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Identifying the systemic importance and systemic vulnerability of financial institutions based on portfolio similarity correlation network

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Abstract

The indirect correlation among financial institutions, stemming from similarities in their portfolios, is a primary driver of systemic risk. However, most existing research overlooks the influence of portfolio similarity among various types of financial institutions on this risk. Therefore, we construct the network of portfolio similarity correlations among different types of financial institutions, based on measurements of portfolio similarity. Utilizing the expanded fire sale contagion model, we offer a comprehensive assessment of systemic risk for Chinese financial institutions. Initially, we introduce indicators for systemic risk, systemic importance, and systemic vulnerability. Subsequently, we examine the cross-sectional and time-series characteristics of these institutions' systemic importance and vulnerability within the context of the portfolio similarity correlation network. Our empirical findings reveal a high degree of portfolio similarity between banks and insurance companies, contrasted with lower similarity between banks and securities firms. Moreover, when considering the portfolio similarity correlation network, both the systemic importance and vulnerability of Chinese banks and insurance companies surpass those of securities firms in both cross-sectional and temporal dimensions. Notably, our analysis further illustrates that a financial institution's systemic importance and vulnerability are strongly and positively associated with the magnitude of portfolio similarity between that institution and others.

Keywords: Systemic risk; Portfolio similarity; Systemic importance; Systemic vulnerability

1 Introduction

With the gradual advancement of financial innovation in recent years, a complex network of correlations between financial institutions has been created as a result of closer contact and mixed business operations across financial institutions. This will lead to the risk that a single financial institution in distress will propagate through the correlation network across the system, ultimately creating financial systemic risk [1, 2]. Because of this risk formation mechanism, many scholars already focus on the central role of financial linkages that cause systemic risk [3, 4]. Now, the study on the financial correlation network is broadly divided into two categories. The first is the direct correlation network, which forms by connecting different market entities via direct creditor-debtor relationships [5]. When a market entity fails to deliver on a debt contract, the risk spreads to the direct correlation network. The second is the indirect correlation network, which is created by the entities' indirect connection through the ownership of common assets [6]. When some banks experience asset losses, they must sell some assets due to leverage ratio constraints, which causes asset values to fall, affecting other banks that hold the assets and causing risk contagion. Many studies have analyzed the systemic risk in the direct correlation network [7, 8]. A significant number of articles have examined bank systemic risk by constructing interbank lending [9, 10] and credit networks [11, 12]. And the two most typical research methods are the EN algorithm [13] and the DebtRank algorithm [14].

However, with the increasing portfolio similarity and mixed business operations among financial institutions, the indirect correlation network among financial institutions has gradually attracted the interest of scholars. Numerous scholars have examined the systemic risk from the perspective of indirect networks and indirect contagion using simulation and empirical methodologies [15]. The research has confirmed that the indirect network is an important channel of the risk contagion and should not be ignored [16]. In addition, scholars have also made a detailed analysis of the risk contagion mechanism in the indirect network. Currently, there are two major categories of contagion models. One is the threshold model, which holds that banks will only liquidate assets when they go bankrupt [6, 17]. The other is the leverage targeting model. It assumes that if the leverage ratio of the bank does not meet the requirements, it will liquidate the assets [18–20]. In addition to the research mentioned above, many studies have built indirect networks using real data to study the risk contagion of financial systems across various countries [15, 21, 22]. Of course, a few scholars have also examined the systemic risks of financial institutions like funds [23, 24] and insurance firms [25] from the perspective of indirect contagion in order to provide new insights for asset managers and policymakers [26].

In the above-mentioned studies on financial systemic risk, scholars have proposed many measures of systemic risk, but most of them only focus on one aspect of systemic risk. i.e., only pay attention to the systemic importance of financial institutions [27, 28] or the risk exposure of financial institutions [29, 30]. In fact, Systemic risk consists of two aspects: risk spillover caused by network connections among financial institutions and risk exposure to financial institutions, where risk spillovers and exposures reflect the systemic importance and systemic vulnerability of financial institutions, respectively. When considering the correlation network of financial institutions, systemic importance evaluates each financial institution's risk contribution in the risk contagion process. The network model method, the Sharpley value method [31], and CoVaR [32] are the primary systemic importance measurement methods. Ref. [33] first used the network model method to study the risk contagion among banks, but the data required by this method are the transaction data of each financial institution, which are difficult to collect and process in a timely manner. This has a significant impact on China's monitoring of systemic risk. As a result, the Sharpley value method was proposed to assess the degree of systemic importance of various financial institutions by allocating systemic risk to each institution based on the size of each individual contribution [34, 35]. However, the above methods are more complicated to calculate; in contrast, CoVaR can directly measure the risk spillover effects of financial institutions, which is convenient and quick, and therefore is gradually being widely used in the field of risk management [36, 37]. Furthermore, some researchers have used indicators to measure the systemic importance of financial institutions [38]. For the systemic vulnerability, it evaluates the risk borne by each financial institution from other financial institutions, i.e., the entire financial system, in the risk contagion process. The marginal expected loss (MES) method and the SRISK method are the main systemic vulnerability measurement methods. The MES method measures the expected loss of a financial institution in the event of severe turbulence in the financial system and reflects the sensitivity of the financial institution to changes in systemic risk [39], whereas the SRISK indicator measures a financial institution's capital shortfall in the event of a severe market downturn as a function of the institution's size, leverage, and risk [40]. Some other scholars have analyzed the factors influencing systemic importance and systemic vulnerability [41] or constructed contagion and vulnerability indices to measure the degree of systemic importance and vulnerability of banks, respectively [42].

The review of the above literature reveals that the study of systemic risk under the portfolio similarity correlation channel has become popular. Nevertheless, most research has only analyzed the systemic risk caused by a single type of financial institution under this channel and has mainly used banks as a case study. The characteristics of portfolio similarity correlation networks between different types of financial institutions have not been elucidated. Therefore, in order to further investigate systemic risk under the portfolio similarity correlation channel, we concentrate on the portfolio similarity correlation network among different types of financial institutions and measure the systemic risk of financial institutions according to the expanded fire sale contagion model. At the same time, while studying the modeling of portfolio similarity among various financial institutions, the works of Barucca et al. [43] and Caccioli et al. [44] align with our research. Nevertheless, both studies rely on the leverage target model to measure fire sale losses, which deviates from the actual liquidation process of financial institutions. Therefore, we refer to the research conducted by Ramadiah et al. [21] to estimate asset liquidation amounts and price changes in the fire sale process of financial institutions. Using the Ramadiah et al. model, we expand the fire sale model by including real regulatory leverage rates for different financial institutions. Moreover, we study more asset classes held by financial institutions to understand systematic risks related to similarities in their portfolios. This helps us calculate losses for financial institutions more precisely during a crisis. Additionally, most of the literature on assessing systemic importance and vulnerability of financial institutions is based on market data [41, 45]. And there are fewer relevant studies in China. Therefore, considering the complex connections between Chinese financial institutions, we use balance sheet data and complex network methods to study their systemic importance and vulnerability over time and across different institutions. This not only broadens our research perspective, but also provides regulators with more comprehensive references for preventing and mitigating financial systemic risks.

2 Research model and risk indicator

2.1 Portfolio similarity correlation network

The portfolio similarity correlation network is an undirected weighted network of financial institutions that are correlated with each other according to the similarity of their asset portfolio holdings, as shown in Fig. 1. The network's nodes stand for financial institutions,

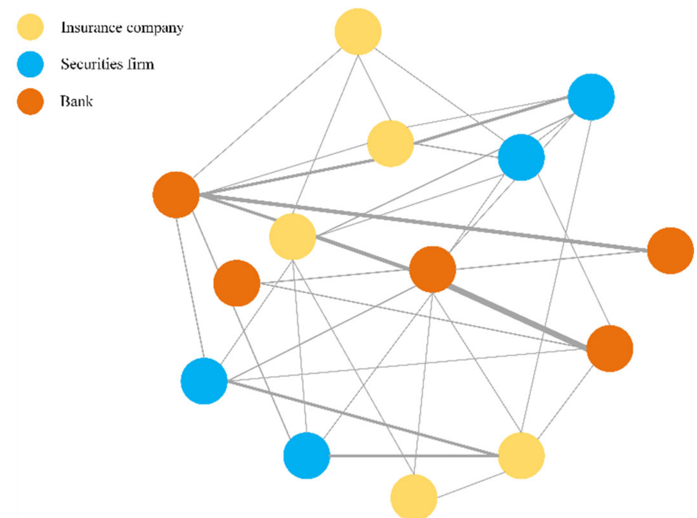


Figure 1 Portfolio similarity association network of financial institutions. (Origin from Barucca et al. (2021)) The yellow nodes represent insurance companies; the blue nodes represent securities firms and the orange nodes represent banks

with different colors denoting various kinds of financial institutions. The connected edges between nodes indicate that the portfolios held by the financial institutions are similar, and the thickness of the edge indicates how much more similar the assets are between the institutions; the thicker the edge, the higher the portfolio similarity between the financial institutions.

There are various ways to measure the level of portfolio similarity between financial institutions, but we employ the cosine similarity proposed by Girardi et al. to more accurately assess the portfolio similarity between different types of financial institutions [46]. The level of portfolio similarity between financial institution i and financial institution j is defined as:

$$cs_{ij} = \frac{\sum_m C_{im} C_{jm}}{\|V_i\| \|V_j\|}. \tag{1}$$

Where C_{im} is the value of asset m held by financial institution i, $\|V_i\|$ is the vector parametrization of the asset portfolio held by financial institution i. The size of portfolio similarity between financial institutions ranges from 0 to 1, with larger values indicating higher portfolio similarity between financial institutions.

2.2 Expanded fire sale contagion model

The portfolio similarity correlation network reveals that financial institutions are interconnected due to the similarity of their asset portfolios. The fire sale contagion model takes portfolio similarity among financial institutions into account and assumes that as asset prices fall, financial institutions will sell the related assets at a lower price to meet regulatory leverage requirements. A massive sell-off of assets leads to a glut of assets in the market, resulting in a further decline in asset prices, which causes other financial institutions associated with them to suffer losses, triggering systemic risk. Consequently, the fire sale contagion model is good for measuring the systemic risk that financial institutions suffer from price declines under the portfolio similarity correlation channel.

Two main types of fire sale contagion models are included in the existing studies: one is the threshold model, which assumes that financial institutions liquidate their assets only when losses are large enough to cause insolvency and no longer participate in the subsequent contagion process [6]. The other is the leverage targeting model. This model assumes that when the financial institutions' leverage falls short of their goal leverage, they must liquidate part of their assets [18]. Nevertheless, Ramadiah et al. discover that the actual fire sale behavior of financial institutions lies between the threshold model and the leverage target model [47]. Therefore, in order to capture a more realistic systemic risk, we refer to the results of Ramadiah et al. to estimate the liquidation volume and price fluctuations of assets during the fire sale process of financial institutions. Using Ramadiah et al.'s model, we incorporate the actual regulatory leverage rates of different types of financial institutions as leverage targets. Additionally, we expand the asset classes held by financial institutions to develop an expanded fire sale model. This model serves as a tool for exploring systematic risk under the correlation channel of portfolio similarity among financial institutions.

2.2.1 Structure of the balance sheet

In this study, we consider a financial system with N financial institutions (including banks, insurance companies, and securities firms) and M categories of illiquid assets (see the data description section for specific categories).

Assume that at time t, the cash held by financial institution i is C_i^t, its portfolio of illiquid assets is A_i^t, and its other assets is Q_i^t. P_m^t is the price of asset m at time t, and $\{O_{i1}^t, \dots, O_{iM}^t\} \geq 0$ is the portfolio of illiquid assets of financial institution i at time t. Therefore, $A_i^t = \sum_{m=1}^{M}(O_{im}^t \times P_m^t)$ indicates the overall value of the financial institution's portfolio of illiquid assets. For simplicity, we assumed that the initial price of each illiquid asset is one, i.e., $P_m^0 = 1, \forall m \in \mathrm{M}$. And illiquid assets may suffer price losses throughout the fire sale process, but the price of cash always remains constant; other assets Q_i^t, which are asset types other than cash and illiquid assets, such as interbank assets, are also unaffected by the fire sale.

Moreover, we assume that the liabilities of financial institution i is L_i^t and the equity is E_i^t. Therefore, the total assets T_i^t and total liabilities B_i^t of financial institution i are expressed as:

$$T_i^t = C_i^t + A_i^t + Q_i^t; \qquad B_i^t = L_i^t + E_i^t. \tag{2}$$

2.2.2 Contagion process of fire sale under external shocks

Assume that after a shock θ_m ($\theta_m \in [0,1]$), the price of asset m falls to P_m^1 at time $t = 1$, thus $P_m^1 = (1 - \theta_m) \times P_m^0$. For any asset m,there is $P_m^1 \leq P_m^0$, and there must be at least one class of asset prices that satisfy $P_m^1 < P_m^0$. Financial institution i owning asset m will experience a direct loss as a result of the shock, i.e., $Loss_i = \sum_{m=1}^{M}(O_{im}^1 \times (P_m^0 - P_m^1))$. At this point, the total assets, equity, and liabilities of the financial institution i are described as:

$$T_i^1 = T_i^0 - Loss_i; \qquad E_i^1 = E_i^0 - Loss_i; \qquad L_i^1 = L_i^0. \tag{3}$$

Subsequently, financial institution i then acts in response to the direct losses it experiences. If the loss is great for $E_i^1 < 0$, the financial institution i becomes insolvent, and it must liquidate all of its assets. And the financial institution i exits the portfolio similarity correlation network and is not involved in the subsequent contagion process. On the other hand, if the financial institution experiences a loss and its regulatory leverage no longer complies with regulatory requirements, it must sell off part of its assets. Here, the regulatory leverage ratio is defined as capital divided by total assets. Hence, financial institution i must liquidate some of its assets when Eq. (4) is no longer satisfied.

$$\lambda_i^1 = \frac{E_{i,1}}{T_{i,1}} \geq \lambda_i^\alpha. \tag{4}$$

Where λ_i^1 is the regulatory leverage ratio at time $t = 1$, λ_i^α is the regulatory leverage ratio requirement, where α is used to differentiate the regulatory leverage ratios of different types of financial institutions.

In this paper, a one-parameter non-linear function $H_i^1(\sigma)$ is introduced to capture the liquidation process of financial institutions [47]. By introducing regulatory leverage into the Ramadiah et al. model, we can get the total value of assets to be liquidated by financial institution i is represented in Eq. (5).

$$Z_i^1 = H_i^1(\sigma) \times \left(T_i^1 \min\left\{ 1 - \frac{E_i^1}{T_i^1 \lambda_i^\alpha}, 1 \right\} \right). \tag{5}$$

In Eq. (5), $H_i^1(\sigma) = \min\{e^{q(\sigma_i^1 - \lambda_i^\alpha)}, 1\}$, where σ_i is the absolute return on assets, $\sigma_i^1 = -\frac{T_i^1 - T_i^0}{T_i^0}$. And q ($q \in (0, \infty)$) is a parameter that is related to a financial institution's propensity to follow threshold liquidation dynamics.

For ease of exposition, we suppose that financial institution i will keep its current asset portfolio weighting unchanged, i.e., sell off its assets proportionally. Meanwhile, the price of an asset will alter as a result of its fire sale. And referring to the model of Ramadiah et al. [47], the price of asset m after it has been affected by the fire sale can be described as:

$$P_m^2 = \left(1 - \mu \frac{\sum_i^N \phi_{im}^1}{\sum_i^N O_{im}^0} \right) \times P_m^1. \tag{6}$$

Where μ is a parameter reflecting the market response to asset liquidation, with higher values of a indicating greater illiquidity of assets. ϕ_{im}^1 denotes the total amount of assets m sold by financial institution i, $\phi_{im}^1 = \frac{O_{im}^1 P_m^1}{T_i^1} Z_i^1$.

When financial institutions conduct the fire sale, they will experience two types of losses: a mark-to-market loss on their remaining assets and a loss on the decline in value of the assets sold at the time of the sale [19]. Additionally, it is presumed that the asset price at the midpoint of the pre-selling and post-selling times is subtracted from the selling assets. Therefore, the contagion loss for financial institution i after the first round of the fire sales is:

$$FLoss_{i,1} = \sum_{m=1}^{M} O_{im}^2 \times \left(P_m^1 - P_m^2 \right) + \frac{1}{2} \sum_{m=1}^{M} \phi_{ik}^1 \frac{P_m^1 - P_m^2}{P_m^1}. \tag{7}$$

In Eq. (7), the portion preceding the plus sign represents the mark-to-market loss on the remaining assets, and the portion following the plus sign represents the loss on the portion of the assets sold off.

The preceding is a summary of the improved fire sales contagion model's first round of contagion. As asset prices are updated, i.e., as losses from the fire sale contagion occur, the total assets and leverage of the financial institutions will change again, which causes them to liquidate some of their assets once more, triggering a new round of contagion. And this cycle will continue until there are no more financial organizations in the network that need to liquidate their assets.

2.3 Indicators for measuring systemic risk

When performing a fire sale of assets, multiple rounds of contagion processes frequently occur. However, including too many cycles of asset liquidation can often reduce the effectiveness of stress testing models [47]. Therefore, we utilize the frameworks proposed by Greenwood et al. and Duarte et al. to establish a metric for assessing systemic risk based on the contagion losses following the initial round of fire sales [18, 48].

2.3.1 Systemic risk indicator: SR

Systemic risk (*SR*) is a measure of the financial system's systemic risk. In this study, it is defined as the ratio of contagion losses to the initial total equity after the first round of fire sales for financial institutions in the improved fire sale contagion model, as in Eq. (8).

$$SR = \frac{\sum_i FLoss_{i,1}}{\sum_i E_i^0}. \tag{8}$$

2.3.2 Systemic important financial institution indicator: SIFI

Systemically important financial institutions (*SIFI*) assess how much each financial institution contributes to the spread of risk; the higher the risk share, or the higher the value of the indicator, the more important the financial institution. Therefore, the indictor is defined as the ratio of the contagion loss of each financial institution after the first round of fire sales to the contagion loss of all financial institutions in the improved fire sale contagion model, as shown in Eq. (9).

$$SIFI = \frac{FLoss_{i,1}}{\sum_i FLoss_{i,1}}. \tag{9}$$

2.3.3 Systemic vulnerable financial institution indicator: SVFI

Systemic Vulnerable Financial Institutions (*SVFI*) measure the risk that each financial institution faces from other financial institutions, i.e., the financial system, during the risk contagion process. The financial institution is more vulnerable, and the more risk it takes on, the higher the measure's value. Therefore, the systemic vulnerable financial institution indicator is defined as the ratio of the contagion loss of each financial institution after the first round of fire sales to its initial equity value in the improved fire sale contagion model, as shown in Eq. (10).

$$SVFI = \frac{FLoss_{i,1}}{E_i^0}. \tag{10}$$

Table 1 Descriptive statistics table of the data

Indicator	Mean	St. dev.	Max	Min
Derivative financial instruments	11,904	23,677	171,738	0
Net loans and advances to customers	1,724,241	3,822,593	20,109,200	0
Investment properties	2281	9315	101,690	0
Fixed assets	24,767	55,391	270,017	60
Intangible assets	2994	6173	33,428	0
Deferred tax assets	13,514	24,532	143,027	0
Other assets	474,974	1,489,419	9,078,534	0
Debt investments	293,554	644,560	4,946,741	0
Other debt investments	161,140	288,123	1,857,222	0
Investments in other equity instruments	9565	35,921	282,185	0
Cash and balances with central banks	318,103	709,074	3,613,872	4383
Total assets	3,477,932	6,849,858	35,171,383	20,019

3 Description of data and parameters

3.1 Descriptive statistics of data

We used the balance sheet data of financial institutions from 2017 to 2021 and selected the sample financial institutions according to the following principles: 1) The listing time is earlier than January 1, 2017; 2) There were no ST or ST* situation during the sample period, that is there are no abnormalities in the financial or other conditions during the sample period, posing a risk of delisting; 3) The industry classification results for financial institutions remained unchanged during the sample period. In conclusion, 56 financial organizations were chosen as the research objects, and they were categorized into 24 banks, 4 insurance companies, and 28 securities firms based on the China Securities Regulatory Commission's industry categorization findings for the third quarter of 2021. The research data were obtained from the CSMAR[1] database and the annual reports of financial institutions, with the data unit being millions of RMB.

This paper represents the institution's portfolio by considering multiple asset classes, specifically including the following 10 illiquid assets. In this section, we provide the descriptive statistics for cash and balances with central banks, the total assets, and the ten illiquid assets. The ten illiquid assets are derivative financial instruments, net loans and advances to customers, investment properties, fixed assets, intangible assets, deferred tax assets, other assets, debt investments, other debt investments, and investments in other equity instruments, which will be impacted by the fire sale. The amount of assets held by financial institutions varies greatly, as shown in Table 1. Net loans and advances to customers, along with other assets, debt investments, and cash and balances with central banks, are significantly larger in size compared to investment properties and intangible assets, which are comparatively smaller.

3.2 Description of parameters

This research focuses on four key parameters: regulatory leverage ratio requirements for financial institutions (λ_i^α), propensity parameters for financial institutions to follow the threshold model (q), market response parameters for asset liquidation (μ), and the percentage of external shocks (θ_m). The values used in the empirical analysis for these parameters are described below.

[1] https://data.csmar.com/.

(1) Regulatory leverage ratio requirements for financial institutions (λ_i^{α}). According to the provisions in the Guidelines for the Supervision of Leverage Ratios of Commercial Banks, the Measures for the Management of Capital of Financial Assets Investment Companies, and the Measures for the Management of Risk Control Indicators of Securities Firms, we set the regulatory leverage ratio requirements for banks, insurance companies and securities firms at 4%, 6% and 8%, respectively.

(2) Propensity parameters for financial institutions to follow the threshold model (q). The range of the propensity parameters in the real liquidation model of financial institutions is between 20 and 30 [47]. Here, for convenience in the calculation, we set $q = 20$.

(3) Market response parameters for asset liquidation (μ). Except for cash, all assets are assumed to have the same market response parameters. According to Ramadiah et al., the range of the market response parameters for illiquid assets is between 0.6 and 1 [47]. Since the assets considered in this research are illiquid, we set $\mu = 0.6$.

(4) The percentage of external shocks (θ_m). The interval of change for external shocks during the systemic risk phase is [deleveraging minimum shock, all bankruptcy minimum shock]. External shocks within this interval will lead to risky contagion within the financial system. Therefore, to ascertain the percentage of external shocks that cause risk contagion in the financial system during the sample period, we set the external shocks to $[0.001, 1]$ and simulate them in the model in steps of 0.001. Based on the simulation results, the proportion of external shocks is set to 0.037 in order to ensure that risk contagion occurs in all years of the sample period and to analyze the systemic importance and vulnerability of financial institutions more accurately in both cross-sectional and temporal dimensions. This value represents the minimum proportion of shocks that is necessary for risk contagion to occur in all years of the sample period.

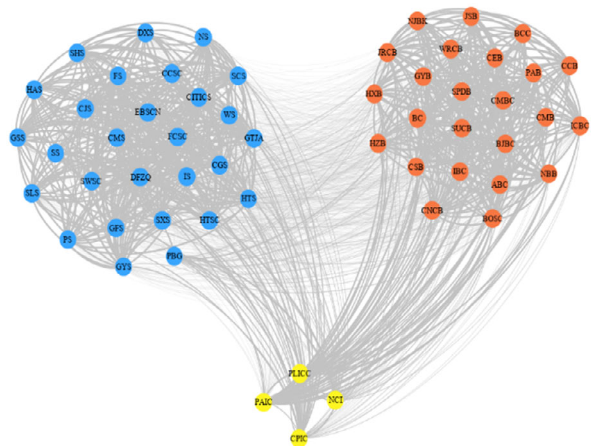
4 Empirical results

4.1 Portfolio similarity correlation network of 56 Chinese financial institutions

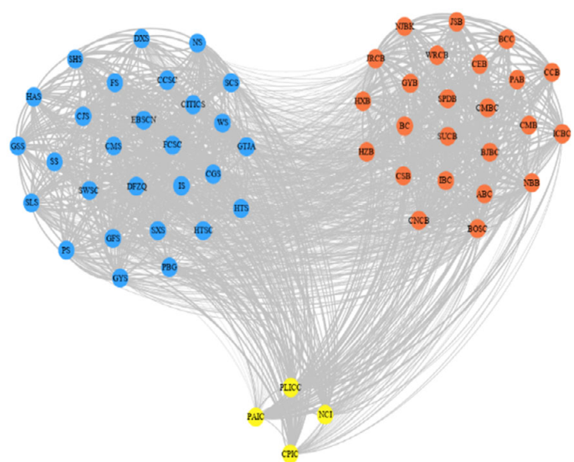
Based on the description of the portfolio similarity correlation network in Sect. 2.1, we calculated the size of portfolio similarity among individual financial institutions using the balance sheet data of 56 financial institutions in China from 2017 to 2021 and plotted the portfolio similarity correlation network of 56 financial institutions in China from 2017 to 2021 as shown in Fig. 2.

As seen in Fig. 2, financial institutions have a strong portfolio similarity correlation among themselves, providing a channel for systemic risk contagion. And from 2017 to 2021, portfolio similarity between financial institutions of the same type was high, while there was a significant change in portfolio similarity among different types of financial institutions, particularly from 2017 to 2018. In addition, to provide a more visual representation of the changes in the portfolio similarity association among financial institutions, we calculate the average portfolio similarity size among multiple financial institutions for each year, and the results are shown in Table 2 and Table 3.

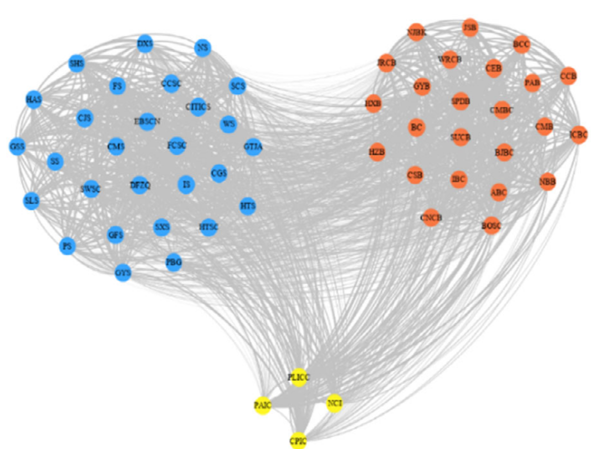
Tables 2 and 3 show that portfolio similarity between financial institutions of the same type is strong and varies less, while portfolio similarity between different types of financial institutions is relatively low and varies substantially. It is noteworthy that the greatest portfolio similarity is found between banks and insurance companies, which remains at around 0.5, indicating that risks from banks or insurance companies have a high potential to be transmitted to each other. On the other hand, banks and securities firms show a



(a)



(b)



(c)

Figure 2 Portfolio similarity correlation network from 2017 to 2021 for 56 financial institutions in China. Figure 2(a) to Fig. 2(e) depict the portfolio similarity correlation network map from 2017 to 2021, with orange nodes representing banks, yellow nodes representing insurance companies, and blue nodes representing securities firms, and the thickness of the connected edges reflecting the magnitude of portfolio similarity between financial institutions. Note that the names of financial institutions in Fig. 2 are represented by their English abbreviations, and the specific correspondence is shown in the Appendix

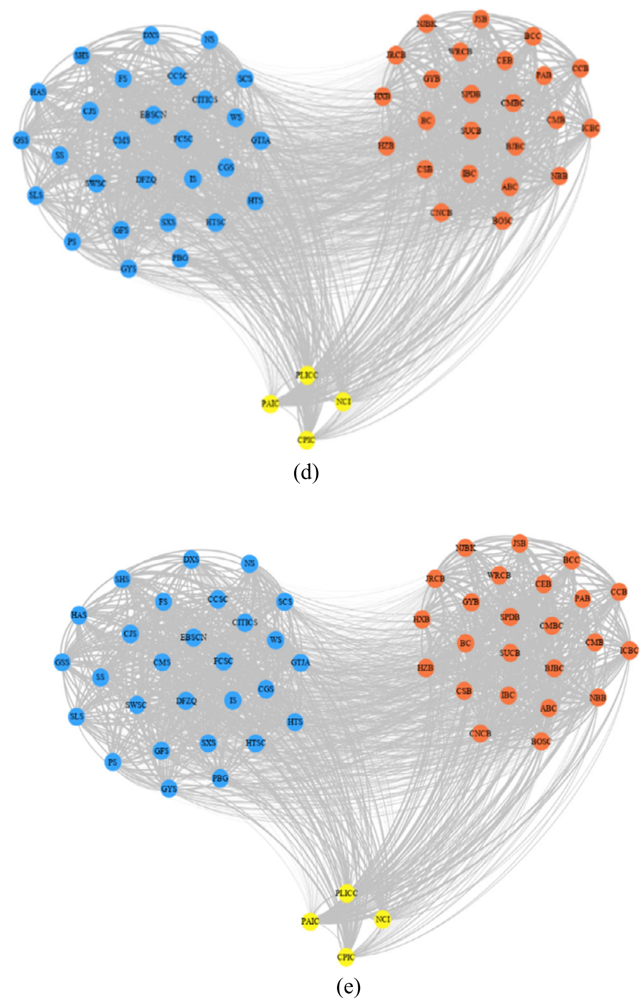


Figure 2 Continued

Table 2 The change in average portfolio similarity between the same types of financial institutions

	2017	2018	2019	2020	2021
Bank-Bank	0.9886	0.9401	0.9286	0.9451	0.9453
Insurance company-Insurance company	0.7496	0.7329	0.7234	0.7140	0.7184
Securities firm-Securities firm	0.8861	0.8137	0.7914	0.8328	0.8611

lower portfolio similarity, with assets remaining largely similar at around 0.2 from 2018 to 2021, except for a significant upward trend from 2017 to 2018, so the risk spread between banks and securities firms through this channel is relatively low. From the perspective of changing trends, portfolio similarity between banks and insurance companies follows a similar trend to the size of portfolio similarity between banks and securities firms, both increasing and then stabilizing, whereas portfolio similarity between insurance companies and securities firms is more variable, increasing significantly from 2017 to 2018, but then decreasing from 2018 to 2021.

In addition, Barucca et al. found that some institution types hold debt and equity portfolios that are more similar to those held by other types, which is similar to our findings

Table 3 The change in average portfolio similarity between different types of financial institutions

	2017	2018	2019	2020	2021
Bank-Insurance company	0.5047	0.5304	0.5290	0.4552	0.5181
Bank-Securities firm	0.0335	0.2249	0.2058	0.1730	0.1798
Insurance company-Securities firm	0.2990	0.5293	0.4497	0.4867	0.3977

Table 4 Systemic risk in China's financial system from 2017 to 2021

	2017	2018	2019	2020	2021
SR	0.0069	0.1765	0.0054	0.0056	0.0018

[43]. Furthermore, their research showed that both unit-linked and non-unit-linked insurance company debt holdings are highly similar to each other's debt holdings as well as to those of banks. To a lesser extent, they are also similar to those of investment funds. In our study, we observed that the overall asset similarity between insurance companies and banks is higher than that between insurance companies and securities firms. Therefore, banks and insurance companies need to be particularly aware of risks from the asset similarity channel with respect to each other.

In conclusion, we have achieved a preliminary knowledge of the portfolio similarity correlation among financial institutions and its changes by analyzing the portfolio similarity correlation network of financial institutions in China. Nevertheless, the risk propagation information reflected in the network is limited. As a result, we have examined the systemic importance and systemic vulnerability of financial institutions on this basis in order to better capture the systemic risk of financial institutions under this portfolio similarity connection.

4.2 Systemic risk based on portfolio similarity correlation network

Table 4 depicts the trend of the systemic risk for each year of the sample period at a shock of 0.037. As shown, the systemic risk of China's financial system increases and then decreases from 2017 to 2021, with a significant increase from 2017 to 2018, confirming the impact of the 2018 "stock market crash" on China's financial system to some extent. And from 2019 to 2021, the systemic risk has been at a low level, with a small fluctuation. This indicates that our financial system as a whole is in a more stable state as a result of the implementation of various policies in recent years to avoid systemic risk in China.

To ensure the accuracy of the results, we set out to investigate whether propensity parameters for financial institutions to follow the threshold model (q) and market response parameters for asset liquidation (μ) have an impact on systemic risk. Figures 3 and 4 present the data and trends related to systemic risk under different values of parameters q and μ. As seen in these figures, the trend of systemic risk in China remains unchanged in 2017-2021 regardless of how the parameters q and μ change. And, both figures indicate a higher level of systemic risk in 2018. These findings strengthen our confidence in the robustness of the results. Specifically, we note that as the value of parameter q increases, the level of systemic risk decreases. Conversely, as the value of parameter μ rises, the level of systemic risk also rises; yet, it's worth mentioning that even under these conditions, the overall change remains quite small.

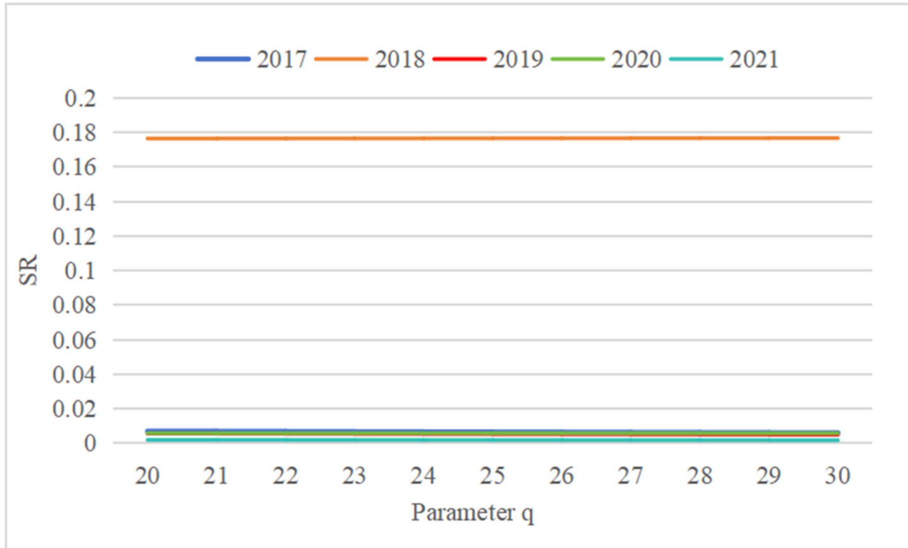


Figure 3 Systemic risk under changes in parameter q

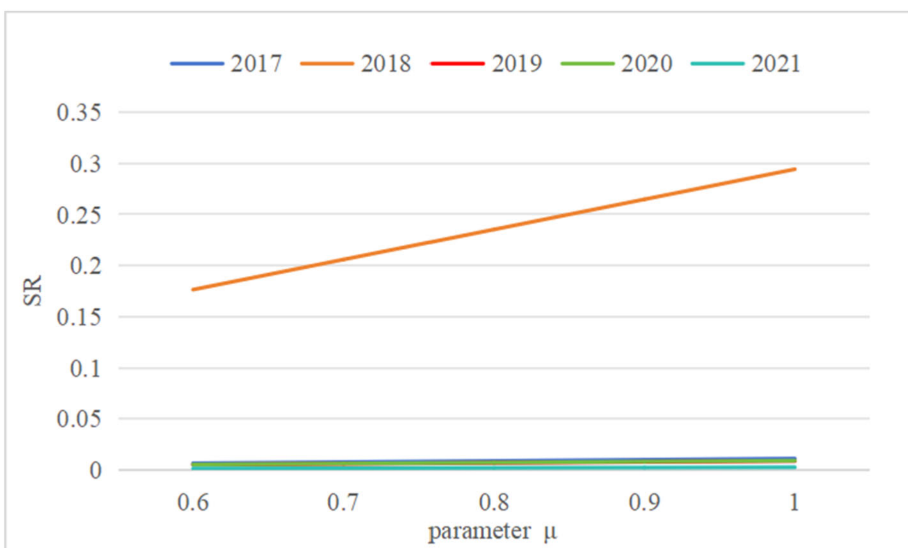


Figure 4 Systemic risk under changes in parameter μ

4.3 Cross-sectional characteristics of systemic importance and systemic vulnerability of financial institutions

Table 5 shows the cross-sectional characteristics of the systemic importance of 56 financial institutions in China. And the names of financial institutions in Table 5 are represented by their English abbreviations, and the specific correspondence is shown in the Appendix. The systemic importance ranking is based on the mean value of *SIFI* for each financial institution from 2017 to 2021, while the portfolio similarity ranking is based on the mean value of the size of portfolio similarity between each financial institution and other finan-

Table 5 Cross-sectional characteristics of the systemic importance of 56 financial institutions

Financial institution	Systemic importance ranking	Portfolio similarity ranking	Mean	St. dev	Min	Max
ICBC	1	3	0.16716	0.01286	0.15228	0.18328
CCB	2	4	0.14457	0.00883	0.13600	0.15663
ABC	3	7	0.14013	0.01078	0.12454	0.15738
BC	4	5	0.12399	0.01106	0.11380	0.14270
BCC	5	6	0.05222	0.00580	0.04324	0.06079
CMB	6	9	0.03649	0.00339	0.03017	0.03925
CMBC	7	1	0.03632	0.00394	0.03210	0.04202
SPDB	8	20	0.03462	0.00392	0.03005	0.03985
CNCB	9	22	0.03372	0.00436	0.02800	0.03899
IBC	10	12	0.03177	0.00521	0.02384	0.03860
CEB	11	2	0.02804	0.00238	0.02486	0.03132
PAB	12	24	0.01790	0.00265	0.01483	0.02138
HXB	13	23	0.01514	0.00221	0.01231	0.01840
BJBC	14	21	0.01264	0.00224	0.00969	0.01620
BOSC	15	16	0.01129	0.00257	0.00856	0.01566
JSB	16	18	0.01009	0.00162	0.00786	0.01174
NBB	17	10	0.00660	0.00181	0.00406	0.00881
NJBK	18	14	0.00619	0.00126	0.00414	0.00750
HZB	19	11	0.00541	0.00150	0.00346	0.00766
GYB	20	8	0.00229	0.00052	0.00168	0.00312
CSB	21	19	0.00093	0.00012	0.00075	0.00107
WRCB	22	17	0.00086	0.00015	0.00068	0.00103
JRCB	23	15	0.00072	0.00016	0.00056	0.00100
SUCB	24	13	0.00061	0.00010	0.00050	0.00072
Subtotal	–	–	0.03882	0.00359	0.00050	0.18328
GFS	1	13	0.00130	0.00067	0.00071	0.00260
CITICS	2	12	0.00110	0.00056	0.00031	0.00198
HTS	3	25	0.00100	0.00058	0.00019	0.00157
GTJA	4	6	0.00084	0.00028	0.00046	0.00120
DFZQ	5	26	0.00076	0.00048	0.00050	0.00171
HTSC	6	22	0.00074	0.00036	0.00029	0.00127
SHS	7	2	0.00072	0.00033	0.00040	0.00128
CGS	8	9	0.00071	0.00028	0.00023	0.00100
CMS	9	3	0.00067	0.00026	0.00036	0.00102
EBSCN	10	11	0.00048	0.00032	0.00017	0.00104
GSS	11	5	0.00041	0.00018	0.00015	0.00067
FS	12	14	0.00038	0.00017	0.00018	0.00068
IS	13	4	0.00034	0.00016	0.00017	0.00062
GYS	14	18	0.00033	0.00019	0.00015	0.00069
DXS	15	16	0.00032	0.00020	0.00016	0.00070
CJS	16	10	0.00024	0.00011	0.00005	0.00034
SS	17	27	0.00019	0.00006	0.00012	0.00027
SCS	18	8	0.00016	0.00011	0.00005	0.00036
SWSC	19	7	0.00013	0.00006	0.00008	0.00024
NS	20	23	0.00013	0.00014	0.00001	0.00039
HAS	21	1	0.00008	0.00002	0.00005	0.00010
SLS	22	20	0.00008	0.00005	0.00001	0.00013
CCSC	23	21	0.00006	0.00003	0.00002	0.00010
WS	24	17	0.00005	0.00004	0.00001	0.00011
FCSC	25	24	0.00005	0.00004	0.00001	0.00011
SXS	26	15	0.00005	0.00003	0.00001	0.00009
PBG	27	28	0.00005	0.00003	0.00002	0.00011
PS	28	19	0.00004	0.00004	0.00001	0.00012
Subtotal	–	–	0.00041	0.00018	0.00001	0.00260
PAIC	1	2	0.03528	0.00526	0.02828	0.04022
PLICC	2	3	0.02020	0.00576	0.01239	0.02712
CPIC	3	1	0.00803	0.00176	0.00651	0.01123
NCI	4	4	0.00535	0.00204	0.00335	0.00898
Subtotal	–	–	0.01722	0.00182	0.00335	0.04022
Total	–	–	0.01786	0.00298	0.00001	0.18328

cial institutions from 2017 to 2021 before the shock. Both are ranked by different types of financial institutions.

From the perspective of different types of financial institutions, the mean values of *SIFI* for banks, securities firms, and insurance companies are 0.03882, 0.00041, and 0.01722, respectively, as shown in Table 5. That means banks have the highest systemic importance, followed by insurance companies and securities firms. Hence, banks and insurance companies should be a top concern for financial regulators because they contribute more to the systemic risk resulting from portfolio similarity correlations than securities firms.

Next, from the perspective of a single type of financial institution, firstly, the mean of *SIFI* for China's five largest state-owned banks is high, reflecting their high systemic importance, greater contribution to the risk of the financial systems, and the fact that they are a top concern for financial regulators. Second, urban commercial banks are ranked low overall, with joint-stock commercial banks like Hua Xia Bank being ranked medium in terms of systemic importance. However, some banks, like China Everbright Bank and Bank of Beijing, also have relatively high mean values of *SIFI*, so their potential risk contribution to the financial system cannot be ignored. For securities firms, the mean values of *SIFI* are significantly lower than those of banks and insurance companies. Even the mean values of *SIFI* for the top two securities firms, GF Securities and CITIC Securities, are at the low end of the range for banks and insurance companies. As a result, the risk contribution of securities firms to the systemic risk resulting from portfolio similarity correlation is lower, which is related to the smaller range of assets held by securities firms themselves and the lower total assets. Finally, Ping An of China has the highest mean values of *SIFI* among insurance companies as well as the highest mean among banks and a large portfolio similarity size. This reflects Ping An of China's importance in the overall financial system and is inextricably linked to its strong overall strength and the adoption of a business model that spans multiple businesses across multiple financial sectors.

In addition, we calculated the Spearman correlation coefficient between the value of systemic importance and the value of portfolio similarity for the 56 financial institutions to determine whether the size of portfolio similarity between a financial institution and other financial institutions impacts the systemic importance of that institution. The correlation coefficient came out to be 0.4785, which is significant at the 0.001 level. This indicates that the correlation of financial institutions based on portfolio similarity is one of the factors that triggers systemic risk in the financial system. Additionally, the systemic importance of a financial institution is strongly and positively associated with the magnitude of portfolio similarity between that institution and other financial institutions.

Table 6 shows the cross-sectional characteristics of systemic vulnerability for 56 financial institutions in China. Similarly, the names of financial institutions in Table 6 are represented by their English abbreviations, and the specific correspondence is shown in the Appendix. The systemic vulnerability ranking is based on the mean value of each financial institution from 2017 to 2021 according to the different types of financial institutions, and the portfolio similarity ranking is also based on the mean value of the size of portfolio similarity between each financial institution and other financial institutions from 2017 to 2021 before the shock.

As shown in Table 6, the mean values of *SVFI* for banks, securities firms, and insurance companies are 0.03837, 0.00480, and 0.02703, respectively, which exhibit the same characteristics as systemic importance. Therefore, securities firms have lower systemic

Table 6 Cross-sectional characteristics of systemic vulnerability of 56 financial institutions

Financial institution	Systemic importance ranking	Portfolio similarity ranking	Mean	St. dev	Min	Max
CMBC	1	1	0.05613	0.10032	0.00206	0.25673
ABC	2	7	0.05425	0.09661	0.00212	0.24743
CEB	3	2	0.05394	0.09606	0.00204	0.24601
BC	4	5	0.04771	0.08505	0.00183	0.21777
CCB	5	4	0.04576	0.08068	0.00200	0.20708
ICBC	6	3	0.04530	0.08027	0.00182	0.20580
PAB	7	24	0.03863	0.06751	0.00197	0.17362
JSB	8	18	0.03815	0.06412	0.00214	0.16629
HZB	9	11	0.03783	0.06078	0.00266	0.15917
WRCB	10	17	0.03777	0.06297	0.00231	0.16360
SPDB	11	20	0.03744	0.06400	0.00197	0.16538
SUCB	12	22	0.03712	0.06282	0.00211	0.16269
BCC	13	6	0.03683	0.06232	0.00201	0.16142
HXB	14	23	0.03396	0.05716	0.00212	0.14822
BOSC	15	16	0.03329	0.05514	0.00215	0.14345
CMB	16	9	0.03325	0.05646	0.00170	0.14612
CSB	17	19	0.03310	0.05613	0.00189	0.14528
NJBK	18	14	0.03257	0.05298	0.00230	0.13843
JRCB	19	15	0.03235	0.05336	0.00211	0.13895
NBB	20	10	0.03164	0.05011	0.00221	0.13156
GYB	21	8	0.03146	0.05254	0.00216	0.13643
SUCB	22	13	0.03130	0.05291	0.00204	0.13705
IBC	23	12	0.03064	0.05112	0.00196	0.13282
BJBC	24	21	0.03049	0.05053	0.00174	0.13147
Subtotal	–	–	0.03837	0.01534	0.00170	0.25673
SS	1	27	0.00848	0.01483	0.00023	0.03811
DXS	2	16	0.00767	0.01255	0.00033	0.03268
GFS	3	13	0.00725	0.01203	0.00033	0.03125
HTS	4	25	0.00661	0.01214	0.00009	0.03089
GYS	5	18	0.00648	0.01088	0.00035	0.02819
DFZQ	6	26	0.00612	0.00974	0.00032	0.02552
IS	7	4	0.00608	0.01061	0.00017	0.02727
EBSCN	8	11	0.00599	0.01031	0.00011	0.02657
FS	9	14	0.00578	0.01000	0.00035	0.02576
SHS	10	2	0.00566	0.00949	0.00014	0.02460
NS	11	23	0.00551	0.00962	0.00002	0.02469
CGS	12	9	0.00539	0.00915	0.00029	0.02367
CMS	13	3	0.00509	0.00889	0.00013	0.02286
GSS	14	5	0.00497	0.00884	0.00011	0.02263
CJS	15	10	0.00456	0.00772	0.00016	0.01999
SCS	16	8	0.00431	0.00736	0.00006	0.01899
SWSC	17	7	0.00412	0.00713	0.00012	0.01837
SXS	18	15	0.00379	0.00711	0.00002	0.01801
CCSC	19	21	0.00377	0.00674	0.00004	0.01723
HTSC	20	22	0.00375	0.00627	0.00012	0.0162
CITICS	21	12	0.00367	0.0061	0.00015	0.01601
HAS	22	1	0.00360	0.00626	0.00019	0.01611
GTJA	23	6	0.00356	0.00607	0.00016	0.01569
FCSC	24	24	0.00338	0.00593	0.00003	0.01522
SLS	25	20	0.00291	0.00515	0.00005	0.01319
PS	26	19	0.00258	0.00447	0.00004	0.01149
WS	27	17	0.00207	0.00367	0.00002	0.00940
PBG	28	28	0.00140	0.00226	0.00007	0.00591
Subtotal	–	–	0.00480	0.00285	0.00002	0.03811
NCI	1	4	0.03286	0.05369	0.00201	0.13998
CPIC	2	1	0.02670	0.04572	0.00140	0.11805
PAIC	3	2	0.02481	0.04208	0.00138	0.10891
PLICC	4	3	0.02373	0.03863	0.00209	0.10090
Subtotal	–	–	0.02703	0.00560	0.00138	0.13998
Total	–	–	0.02078	0.02950	0.00002	0.25673

vulnerability and relatively lower risk exposure compared to banks and insurance companies.

From the perspective of a single type of financial institution, the mean values of *SVFI* for China's four largest banks are high, indicating that negative shocks to the financial system will be transmitted more to these four banks. Furthermore, Minsheng Bank and China Everbright Bank ranked highly in terms of systemic vulnerability, even higher than large banks like Bank of China and Industrial and Commercial Bank of China, which could be attributed to their strong portfolio similarity. As a result, in the event of a crisis, Minsheng Bank and China Everbright Bank would face a greater risk of spillover. At the same time, we observe that the mean values of *SVFI* for national joint-stock commercial banks like Hua Xia Bank and city commercial banks like Bank of Shanghai are not significantly different but are higher than those of insurance companies like China Pacific Insurance. This implies that national joint-stock commercial banks and city commercial banks are exposed to similar spillovers but still have significant risk exposures in the event of a crisis. In addition, with the overall risk of China's securities firms having increased in recent years, the regulator should pay attention to securities firms with relatively high values of *SVFI* in this area to achieve the goal of preventing and mitigating systemic risk, even though the overall systemic vulnerability ranking of securities firms is low. For insurance companies, Xinhua Insurance has a high level of systemic vulnerability but a low level of systemic importance. This indicates that Xinhua Insurance has a smaller contribution to the overall financial systemic risk than other insurance companies, but is subject to more risk spillover and is likely to trigger extreme situations such as insolvency when shocks are too large.

Similarly, we calculated the Spearman correlation coefficient between the value of systemic vulnerability and the value of portfolio similarity for the 56 financial institutions. Similar to the findings regarding systemic importance, the correlation coefficient turned out to be 0.6585, which is highly significant at the 0.001 level. This indicates that the systemic vulnerability of a financial institution is strongly and positively associated with the magnitude of portfolio similarity between that institution and other financial institutions.

In conclusion, the analysis of the cross-sectional characteristics of systemic importance and systemic vulnerability of financial institutions under the portfolio similarity correlation network can help regulators target individual regulators from three aspects. First, regulators should concentrate their efforts on financial institutions with high systemic importance and vulnerability, such as China's large four banks, which are inherently more stable. Particularly Minsheng Bank, as it has a high *SIFI* and *SVFI* value; even though its systemic vulnerability is higher than that of the Four banks, its ability to resist risk is much lower. In the event of a shock, such financial institutions will increase the likelihood of risk contagion and financial system instability. Second, regulators should be concerned about the financial institutions with a mismatch between systemic importance and systemic vulnerability. One is that financial institutions like Xinhua Insurance, which have significant systemic vulnerability but low systemic importance, should work to increase their ability to resist risks. The other is a financial institution like the Bank of Communications, with great systemic importance but low systemic vulnerability. Losses in this category of financial institutions are more likely to cause risk spillovers to the financial system, and the key to its regulation lies in reducing its level of risk spillovers. Finally, it's worth focusing on the financial institutions with low systemic importance and vulnerability. They cannot significantly affect the stability of the financial system in the short term, but it is crucial to prevent them from endangering it by engaging in risky investment practices themselves.

4.4 Time-series characteristics of systemic importance and systemic vulnerability of financial institutions

Through the analysis of cross-sectional characteristics in Sect. 4.3, we understand the status of systemic importance and systemic vulnerability of individual financial institutions at the time point. Furthermore, to help regulators understand the trend of risk changes in the financial system over a certain period, so that they can formulate more scientific and reasonable initiatives to prevent and warn financial risks, the time-series characteristics of systemic importance and systemic vulnerability of different financial institutions from 2017 to 2021 will be explored next.

Tables 7 and 8 show the results. Overall, the relative systemic importance and systemic vulnerability of different types of financial institutions did not remain constant over the sample period, and the mean values of *SIFI* and *SVFI* for banks and insurance companies are consistently higher than for securities firms. Moreover, during the 2018 stock market crash period, the risk spillover from banks and insurance companies to the overall financial system was significantly higher than that of the securities firms, and the risk spillover from the financial system to banks and insurance companies was also significantly higher than that of the securities firms. This is consistent with the findings of Caccioli et al. [44]. Consequently, banks are predominantly the most systemically important institutions in different financial systems.

On the other hand, we observe from Table 7 that the mean values of *SIFI* for banks and securities firms did not change significantly over the sample period and remained largely stable, indicating that the systemic importance of banks and securities firms was relatively stable over the sample period, while insurance companies experienced a small amount of volatility. However, as shown in Table 8, the time-series characteristics of financial institutions' systemic vulnerability exhibit very different characteristics of change from systemic importance. From 2017 to 2018, the systemic vulnerability of banks, insurance companies, and securities firms increased substantially, with banks showing the largest change, while from 2018 to 2019, the systemic vulnerability of banks, securities firms, and insurance companies showed a clear downward trend, and from 2019 to 2021, they exhibited a lower level of systemic vulnerability with minimal change. This indicates that as China

Table 7 Time-series characteristics of systemic importance of different financial institutions from 2017 to 2021

	2017	2018	2019	2020	2021
Bank	0.03727	0.03908	0.03846	0.03885	0.03795
Securities firm	0.00073	0.00039	0.00018	0.00045	0.00028
Insurance company	0.02126	0.01276	0.01799	0.01376	0.02030

Table 8 Time-series characteristics of systemic vulnerability of different financial institutions from 2017 to 2021

	2017	2018	2019	2020	2021
Bank	0.00852	0.16928	0.00628	0.00572	0.00206
Securities firm	0.00146	0.02131	0.00035	0.00075	0.00016
Insurance company	0.00850	0.11696	0.00451	0.00344	0.00172

has strengthened its prevention and safeguards against financial systemic risks in recent years, financial institutions have become exposed to lower levels of risk spillovers and the financial system has become relatively more stable.

It is also worth noting that the variation tendency in systemic risk under the portfolio similarity correlation channel is similar to the variation tendency in the time-series characteristics of systemic vulnerability. This reflects the fact that systemic risk measured in terms of contagion loss is overwhelmingly a reflection of the vulnerability of financial institutions. As a result, analyzing the systemic importance and systemic vulnerability of financial institutions separately provides a more comprehensive understanding of the evolution of systemic risk.

5 Conclusions

In this study, we first constructed the portfolio similarity correlation network model and improved the fire sales contagion model to describe the risk contagion mechanism under the portfolio similarity correlation channel. And then we defined risk indicators such as systemic risk, systemically important financial institutions, and systemically vulnerable financial institutions to measure the changes in systemic risk and the systemic importance and vulnerability of financial institutions under the portfolio similarity correlation channel. Finally, we used the balance sheet data of 56 financial institutions from 2017 to 2021 for the empirical study. In the empirical study, we built the portfolio similarity correlation networks of 56 Chinese financial institutions, revealing portfolio similarity correlation and risk propagation among financial institutions. Meanwhile, we also analyzed the cross-sectional and time-series characteristics of the systemic importance and systemic vulnerability of China's financial institutions and explored the relationship between the size of portfolio similarity between financial institutions and other financial institutions and their systemic importance and systemic vulnerability.

In general, this paper draws some useful conclusions. First, we found that the density of the portfolio similarity correlation network among 56 financial institutions in China is high, i.e., there is a strong portfolio similarity association among the 56 financial institutions in the sample period. Among them, banks and insurance companies show a high level of portfolio similarity to each other, while banks and securities firms show a low level of portfolio similarity to each other, and this variability changes over time. Meanwhile, the analysis of the cross-sectional and time-series characteristics of financial institutions' systemic importance and systemic vulnerability reveals that banks and insurance companies have higher systemic importance and securities firms have lower systemic importance during the sample period, as does financial institutions' systemic vulnerability. Especially, the systemic importance and systemic vulnerability of a particular financial institution are strongly and positively associated with the magnitude of portfolio similarity between that institution and others. Also, we found that the systemic risk indicator set from the contagion loss is overwhelmingly a reflection of the vulnerability of financial institutions. Therefore, it is necessary to analyze systemic risk in terms of both systemic importance and systemic vulnerability. In addition, a thorough analysis of the cross-sectional and time-series characteristics of these two aspects will assist government regulators in developing more scientific and rational regulatory policies. In addition, it would be interesting to expand the study to a wider time period, and to a wider range of financial institutions, and we will be working on this in future studies.

Appendix

Table 9 Financial institution and their English abbreviation

Financial institution	English abbreviation	Financial institution	English abbreviation
Ping An Bank	PAB	GF Securities	GFS
Bank of Ningbo	NBB	Changjiang Securities	CJS
Bank of Jiangyin	JRCB	Shanxi Securities	SXS
Shanghai Pudong Development Bank	SPDB	Western Securities	WS
Hua Xia Bank	HXB	Guosen Securities	GSS
Minsheng Bank	CMBC	First Capital Securities	FCSC
China Merchants Bank	CMB	CITIC Securities	CITICS
Bank of Wuxi	WRCB	Sinolink Securities	SLS
Bank of Jiangsu	JSB	Polaris Bay Group	PBG
Bank of Hangzhou	HZB	Southwest Securities	SWSC
Bank of Nanjing	NJBK	Haitong Securities	HTS
Bank of Changshu	CSB	Huaan Securities	HAS
Industrial Bank	IBC	Oriental Securities	DFZQ
Bank of Beijing	BJBC	China Merchants Securities	CMS
Bank of Shanghai	BOSC	Pacific Securities	PS
Agricultural Bank of China	ABC	Dongxing Securities	DXS
Bank of Communications	BCC	Guotai Junan Securities	GTJA
Industrial and Commercial Bank of China	ICBC	Central Plain Securities	CCSC
China Everbright Bank	CEB	Industrial Securities	IS
China Construction Bank	CCB	Soochow Securities	SCS
Bank of China	BC	Huatai Securities	HTSC
Bank of Guiyang	GYB	Everbright Securities	EBSCN
China Citic Bank	CNCB	China Galaxy Securities	CGS
Sunong Bank	SUCB	Founder Securities	FS
Maccura Biotechnology	SHS	Ping An Insurance (Group) Company of China	PAIC
Northeast Securities	NS	New China insurance	NCI
Guoyuan Securities	GYS	China Pacific Insurance (Group) Company	CPIC
Guohai securities	SS	China Life Insurance (Group) Company	PLICC

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Abbreviations
Not applicable.

Data availability
As described in the paper, the data are available from the following public database https://data.csmar.com/.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author contributions
MS and HF designed the study. MS analyzed and interpreted the data. MS and HF performed the experiments, analyzed the empirical results, and wrote the paper. All authors read and approved the final manuscript.

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