Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 4507275, 9 pages
https://doi.org/10.1155/2022/4507275

Research Article

Risk Measurement of Local Government Debt Based on Complex Networks: Taking China's Urban Investment Bonds as an Example

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Received 11 April 2022; Revised 20 May 2022; Accepted 26 May 2022; Published 22 June 2022

Academic Editor: Kuruva Lakshmanna

For many countries, the systemic risk of local government debt is a matter of concern, but at present, there is little analysis in this area. The complex network based on information analysis provides an effective tool for analyzing the system risk between networks. This paper takes China as an example and takes the provincial urban investment bonds as the object for research. The regional network constructed with the interest rate data of urban investment bonds represents the overall systemic risk of these bonds. The main conclusions are as follows: provincial nodes in western and central areas (underdeveloped areas) are more important in the system, and they are more easier to form debt defaults. For an interconnected urban investment bond network, the higher the default risk of an individual, the greater the risk of the entire system. Finally, based on the indicators obtained from the provincial urban investment bond network model, this paper puts forward policy suggestions for the prevention of urban investment bond risks.

1. Introduction

Urban investment bonds are one of the important means of local government financing. In 2020, the issuance scale of urban investment bonds in China has reached 4.3 trillion yuan, and the existing urban investment bonds have reached 11.08 trillion yuan, with a total of 13,600 existing bonds. As "quasi-municipal bonds," urban investment bond financing can avoid government supervision and allow local finance to take on greater responsibility for public utility development with less financial resources.

However, while local governments undertake the responsibility for infrastructure construction with "hidden debts," they are also burdened with huge debts. According to data from China's Ministry of Finance, in 2020, the national debt balance of local governments was 25.7 trillion yuan, an increase of 20.7% compared with 21.3 trillion yuan at the end of December 2019. Among them, in the balance of local government debt, government bonds accounted for the highest proportion, accounting for more than 99%. Meanwhile, government bonds account for more than a quarter of China's GDP in 2020. These facts show that the financial pressure of Chinese local governments is accumulating further. On November 10, 2020, "20 Yongmei SCP003" issued by Yongcheng Coal and Electricity Holding Group Co., Ltd. in China was declared unable to repay the principal and interest in full on the due date due to the broken capital chain and a serious lack of liquidity. This company was finally judged to be in default with an amount of up to 1.032 billion yuan. The credit ratings in Chinese firms which are issued by the domestic rating agencies are found to be much higher than the ratings which are issued by the global rating agencies. The distribution is normally centered at higher levels in case of domestic ratings. The median and average of the domestic ratings are comparatively higher than the global ratings in terms of seven notches, namely, AA, Aa2 vs. BBB or Baa3. These ratings typically act as a function of depicting the view of the agency to adopt rating symbols. It thus helps to compare and rank the various risks by domestic and global agencies. The domestic ratings given to the firms by domestic as well as global agencies are categorized as AA, AA+, and AAA. Marked by the default of AAA-rated state-owned enterprises, interest rates on bonds issued by a series of high-credit-rated state-owned enterprises began to rise, and the market was highly nervous due to unstable investor sentiment.

The issuance scale of urban investment bonds is a measure of the level of local government debt, and the linkage effect between the spreads of urban investment bonds in various regions can reflect the spread of risks between regions. Therefore, this paper will take the provinces of China as examples to study. Based on the level of urban investment bond spread between provinces as the basic data, a risk network model of provincial urban investment bonds is constructed to reflect the risk level of local government debt [1].

The main contribution of this paper is to apply the complex network theory to the research of local government investment and financing platforms and to further enrich the research on the risk contagion of local government investment and financing platforms by establishing a cross-regional network. This paper will also use various network analysis methods and network metrics to analyze the systemically important nodes in the network and locate their corresponding local government investment and financing platforms. Finally, according to the risk contagion path, this paper proposes corresponding measures to prevent the risk of debt default.

The organization of the paper is as follows: Section 2 presents a detailed review of literature relevant to existing work done on urban investment bond and systemic risks. Section 3 provides detailed description of the data source. Section 4 presents the proposed urban investment bond network model, and its related empirical analysis is presented in Section 5. Section 6 presents the implementation results relevant to main features and economic significance of the provincial urban investment bond network. Finally Section 7 consolidates the work done in the form of Conclusion.

2. Related Literature

2.1. Urban Investment Bonds and Systemic Risk. Urban investment bonds are off-balance sheet debts of local governments, that is, “hidden debts.” The ultimate debtor is the local government. Once a risk occurs, it will be transformed into a local government debt risk, which will then spill over to the higher-level and lower-level governments, making local debt a central government debt, which ultimately leads to systemic risks. Due to the interconnectedness of regional economies, there are risk linkages and “systemically important nodes” in the urban investment bond network [2, 3].

The concept of a systemically important node can be analogized to a systemically important organization. For a systemically important institution, its size is relatively large, and it is generally recognized as “too big to fail”; however, once a real default, it will have a huge impact on market confidence, thereby raising investors’ concerns about defaults by

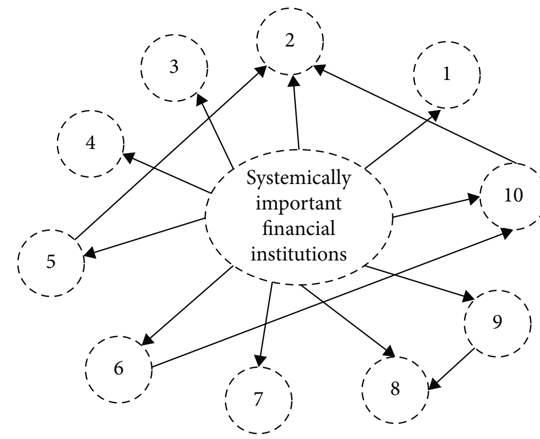

Figure 1: Complex financial network with systemically important institution.

other institutions in the market. In recent years, some scholars have put forward the argument that “the connection is too tight to fail” [4]. “Too tight to fail” refers to the close linkage between systemically important institutions and other small and medium-sized institutions. Once a default occurs, it will have a shock to all related institutions in the market, resulting in the collapse of the entire market.

From a theoretical point of view, a systemically important institution is like a domino in a complex financial network. Once it collapses, it will cause the collapse of the system as a whole, resulting in serious negative externalities. In a stable and interconnected system, any slight change can have a chain reaction, and systemically important institutions are not only large and complex, but also interconnected, as shown in the example of Figure 1. Once a crisis occurs, it will cause more than normal losses to the system.

From the perspective of real cases, in the history of the 2008 international financial crisis, we can find that systemically important institutions play a major role in risk transmission. At that time, the subprime mortgage crisis caused the top investment banks in the United States to be in trouble. Among them, Stearns was acquired by JPMorgan Chase, Lehman Brothers went bankrupt, and American International Group (AIG) was bailed out by the Federal Reserve. The American International Group, which was bailed out by the Federal Reserve, is a large financial company with business coverage in more than 130 countries around the world and its main business in insurance. During the subprime loan crisis, AIG experienced a liquidity crisis when its subsidiary AIG Financial Products Corp defaulted on a large number of debt-backed securities in 2007 due to its large-scale purchase of CDOs and issuance of CDS. The vast majority of the world’s banks and insurance companies have direct or indirect relationships with AIG through equity or business affiliations. According to AIG’s 2008 annual report, it provides more than $400 billion in credit protection for banks and other customers around the world through CDS, and it is deeply involved in the foreign exchange market and interest rate market. Once AIG goes bankrupt, the world economy will be greatly affected [5].

In the urban investment bond risk network, the systemically important node is reflected in the fact that the institution occupies an important position in the entire risk network. The institution itself has higher risks, complex financing relationships, and is more closely related to other nodes in the network. Once a systemically important node defaults, it will cause market panic, lead to the flight of a large number of funds, and further increase the price of these bonds, resulting in an increase in regional interest rate spreads, increased risks, and a positive feedback. Such a conduction path will cause more than normal losses to the entire urban investment bond network. Therefore, in the urban investment bond risk network, enough attention should be paid to systemically important nodes. For the issuance of bonds in these regions, the regulatory authorities should carry out stricter supervision on the use of debt funds.

2.2. Complex Networks and Systemic Risk Measurement. There are many methods to measure systemic risk, including comprehensive index method, vector autoregression and its variants, and network model. Before the financial crisis in 2008, the mainstream systemic risk measurement method was the comprehensive index method, that is, to construct a comprehensive index system to judge the overall operation situation of the economy [6]. Typical comprehensive indicator systems include the following [7]: Financial Stress Indicators (FSIs) and Financial Soundness Indicators (FSIs). Financial Stress Indicator in an index that helps to measure the level of financial stress in an economy, region, or subregion. It basically encompasses four financial markets, namely, the banking sector, the foreign exchange market, the equity, and the debt market. The Financial Soundness Indicator (FSI) was developed by International Monetary Fund (IMF). This indicator was developed in association with the international community with the primary aim of conducting analysis and assessments of the strengths and vulnerabilities of financial systems, corporates, and other household counterparts. Some scholars use a network vector autoregressive model (NAR) to study the risk of local debt in China and its spillover effect [8] and found that there is a risk transmission effect from the urban investment bond network to the local bond network. In recent years, with the complexity of the financial structure, more and more scholars have begun to use complex networks to study systemic risk. For example, Billio et al. [9] used complex networks to study the correlation and systemic risk between the financial sector and the insurance sector and found that each financial sector showed asymmetric characteristics in the complex network, and the banking sector plays a more important role in the financial system. Yang [10] used the post-Lasso method to construct a risk spread network for urban investment bonds and found that platforms with higher short-term debt ratios have stronger risk contagion ability. Cao and Kong [11] used the TENET method to build a risk-related network with the theme of fintech, banking, and security institutions. This network integrates the PMFG maximum plane filter graph method, which can analyze the risk contagion relationship between fintech and traditional financial entities. They found that compared with banks and securities, fintech has the strongest internal and external risk contagion, and the financial crisis has strengthened the cross-sectoral nature of risk contagion. Yin [12] found that network relationship is an important core of modern risk measurement. Through network analysis, the liquidity effect of risk between nodes in the system can be better observed, thereby reducing the impact of the "dominoes" effect of financial institutions.

3. Data Source

This paper uses the data on the regional spread of urban investment bonds to construct the risk network of provincial urban investment bonds in 31 provinces in China (Hong Kong, Macau, and Taiwan are not included due to data acquisition reasons). Through the analysis of the correlation between provinces, a complex network model of risk contagion of provincial urban investment bonds is constructed. The main reason for using this data is that the data on the regional spread of urban investment bonds is a market-oriented data, and the complex network model formed by it also has market-oriented attributes. Compared with nonmarket-oriented data, market-oriented data can reflect information more accurately and quickly and timely reflect the daily changes of risk conditions in various regions.

In the research of urban investment bonds in the wind database, this paper extracts the data of AAA, AA+, and AA level regional interest rate spreads and uses them as the basic data to analyze the risk contagion network of urban investment bonds between cities. Among them, the regional interest spread data is obtained by calculating the difference between the interest rate of the existing bonds in the province and the interest rate of the CDB bonds in the region on that day (excluding the perpetual bonds and asset-backed securities) and weighted by the balance of the bonds. In this paper, the Shandong Province is considered as an example to illustrate the facts. On April 2, 2021, there were a total of 140 AAA-level urban investment bonds in Shandong Province. We obtained the ChinaBond valuation yield-to-maturity of these bonds through the bond prices and then calculated the interest rate difference between each bond and the CDB bonds of the corresponding maturity; finally, a weighted calculation is carried out with the bond balance as the weight to obtain the final regional interest rate spread in Shandong Province on that day.

4. Urban Investment Bond Network Model

Urban investment bonds represent the "hidden debt" of local governments, and local government debt risks are linked to the systemic risks of the entire economy [13]. Constructing an urban investment bond network model can better measure the risk level of this network and obtain important nodes in the urban investment bond network [14]. In the urban investment bond network model, provinces are used as nodes of the network model. This paper uses data from the wind database and obtains regional spreads. The Granger casualty test was performed which helps in determining if a time series acts as a factor in offering useful information for the forecasting of another time series, as an example, if the stock price of company A would help to predict the stock price of company B. Considering the same logic, the first-order lag Granger causality test was performed between the two provinces. If the obtained p value was less than 5%, it was considered that there was an association between the two nodes. There are three more important indexes in the network model: degree centrality coefficient, closeness centrality coefficient, and clustering coefficient.

Centrality analysis helps to quantify the node capacity in order to influence or be influenced by other nodes in the connecting network topology. The degree of centrality coefficient is the easiest measure of centrality which reflects the capability of the degree of a node in counting its relevant social connections. The degree centrality coefficient expresses the importance of the node in the network by the degree of the node. The higher the degree centrality coefficient, the more important the node is in the network; the lower the degree centrality coefficient, the less connection the node has with other nodes. For a network G with node g, the degree centrality of node i is the total number of direct connections between i and other $(g-1)$ nodes.

$$C_D(N_i) = \sum_{j=1}^{g} x_{ij}(i \neq j). \tag{1}$$

To eliminate the effect of network size, Wasserman and Faust [15] proposed a standardized measurement formula that divides the network size on the basis of the above formula:

$$C'_D(N_i) = \frac{C_D(N_i)}{g-1}. \tag{2}$$

Closeness centrality measures how close a node is to other nodes in the network. For a directed graph of node size g, the closeness centrality coefficient is calculated as the reciprocal of the distance from point i to another $(n-1)$ number of other reachable nodes.

$$C(i) = \frac{n-1}{\sum_{o=1}^{n-1} d(o,i)}, \tag{3}$$

where $d(o,i)$ represents the shortest path from node i to node o and n represents the number of nodes that node i can reach. For a directed graph, n refers to the in-degree of i. If a node's proximity coefficient is higher, then it is more important in the network.

The clustering coefficient is used to describe the clustering characteristics of a complex network, that is, the probability that two nodes adjacent to the third node are also adjacent. Girvan and Newman [16] pointed out that complex networks have the characteristics of clustering and explained that the clustering coefficient is generally between 0.1 and 0.5 in the real world.

In the process of calculating the average clustering coefficient, this paper adopts the calculation method improved by Schank and Wagner [17].

$$C = \frac{1}{V'} \sum_{v \in V'} c(v), \tag{4}$$

where V is all nodes in the network, V' is a set of nodes with edges greater than 2, and $c(v)$ is the ratio between the number of triangles in the network and the number of combinations of three nodes in the network that cannot form a triangle and whose side length is 2.

5. Empirical Analysis

Billio et al. measured systemic risk and believed that the institutional network constructed using Granger causality test could better measure systemic risk. Therefore, this paper chooses Granger causality test as the basic method to construct the correlation between urban investment bonds. When building the intercity network relationship, the first step is to integrate the regional interest spread data of 29 provinces (Tibet and Qinghai provinces were excluded due to lack of data) through python; then, a stationarity test is performed on the data of each province. Taking Beijing as an example, this paper conducts an autocorrelation test on the regional interest spread data in Beijing. As can be seen from Figure 2, the autocorrelation coefficient decays rapidly below the p value, and the data can be considered stationary. The same test is performed on the data of the other 28 provinces, and the result is that they all pass the test.

Next, we use the first-order lag Granger causality test to determine whether there is a causal relationship between the regional interest rate differences between the two provinces and build a network with a 5% confidence level as the threshold. That is to say, if the p value of the Granger causality test for the regional spread between the two provinces is less than 5%, then an edge from province A to province B is added, where province A is the Granger cause of province B, and the edge of the weight is the bond balance of province A. As shown in Figure 3, the size of each point represents the number of edges of the node, that is, the node degree. For the AAA-level urban investment bond network, some provinces (such as Tianjin, Guangxi, and Jilin) have high node degrees, while other provinces (such as Gansu, Ningxia, and Xinjiang) have low node degrees.

For AA+-rated bonds, in the regional interest rate spreads network (Figure 4), Ningxia, Yunnan, and Tianjin provinces have higher node degrees, while Guangdong, Zhejiang, and Beijing provinces have lower node degrees. Compared with the directed graph of the regional spread of AAA-rated urban investment bonds, the network density constructed by the regional spread of AA+-rated urban investment bonds is higher and the risk is higher.

For AA-rated bonds, in the regional interest rate spreads network (Figure 5), provinces such as Tianjin, Hunan, and Henan have higher node degrees, while provinces such as Guizhou, Shanghai, and Jilin have lower node degrees. Compared with the directed graph of the regional interest rate spreads of AA+ urban investment bonds, the network

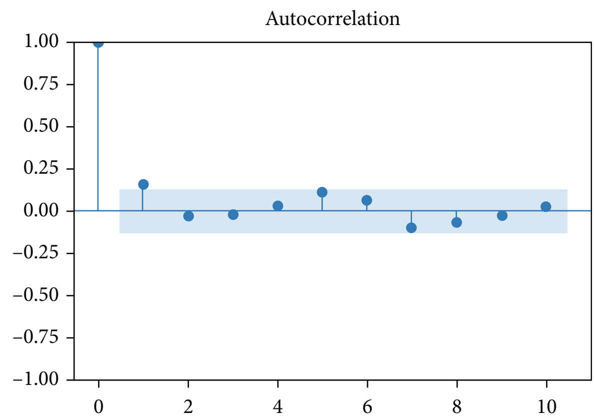

Figure 2: Autocorrelation test of regional interest rate spreads of urban investment bonds in Beijing.

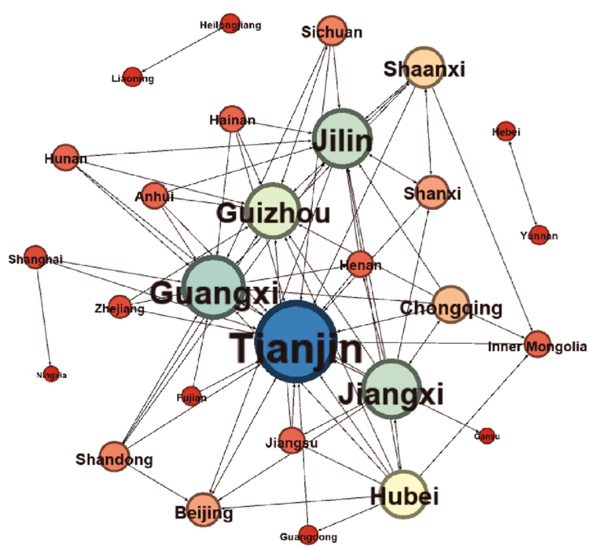

Figure 3: AAA-rated urban investment bond geographical spread network.

density constructed by the AA-rated urban investment bonds is higher, and the risk is also the highest among the three grades of bond spread networks.

Overall, in Figures 3–5, the riskier bonds form more complex networks. Since the complexity of the network represents the relationship of each node in the entire network, it also represents the degree of systemic risk from the perspective of "too tight to fail." Therefore, the AA-rated network has the highest overall risk, while the AAA-rated network has the lowest risk. In terms of node degree, the central and western provinces have higher node degrees, while the eastern coastal provinces with better economic development have lower node degrees.

6. Main Features and Economic Significance of Provincial Urban Investment Bond Network

6.1. Topological Characteristics of the Network. From the above analysis, this paper constructs a complex network with each province as the node, the regional interest spread

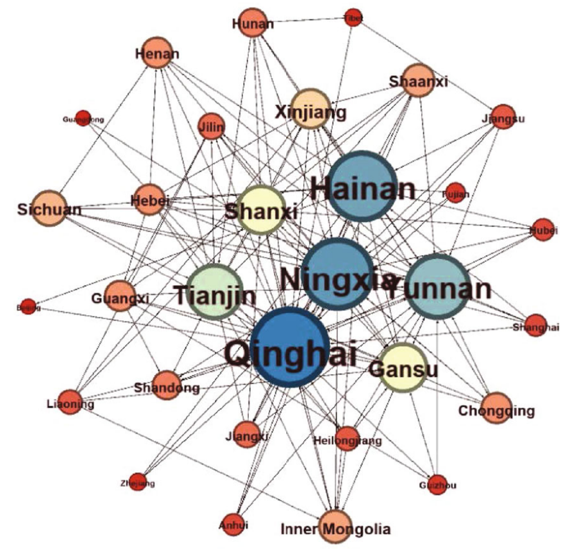

Figure 4: AA+-rated urban investment bond geographical spread network.

relationship between provinces as the edge, and the weight of each edge is the balance of bonds issued by each province. In these three complex networks, the descriptive indicators of their characteristics mainly include node degree, average path length, and clustering coefficient. The three indicators in the three networks are described below:

(1) Node degree and degree distribution of each node

Node degree mainly refers to the number of edges associated with the node, also known as the degree of association. For the network model constructed in this paper, the node degree is divided into in-degree and out-degree, where in-degree refers to the number of edges entering the node, and the out-degree is the opposite, referring to the number of edges starting from the node. The out-degree is the opposite, referring to the number of edges starting from the node. Node degree can intuitively describe the degree of importance of the node. The greater the degree of a node, the more other nodes associated with the node, so the more important the node is.

The average degrees of the three directed graphs are 5.82, 11.14, and 19.37, respectively. In the AAA-rated network, each node is connected to an average of 5.82 nodes; in the AA+-rated network, each node is connected to an average of 11.14 nodes; in the AA-rated network, each node is connected to an average of 19.37 nodes. We can get that the average degree of the network composed of AAA-rated bonds is the lowest, and the network composed of AA-rated bonds is the highest; that is to say, the connections between nodes in the network composed of high-grade bonds are more few.

Judging from the distribution of node degrees in each province (Figure 6), among the three types of networks, the node degrees in the central and western regions are higher than those in the eastern regions, which indicates that in the bond market, bonds issued in the central and western

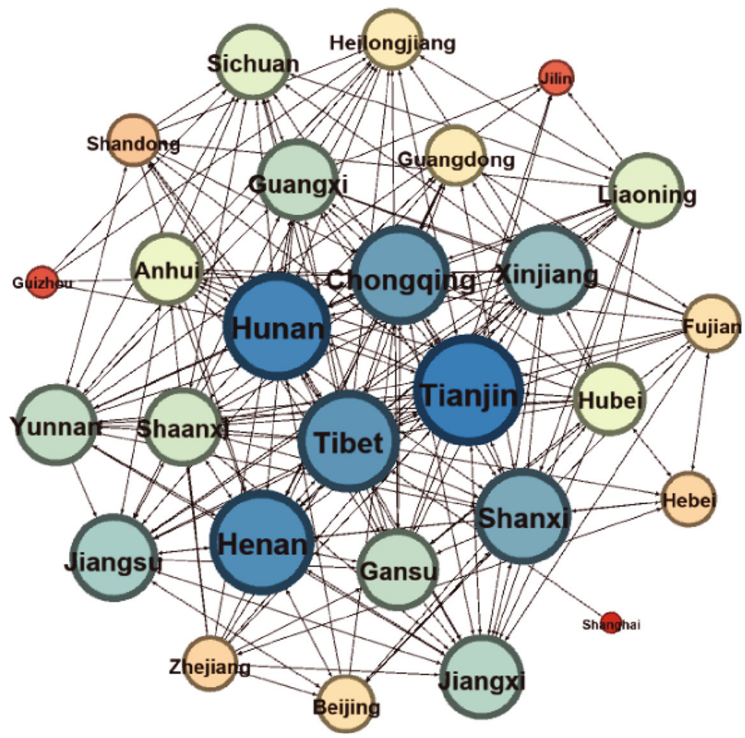

Figure 5: AA-rated urban investment bond geographical spread network.

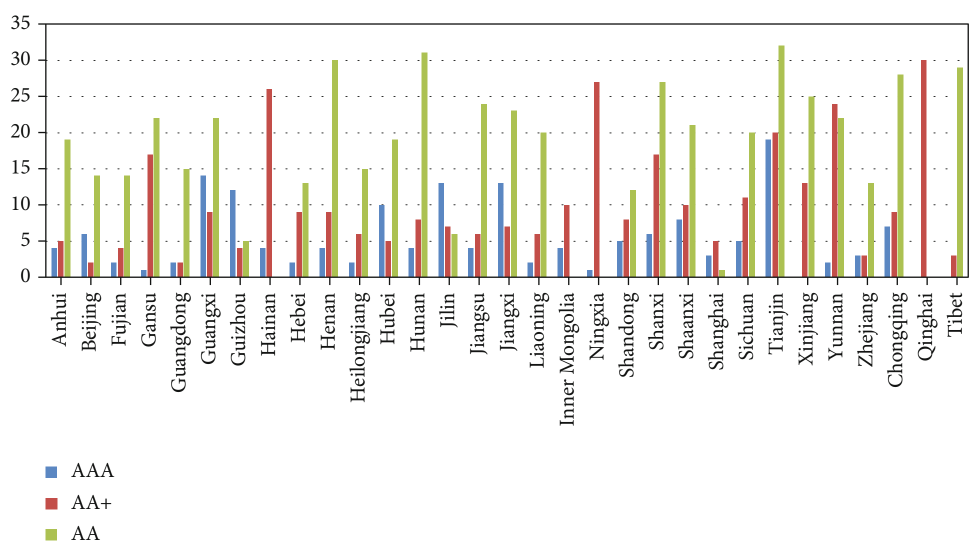

Figure 6: AA-rated urban investment bond network.

regions are higher and the overall risk impact on the market is greater. From a practical point of view, among the credit debt defaults of state-owned enterprises, Liaoning, Hainan, and Tianjin provinces have a larger number of defaulted bonds and a larger balance of defaulted bonds. Therefore, the empirical results are basically consistent with reality.

(2) Degree centrality coefficient and proximity centrality coefficient

Through the calculation of the degree centrality coefficient of the nodes (Figure 7), the coefficient of the AA-rated network in most provinces is higher, while the coefficient of the AAA-rated network is lower. The overall trend of the node degree centrality coefficient in the urban investment bond network of different levels is the same. And the node degree centrality of western and central provinces is higher, indicating that these provinces are more important in the network.

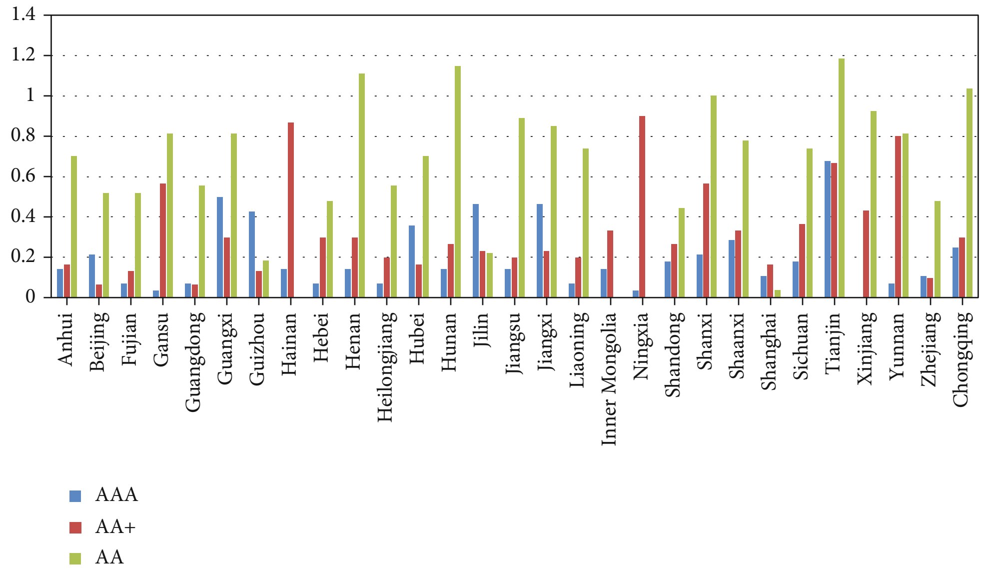

Figure 7: Degree centrality coefficient of AAA, AA+, and AA-rated network nodes.

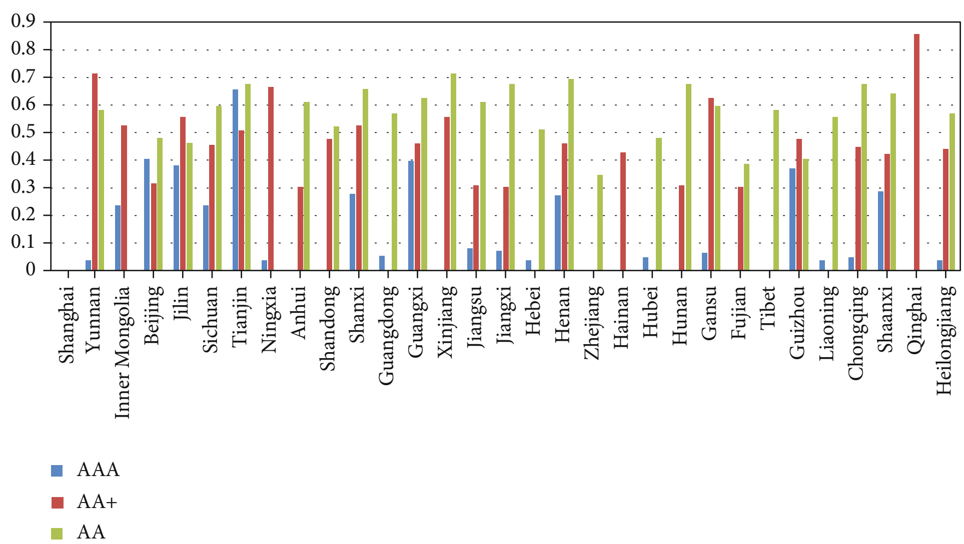

Figure 8: Proximity centrality coefficient of AAA, AA+, and AA-rated network nodes.

The proximity central coefficient is also a measure of centrality which calculates the shortest path between a node and other nodes in a graph. The more centralized a node is, it is closer to the other nodes. The proximity centrality coefficients in the network diagram of urban investment bonds with different ratings also show the same trend (Figure 8). As can be seen from Figure 8, Yunnan, Henan, and Tianjin provinces have higher coefficients, indicating that these nodes are more important in the network.

(3) Clustering coefficient

In the specific calculation of the clustering coefficient, since the degree of nodes in Xinjiang and Inner Mongolia is zero, these two nodes are deleted when the clustering coefficient is calculated. After removing the nodes with zero node degree, this paper calculates the clustering coefficients of AAA, AA+, and AA-rated regional spread networks, which are 0.1211, 0.3062, and 0.3516, respectively.

We can find that the clustering coefficient of the AA-rated network is the largest, indicating that the network is more inclined to group characteristics and the hierarchical structure is more ambiguous; the clustering coefficient of the AAA-rated network is the smallest, indicating that the network is less inclined to group characteristics, and the connections of each node are not so close.

6.2. Economic Significance. The regional network constructed with the interest rate data of urban investment bonds represents the overall systemic risk of these bonds. Intuitively, it is observed that the denser the network, the higher the systemic risk of the entire system. From the results, the overall risk level of the AA-rated network is the highest, and the overall risk level of the AAA-rated network is the lowest. From the indicators, the clustering center coefficient of each network also shows that the AA-rated network has the highest clustering coefficient and the AAA-rated network has the lowest clustering coefficient; that is to say, the network formed by high-risk bonds has more group characteristics, while the group characteristics of the network of low-risk bonds are less obvious. It can be considered that in the network of high-risk bonds, once a province defaults, other similar provinces also have a high probability of default.

From the perspective of each node, the node degree centrality coefficient and the proximity centrality coefficient both indicate that the parameter value of each node in the high-risk network is higher, while the parameter value of each node in the low-risk network is lower. From the perspective of systemically important nodes, although the importance nodes in different rated networks are not the same, compared with the eastern coastal areas, the central and western provinces have higher node degree centrality coefficient and proximity centrality coefficient index values.

In general, provinces in the central and western regions are more important in the system. In reality, the provinces in the central and western regions have low local fiscal revenue, and when there is a problem with the urban investment and financing platform, it is more likely to cause debt default. Therefore, the market assigns higher risk premiums to bonds issued by financing platforms in these provinces. In addition, the clustering effect of the network formed by high-risk grade bonds is more obvious, and the default of a financing platform is more likely to lead to the default of urban investment platforms at the same level. For an interconnected urban investment bond network, the higher the default risks of an individual, the greater the risk of the entire system.

7. Conclusion

Taking the local financing platform as the research starting point, this paper attempts to reflect the systemic risk of debt among provinces by studying the risk contagion of local government bonds and determines the important nodes in the system through some network characteristic indicators.

First, this paper constructs the risk network of these bonds by using the regional interest spread data of urban investment bonds in various provinces and studies the risks of the urban investment bond network from the perspectives of different bond types and different provinces. By comparing AAA, AA+, and AA-rated urban investment bonds, it is found that the intercity urban investment bond risk network constructed by AA-rated bonds has the highest density and the highest level of complexity. Since the complexity of the network represents the systemic risk level of the entire network, the risk of the entire system is correspondingly higher. The network clustering effect formed by high-risk grade bonds is more obvious, and the default of one urban investment financing platform is more likely to lead to the default of the same level of urban investment financing platform. In this regard, we can infer the following conclusions: for an interconnected city investment bond network, the higher the individual default risk, the greater the risk of the entire system.

Second, by analyzing the related network topological characteristic indicators of bonds with different ratings, this paper finds that the bond networks in the western and central provinces have relatively high node degrees, while those in the eastern coastal provinces with better economic development have relatively low node degrees. This shows that in the intercity urban investment bond risk network, the bonds issued by the western and central provinces have a greater impact on the overall risk of the market, and it is more likely to cause systemic risks when their urban investment and financing platforms have problems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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