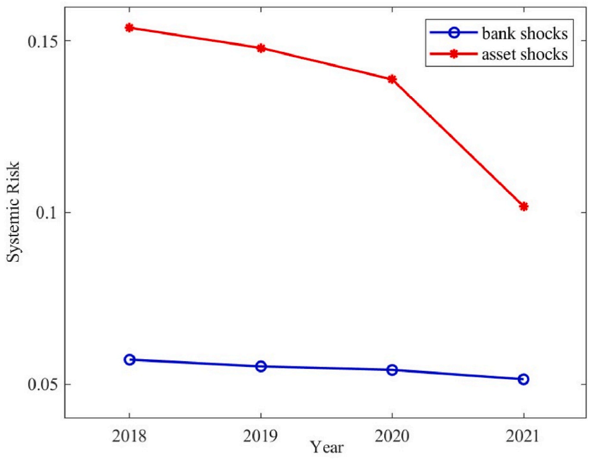
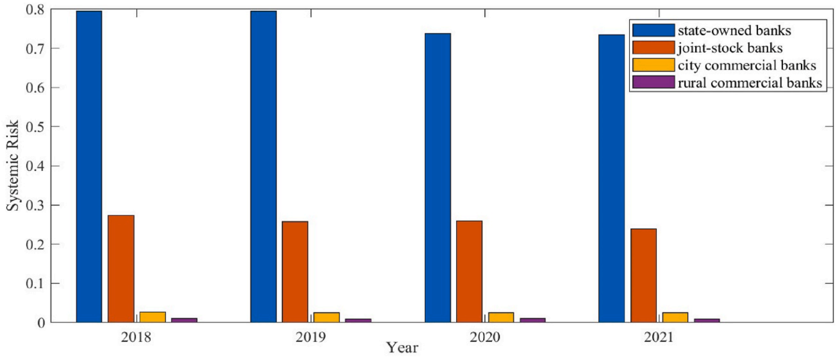
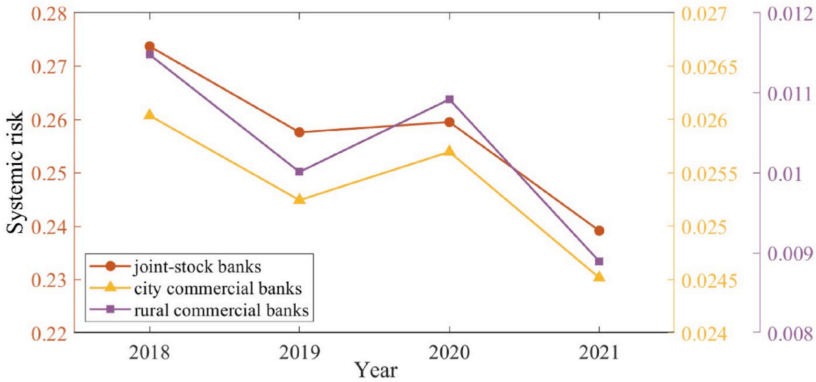


Fig. 3. Systemic risk of different years under the conditions of bank and asset shocks from 2018 to 2021. The red line represents the results of shocks to banks, while the blue line represents the results of shocks to assets. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



(a) Systemic risk triggered by the four types of banks.



(b) Systemic risk triggered by joint-stock banks, city commercial banks and rural commercial banks.

Fig. 4. The changes in systemic risk triggered by different types of banks from 2018 to 2021. (a) Provides an overall view of the risks caused by four types of banks, and (b) shows the systemic risks caused by joint-stock banks, city commercial banks, and rural commercial banks.

COVID-19 pandemic.

4.3. Analysis of systemic risk triggered by different assets

The real economy and the banking industry are inseparably interrelated, making it essential to analyze the systemic risk triggered by different industry loan assets. Fig. 5 displays the systemic risk triggered by various industries from 2018 to 2021. The top five industries with the highest systemic risk values are manufacturing(A), commercial leasing(L), transportation(G), real estate(K), and wholesale and retail trade(F), all of which are vital sectors in China. The systemic risk triggered by each industry has overall shown a declining trend from 2018 to 2021, with most industries experiencing only a slight decrease in systemic risk from 2019 to 2020. In the case of the commercial leasing industry, it posed the highest systemic risk in 2020, largely due to its liquidity being most significantly impacted by the COVID-19 pandemic, leading banks to allocate more loans to aid its recovery.

The manufacturing industry, which China has been vigorously developing, receives the largest scale of bank loans. Therefore, once the manufacturing industry is affected, the systemic risks caused cannot be ignored. The systemic risk induced by different industries reflects the true state of China's economy. For a long time, the Chinese economy has heavily relied on these influential sectors, obtaining substantial loans from areas such as manufacturing, commercial leasing, transportation, and real estate. However, these industries have excessively large asset scales and are easily impacted by banking shocks. Moreover, due to their interconnections with numerous banks, loan losses can easily propagate throughout the system. Even minor losses in these sectors could inflict substantial damage on the banking system. Hence, when monitoring financial stability, greater attention should be paid to price fluctuations in these industries.

We further analyze the systemic risk induced by different industries when subjected to varying degrees of price shocks. As previously mentioned, an asset shock in this study is defined as a proportional decrease in the price of a certain category of assets. In section 4.1, we induced a shock to industry assets by reducing the price of a certain category of assets by 0.1. This section simulates the systemic risk induced by different industries under the shock conditions of a 0.3 and 0.6 decrease in the price of industry assets. As

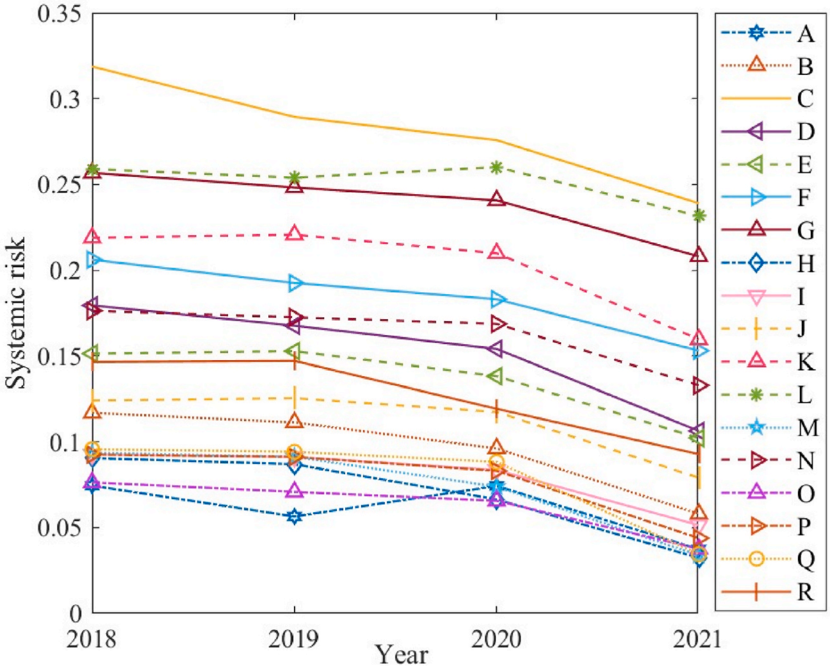


Fig. 5. Systemic risk triggered by different industries from 2018 to 2021. The letters A to R are the identifiers for each industry, with the names corresponding to the identifiers found in Appendix A.

shown in Table 1, it can be found that.

(1) Combined with the 0.1 asset price shock discussed earlier, it can be seen that under all three shock intensities, the manufacturing industry(C) provoked the greatest systemic risk from 2018 to 2021. The main reason is that the manufacturing industry has the largest asset scale in the banking system compared to other industries, and many banks have invested in the manufacturing industry. When the manufacturing industry is shocked, the equity of most banks will suffer losses, thus triggering a larger systemic risk even under smaller shocks.

Table 1
Systemic risk triggered by various industries under different price shock intensities. This table displays the systemic risk induced by different industries when the asset prices in these industries decrease by 0.3 (medium intensity) and 0.6 (high intensity).

industries	Shock intensity 0.3				Shock intensity 0.6			
	2018	2019	2020	2021	2018	2019	2020	2021
A	0.0780	0.0628	0.0776	0.0489	0.0823	0.0707	0.0805	0.0645
B	0.1697	0.1526	0.1342	0.0978	0.2479	0.2133	0.1904	0.1568
C	0.7513	0.6737	0.6513	0.6176	0.9879	0.9778	0.9790	0.9638
D	0.3490	0.3162	0.2994	0.2593	0.5867	0.5318	0.5138	0.4885
E	0.2649	0.2620	0.2471	0.2189	0.4238	0.4121	0.3959	0.3803
F	0.3901	0.3590	0.3587	0.3350	0.5919	0.5428	0.5576	0.5432
industries	Shock intensity 0.3				Shock intensity 0.6			
	2018	2019	2020	2021	2018	2019	2020	2021
G	0.5676	0.5489	0.5477	0.5178	0.7615	0.7423	0.7350	0.7320
H	0.0841	0.0806	0.0657	0.0412	0.0746	0.0711	0.0645	0.0545
I	0.0820	0.0805	0.0751	0.0496	0.0660	0.0645	0.0624	0.0468
J	0.2006	0.2018	0.1861	0.1448	0.3007	0.3045	0.2863	0.2418
K	0.4910	0.4936	0.4807	0.4097	0.7779	0.7715	0.7730	0.7206
L	0.5827	0.5782	0.6212	0.6089	0.8635	0.8651	0.9196	0.9204
M	0.0766	0.0755	0.0625	0.0320	0.0513	0.0519	0.0455	0.0294
N	0.3357	0.3290	0.3428	0.3144	0.5413	0.5322	0.5634	0.5487
O	0.0672	0.0630	0.0591	0.0369	0.0534	0.0513	0.0494	0.0359
P	0.0759	0.0750	0.0693	0.0384	0.0509	0.0507	0.0485	0.0304
Q	0.0988	0.0970	0.0924	0.0504	0.0984	0.0983	0.0984	0.0717
R	0.2982	0.2858	0.2378	0.2055	0.4676	0.4437	0.3921	0.3508

(2) Under all three industry shock intensities, most industries saw the smallest reduction in systemic risk in 2020, and some even experienced a slight increase in systemic risk compared to 2019. This indicates that the COVID-19 pandemic impacted global financial markets, including China's, leading to a higher systemic risk in China's banking system in 2020. However, the systemic risk was brought under control in 2021 due to the economic recovery measures implemented by the Chinese government. The systemic risk triggered by the real estate industry(K) declined most significantly in 2021, which is related to the strict policies implemented by China in the real estate market.

(3) When the price shock magnitude increases to 0.6, the systemic risk triggered by all industries fluctuates from 2019 to 2020, with the commercial leasing industry(L) still showing a significant increase. The manufacturing, transportation, and commercial leasing industries trigger substantial systemic risk each year, particularly the manufacturing and commercial leasing industries, which can cause the entire banking system to collapse annually. The real estate industry also put the banking system in jeopardy from 2018 to 2020, but the systemic risk it triggered in 2021 dropped by about 0.053, a larger reduction than any other industry. This indicates that China's real estate regulatory policies had a significant effect in 2021.

4.4. Validity test of asset price correlation

In a complex economic environment, there is a certain degree of correlation between different industries, the price fluctuations in one industry can, to some extent, cause changes in another industry. Our model takes into account the correlation between asset prices. To test the validity of the model proposed in this paper, we compare the results of risk contagion with asset price correlation and asset price independence.

Figs. 6 and 7 present a comparative analysis of the risk contagion results of asset price correlation and asset price independence under bank shocks and asset shocks. The results of Figs. 6 and 7 show that if the correlation between asset prices is not considered, the systemic risk value will be lower, indicating that ignoring asset price correlation will greatly underestimate the systemic risk of the banking system, leading to erroneous judgments by financial regulators when assessing the systemic risk status of the banking system.

The results from Figs. 6 and 7 further reveal that under asset shocks, the decline in systemic risk, with the assumption of asset price independence, is greater than that under bank shocks, indicating that under asset shocks, the correlation between asset prices has a greater impact on the systemic risk of the banking system. This occurs because shocks to banks directly cause losses to bank equity, leading to asset depreciation through asset sales by the bank. This depreciation is less significant than the depreciation caused by direct shocks to asset prices. Therefore, in regulating financial risks, the government should pay greater attention to the correlation between prices in the real economy sector.

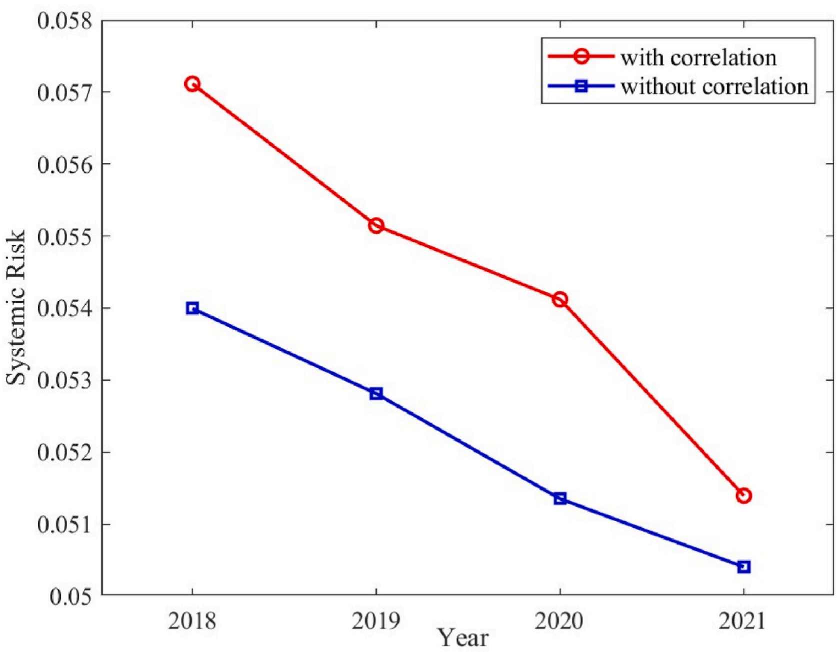


Fig. 6. Systemic risk under bank shocks with both correlated and independent asset prices. The red line represents the results considering asset correlation, while the blue line represents the results when assets are independent. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

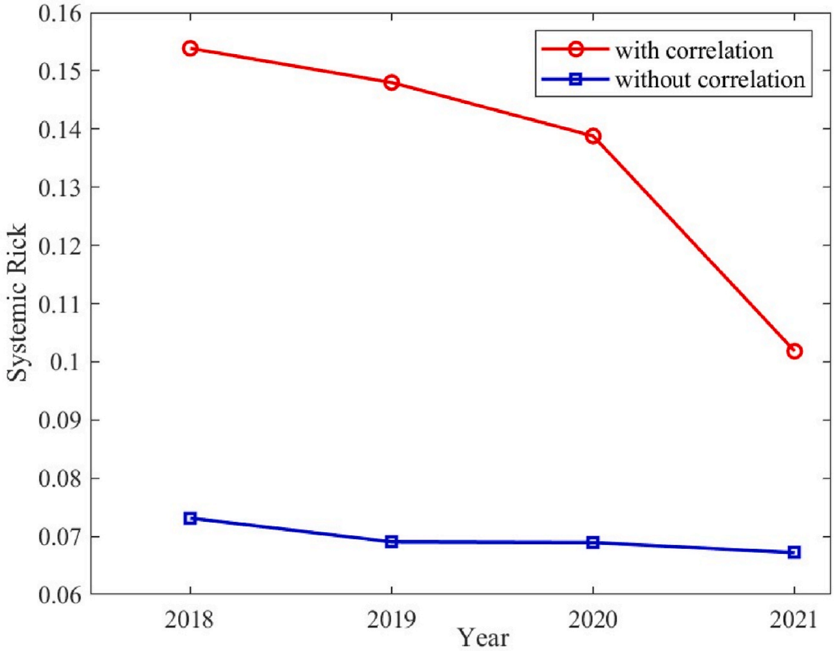


Fig. 7. Systemic risk under asset shocks with both correlated and independent asset prices. The red line represents the results considering asset correlation, while the blue line represents the results when assets are independent. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

5. Conclusion

To a large extent systemic risk arises from the bipartite network of common asset holdings between financial institutions. This paper focus on quantifying systemic risk arising from the bank-asset bipartite network in China's banking system. This works provides, to our knowledge, the first empirical study that consider asset correlation in the DebtRank algorithm to quantify systemic risk in bipartite network. By constructing a bipartite financial network of common asset holdings among 193 Chinese commercial banks from 2018 to 2021, we simulated the contagion process of deleveraging and selling-off within the banking system. We innovatively incorporated asset price correlation into the DebtRank algorithm and conducted a risk contagion analysis using this model. We provided evidence of a certain degree of systemic risk in the biparitete network of commonly held assets by banks, which is also validated in many empirical studies on financial risk. The findings in this paper contribute to a better understanding of Chinese financial systemic risk. We hope this in turn can inform how financial stability is monitored and maintained. The principal conclusions of this paper are as follows.

We showed that regardless of whether the shocks originate from banks or assets, the systemic risk in the Chinese banking system demonstrated a declining trend from 2018 to 2021, indicating that financial risk in China has been broadly well-managed. The systemic risk under asset shocks is higher than that under bank shocks, and the magnitude of changes in systemic risk under asset shocks far exceeds that under bank shocks. This highlights the sensitivity of banks to changes in asset values. Overlooking fluctuations in asset prices can result in an underestimation of systemic risk.

Through analysis of different types of banks, we found that the systemic risk triggered by the two types of large banks, namely state-owned and joint-stock banks, is higher than that of the other two types of smaller banks. The primary reason is that large banks hold a greater volume of assets than small banks, hence the systemic risk effect induced by large banks is more substantial. Should the large banks be impacted, it could prompt a ripple effect across the entire banking system. State-owned banks and joint-stock banks, the two types of large banks, are the epicenters of risk within the China's banking system. In case of default, they could bring about significant negative repercussions to the China's banking system, therefore, the regulatory oversight for these two types of banks should be intensified.

In addition, state-owned banks possess a stronger capability to withstand risks. The systemic risk triggered by state-owned banks has been steadily declining year by year from 2018 to 2021. Although the systemic risks triggered by the other three types of banks are overall on a downward trend, there was a certain degree of increase in each of them in 2020 compared to 2019. The year 2020 marked the onset of the COVID-19 pandemic, which caused turbulence in the global financial markets and dramatic fluctuations in the prices of international financial assets. Various complex factors led to a certain degree of change in the relationships among China's banks. Coupled with China's pandemic control measures, the loan structure of banks to various industries was slightly adjusted, leading to an increase in the systemic risk of China's banking system in 2020. However, state-owned banks, with their stronger risk resilience, were less affected by the COVID-19 pandemic.

Under the three scenarios of price shock intensity set in this study, the manufacturing industry consistently triggered the greatest systemic risk. This is primarily due to the manufacturing sector having the largest asset scale in the banking system relative to other industries and many banks have invested in this sector. The systemic risk induced by the commercial leasing sector saw the most conspicuous rise in 2020, which is attributable to its liquidity status being significantly affected by the COVID-19 pandemic. The decrease in systemic risk triggered by most industries was smallest in 2020, with some industries even experiencing an increase in systemic risk in the same year. In 2021, the Chinese government implemented measures to revive the economy, enabling control of financial systemic risk. The systemic risk triggered by the real estate industry saw the most significant decrease in 2021, with a reduction greater than any other industry, demonstrating the notable effectiveness of China's real estate regulation policies in 2021. When subjected to significant shock, the manufacturing, transportation, and commercial leasing industries each year triggered substantial systemic risks, particularly the manufacturing and commercial leasing sectors, which could cause a collapse in the entire banking system annually.

We showed that the systemic risk associated with correlation in asset prices is higher than that with independent asset prices. Overlooking the correlation among asset prices can significantly underestimate the systemic risk, leading to erroneous judgments by financial regulatory authorities while assessing the systemic risk status of the banking system. Moreover, the correlation among asset prices has a greater impact on the systemic risk of the banking system under asset shocks. Therefore, when regulating financial risks, the government should pay more attention to the correlation among prices in the real economy sectors.

One limitation of this study is that we do not fully consider the direct connections between banks. In fact, financial contagion can also occur through the direct channel of the interbank market. Therefore, it may be beneficial to employ a multi-layer network approach that combines both direct and indirect connections to study systemic risk in finance. Furthermore, the financial institutions considered in this study are solely banks. Expanding the model to encompass other financial institutions (such as securities firms, insurance companies, etc.) could potentially offer a more comprehensive understanding of the risk status within the financial system, and may present a valuable improvement.

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Data availability statement

Data will be made available on request.

Ethics declarations

Informed consent was not required for this study.

CRediT authorship contribution statement

Hong Fan: Writing – review & editing, Supervision, Project administration, Formal analysis, Conceptualization. **Chao Hu:** Writing – original draft, Software, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1
Industry ID and corresponding name

ID	Industry name
A	agriculture
B	mining
C	manufacturing
D	utility and gas
E	construction
F	wholesale and retail
G	transportation

(*continued on next page*)

Table A1 (*continued*)

ID	Industry name
H	information transmission
I	hotel and catering
J	finance
K	real estate
L	commercial leasing
M	scientific research and technology
N	water conservation and environment
O	education
P	health and social work
Q	culture and sports
R	general

Table A2
Bank ID and corresponding name

ID	Bank name	ID	Bank name
1	Industrial and Commercial Bank of China	98	Ganzhou Bank
2	China Construction Bank	99	Yinzhou Rural Commercial Bank
3	Agricultural Bank of China	100	Xiamen Rural Commercial Bank
4	Bank of China	101	Weifang Bank
5	Bank of Communications	102	Laishang Bank
6	Postal Savings Bank of China	103	Changsha Rural Commercial Bank
7	China Merchants Bank	104	Suzhou Rural Commercial Bank
8	Industrial Bank	105	Jiangyin Rural Commercial Bank
9	Shanghai Pudong Development Bank	106	Zhangjiagang Rural Commercial Bank
10	China Citic Bank	107	Bank of Shangrao
11	China Minsheng Bank	108	Bank of Shaoxing
12	China Everbright Bank	109	Leshan Commercial Bank
13	Ping A Bank	110	Shaoxing Rural Commercial Bank
14	Hua Xia Bank	111	Jiangmen Rural Commercial Bank
15	Bank of Beijing	112	Dalian Rural Commercial Bank
16	China Guangfa Bank	113	Dongying Bank
17	Bank of Shanghai	114	Yuhang Rural Commercial Bank
18	Bank of Jiangsu	115	Bank of Quanzhou
19	China Zheshang Bank	116	Kunshan Rural Commercial Bank
20	Bank of Nanjing	117	Hefei Rural Commercial Bank
21	Bank of Ningbo	118	Bank Of Xingtai
22	Huishang Bank	119	Bank Of Yantai
23	Bohai Bank	120	Mianyang Commercial Bank
24	Shengjing Bank	121	Ningbo Commercial Bank
25	Chongqing Rural Commercial Bank	122	Bank of Luzhou
26	Bank of Hangzhou	123	Bank of Jining
27	Beijing Rural Commercial Bank	124	Guiyang Rural Commercial Bank
28	Bank of Jinzhou	125	Bank of Qinhuangdao
29	Shanghai Rural Commercial Bank	126	Changchun Rural Commercial Bank
30	Xiamen International Bank	127	Jinhua Bank
31	Guangzhou Rural Commercial Bank	128	Bank of Jiaxing
32	Bank of Tianjin	129	Bank of Dazhou
33	Chengdu Rural Commercial Bank	130	Jingu Rural Commercial Bank
34	Harbin Bank	131	Zhuhai Rural Commercial Bank
35	Bank of Changsha	132	Maanshan Rural Commercial Bank
36	Bank of Guangzhou	133	Ouhai Rural Commercial Bank
37	Bank of Guiyang	134	Tai'an Bank
38	Bank of Chengdu	135	Huizhou Rural Commercial Bank
39	Bank of Zhengzhou	136	Bank of Suining
40	Bank of Chongqing	137	Bank of Huzhou
41	Jiangxi Bank	138	Yueqing Rural Commercial Bank
42	Bank of Dalian	139	Jiangsu Rugao Rural Commercial Bank
43	Dongguan Rural Commercial Bank	140	Changchun Development Rural Commercial Bank
44	Jiangnan Rural Commercial Bank	141	Zhejiang Shangyu Rural Commercial Bank
45	Jilin Bank	142	Zhejiang Nanxun Rural Commercial Bank
46	Bank of Kunlun	143	Zhejiang Fuyang Rural Commercial Bank
47	Bank of Guizhou	144	Zhejiang Haining Rural Commercial Bank
48	Hunan Bank	145	Jiangsu Taicang Rural Commercial Bank
49	Bank of Gansu	146	Yantai Rural Commercial Bank
50	Hankou Bank	147	Jiangsu Xinghua Rural Commercial Bank
51	Bank of Qingdao	148	Zhejiang Hecheng Rural Commercial Bank
52	Tianjin Rural Commercial Bank	149	Bank of Hainan
53	Shenzhen Rural Commercial Bank	150	Fuqing Huitong Rural Commercial Bank

(*continued on next page*)

Table A2 (*continued*)

ID	Bank name	ID	Bank name
54	Dongguan Bank	151	Jiangsu Taixing Rural Commercial Bank
55	Bank of Jiujiang	152	Hunan Ningxiang Rural Commercial Bank
56	Suzhou Bank	153	Shandong Zhucheng Rural Commercial Bank
57	Lanzhou Bank	154	Zhejiang Jiashan Rural Commercial Bank
58	Shunde Rural Commercial Bank	155	Shandong Longkou Rural Commercial Bank
59	Qingdao Rural Commercial Bank	156	Jiangsu Changjiang Commercial Bank
60	Bank of Guilin	157	Zhejiang Anji Rural Commercial Bank
61	Wuhan Rural Commercial Bank	158	Shandong Rongcheng Rural Commercial Bank
62	Qilu Bank	159	Hebei Zhengding Rural Commercial Bank
63	Fudian Bank	160	Shanxi Yuncheng Rural Commercial Bank
64	Bank of Xi'an	161	Liaoyang Liaodong Rural Commercial Bank
65	Hubei Bank	162	Changde Rural Commercial Bank
66	Chang'an Bank	163	Shandong Anqiu Rural Commercial Bank
67	Xiamen Bank	164	Ningbo Beilun Rural Commercial Bank
68	Bank of Wenzhou	165	Xinjiang Aksu Rural Commercial Bank
69	Jinshang Bank	166	Shandong Zhangdian Rural Commercial Bank
70	Zhejiang Chouzhou Commercial Bank	167	Bank of Xinjiang
71	Hangzhou Rural Commercial Bank	168	Jiangsu Xuyi Rural Commercial Bank
72	Sichuan Tianfu Bank	169	Xiangtan Rural Commercial Bank
73	Guangdong Nanyue Bank	170	Zhejiang Haiyan Rural Commercial Bank
74	Langfang Bank	171	Shanxi Yuxian Rural Commercial Bank
75	Weihai Commercial Bank	172	Liaoning Donggang Rural Commercial Bank
76	Tangshan Bank	173	Zhejiang Xinchang Rural Commercial Bank
77	Guangdong Huaxing Bank	174	Shanxi Pingyao Rural Commercial Bank
78	Zijin Rural Commercial Bank	175	Ningbo Ninghai Rural Commercial Bank
79	Zhangjiakou Bank	176	Zhejiang Qingtian Rural Commercial Bank
80	Taizhou Bank	177	Fujian Changle Rural Commercial Bank
81	Guangxi Beibu Gulf Bank	178	Shaoxing Hengxin Rural Commercial Bank
82	Nanhai Rural Commercial Bank	179	Zhejiang Jiande Rural Commercial Bank
83	Zhuhai China Resources Bank	180	Hubei Qianjiang Rural Commercial Bank
84	Zhejiang Tailong Commercial Bank	181	Zhejiang Longyou Rural Commercial Bank
85	Changshu Rural Commercial Bank	182	Xinjiang Kashgar Rural Commercial Bank
86	Jiutai Rural Commercial Bank	183	Ningbo Zhenhai Rural Commercial Bank
87	Tianjin Binhai Rural Commercial Bank	184	Hubei Xiaogan Rural Commercial Bank
88	Handan Bank	185	Zhejiang Lishui Liandu Rural Commercial Bank
89	Xiaoshan Rural Commercial Bank	186	Zhejiang Chun'an Rural Commercial Bank
90	Wuxi Rural Commercial Bank	187	Fujian Nanping Rural Commercial Bank
91	Haixia Bank of Fujian	188	Zhejiang Jinyun Rural Commercial Bank
92	Bank of Urumqi	189	Huangshi Rural Commercial Bank
93	Bank of Rizhao	190	Hunan Huarong Rural Commercial Bank
94	Bank of Cangzhou	191	Hunan Xiangyin Rural Commercial Bank
95	Bank of Ningxia	192	Qinghai Huzhu Rural Commercial Bank
96	Zhejiang Mintai Commercial Bank	193	Zhejiang Qingyuan Rural Commercial Bank
97	Liuzhou Bank		

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