Debt risk analysis of non-financial corporates using two-tier networks

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Abstract
Purpose – Non-financial corporate debt is one of the important sources of systematic risk in the real economy. Assessing a measure of systematic risk in corporation debt is currently a key challenge. In this regard, we propose a two-tier risk contagion networks model.
Design/methodology/approach – Assessing a measure of systematic risk in corporation debt is currently a key challenge. In this regard, we propose a two-tier risk contagion networks model based on four dimensions: concept definition, data structure, risk contagion network construction, and risk measurement indicators construction. We take the Jiangsu bond issuer guarantee network as a sample area.
Findings – Taking the Jiangsu bond issuer guarantee network as a sample area, we find that there is a strong correlation between the debts of non-financial corporation in China, and it is easy to become a potential regional systematic risk source. In addition, our empirical research also reveals that external risk exposure and node degree of network are two key indicators when identifying key risk-contagion enterprises.
Originality/value – The main contributions of this study are two-fold. First, this article proposes a two-tier risk contagion networks model to measure systematic risk in non-financial corporation. Second, this article describes the structure of the corporate risk contagion network.

Keywords Non-financial corporation, Two-tier networks, Risk contagion
Paper type Research paper

1. Introduction
Forestalling and defusing major risks, keeping the bottom line of systematic financial risks without occurring is one of the focuses of government regulatory agency. In recent years, China's macro leverage ratio has been rising rapidly. Although there has been a steady state in 2018, as of December 2018, China's macro leverage was still above 250 percent. Accurately measuring China's current macro leverage ratio and its internal structure, targeted risk prevention and resolution have important and urgent significance.

Non-financial corporate debt mainly includes bank credit and credit bonds. In recent years, the Chinese bond market has developed rapidly, and the balance of credit bonds has grown from 1.2 trillion a decade ago to about 21 trillion in the beginning of 2019. It is worth noting that while the size of the Chinese bond market is expanding, the number and amount of bond defaults are also growing rapidly. In 2018 alone, the number and amount of defaulted bonds have exceeded twice that of 2017. Compared with traditional bank credit, bond issuers need to comply with certain information disclosure regulations, which makes the market risk of credit bonds have strong linkage, especially the credit risk arising from default events is highly contagious (Edirisinghe *et al.*, 2015). The threat of systematic risk to the financial system lies in its strong contagiousness. The harm to the national economy lies in the possible impact on the real economy. From this perspective, the risk of the credit bond market can be spread in the financial system through the mutual/joint guarantee between the issuers and the information transfer mechanism of the bond market. Since issuers of credit bonds are

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industrial enterprises, the financial risks in this market will directly impact the real economic activities. Therefore, focusing on the research and prevention and control of non-financial corporate debt risks will help to better prevent the risk of the real economy debt, and thus help maintain the stability and security of the financial market.

The issuers of the credit bond, as the main market participants, forms a huge network with other companies through equity, debt, transaction, and guarantee relationships. If we study such a network from the perspective of risk contagion mechanism, the guarantee relationship between enterprises is an extremely important risk contagion path. At present, the external guarantee behavior of China's bond issuers has two characteristics.

First, the average external guarantee ratio of credit bond issuers is at a high level. Higher external guarantee ratios expose companies to greater risk and weaken their ability to withstand sudden credit events. Second, bond issuers have formed a guarantee network with a large number of external companies through mutual guarantee or joint guarantee. Mutual guarantee or joint guarantee means that in the process of issuing bonds, each issuer adds mutual guarantee to each other's bonds to increase their credit ranking.

When a crisis occurs, it is necessary to quickly and accurately identify the source of risk, the path of risk contagion, and key risk contagion nodes within the system to minimize potential losses. Previously, the academic community mainly used the interbank market as the object of systematic risk research. This is because banks dominate the financial system in China, and the banking system has a wide micro-transaction structure as the basic path of risk contagion. Local crises can easily be transmitted and amplified through this system and become systematic risks. However, research on the risk contagion model based on the interconnection network of the guarantee circle in the credit bond market is not sufficient. The framework proposed in this article has strong theoretical significance.

The rest of the article is organized into the following parts. Section 2 introduces relevant literature on financial risk contagion and risk contagion network. Section 3 constructed the two-tier risk contagion networks model. Section 4 comprises the empirical analysis part. Section 5 summarizes the relative findings of the article and provides the conclusions.

2. Literature review

2.1 Financial risk contagion

In recent years, research between leverage ratio and financial risk has become the focus of macro finance research. As one of the most important variables, the leverage ratio was introduced into the early warning system for financial stability. Gigliod *et al.* (2016) examined 19 systematic risk indicators such as leverage ratio, financial market volatility, and spread, and found that leverage ratio has strong predictive ability for macroeconomic downside risks. Liu and Bai (2017) examined the linkage rate of the sector and the contagion of financial risks by constructing an infection multiplier. It is believed that de-leveraging in all sectors can reduce the contagion of financial risks. In measuring the level of financial systematic risk, a more mature research paradigm is to construct a financial stress index or a systematic risk index to measure a country's macro level of risk. The ECB's research team believes that financial pressures are contributed by financial markets, financial institutions, and financial infrastructure, and based on this classification, the CISS index is used to measure the level of financial stress in the EU economies from 1999 to 2011. Bliss *et al.* (2018) considered commercial banks' credit, derivatives, and mutual lending risks, and then constructed a financial stress index based on market volatility.

Moderate leverage is conducive to economic growth and development. Excessive leverage may increase the systematic risk of the economy and is not conducive to long-term economic development. Furthermore, the relative position of each sector in China is quite different in the international comparison. The debt structure of different sectors and the reasons for the increase in debt are different. Therefore, it is necessary to classify and refine the focus of each sector's debt. The problem and the interaction between it and financial risks can be used to control the macro financial risks. The "W-O" comprehensive risk management methodology reveals five characteristics of risk: uncertainty, dynamics, interconnectivity, conflict, complexity (Olson and Wu, 2008, 2011; Wu, 2011; Wu *et al.*, 2014). This methodology provides a good theoretical support for classifying and disposing of financial risks in China.

2.2 Risk contagion network

At present, methods for studying risk contagion and systematic risk among market entities (enterprises, financial institutions and financial markets) mainly include: correlation coefficients; multivariate equations extended by the GARCH model; quantile regression; single exponential method; co-integration analysis; and the Granger causality test based on the VAR method; CVaR derived from VaR (value at risk); extreme value theory; Copula model; social network; and complex network theory (Jia and Dyer, 1996; She *et al.*, 2010; Glasserman and Young, 2015; Evgenidis and Tsagkanos, 2017; D'Errico *et al.*, 2018). Different theoretical methods and analytical tools have different focuses when studying risk contagion problems. Correlation coefficients, GARCH family, VAR and extremum theory, and other methods set the risk dependence between subjects to remain unchanged in the time dimension (Wang and Liu, 2011), which makes it difficult for such methods to simulate the transmission and cascading effects in the risk contagion process; the ability of the GARCH family model to deal with asymmetric dynamic dependence relationships among multiple variables has limitations (Bollerslev *et al.*, 2018); the Copula family model faces difficulties in controlling computational complexity in high-dimensional applications (Oh and Patton, 2018).

Complex networks can be seen as the deep evolution of graph theory, which was born with the development of physics and computer science, marked by two groundbreaking researches in the late 1990s. The first is the proposal of the small world network theory (Watts and Strogatz, 1998), and the second is the proposal of the theory of scale-free networks (Barabási and Albert, 1999; Albert and Barabási, 2002; Barabasi, 2009). Using the network theory to analyze and simulate the risk contagion mechanism between multiple subjects can overcome the limitations of traditional econometric and time series tools. As the modern economic and financial system becomes more and more complicated, the links between financial institutions and financial market are becoming more and more close, which makes the use of complex networks to study the advantages of systematic risk and risk contagion (Ouyang *et al.*, 2015). Allen and Gale (2000) and Freixas (2000) started from the optimal risk-sharing structure of financial institutions and the cascade effect of risk contagion. They first introduced the network theory to analyze the contagion mechanism of default risk, and created the use of the network theory to portray risks. The infection path is the first to analyze the effects of risk contagion. Elliott *et al.* (2014) studied the relationship between cascades of failures in a network of interdependent organizations and network structure. They found integration and diversification have different, nonmonotonic effects on the extent of cascades. Academia mainly uses financial institutions as research objects to measure the systematic risks of financial markets. Liang *et al.* (2017) investigated the debt clearing problem in a debt network with complicated debt relations among various debtors. They developed an algorithm to simplify the whole debt in the debt chain. Scholars measure the level of financial systematic risk by measuring the individual risk level of financial institutions and the degree of risk-related relationship between them (Schnabl, 2012; Veld *et al.*, 2014; Aldasoro, 2018; Dell *et al.*, 2017). Mistrulli (2011) uses the maximum entropy method to estimate the exposure matrix between banks based on the financial statement data, revealing the potential systematic risk level of the risk exposure network between different banks. Further, scholars have also studied the relationship between network topology and risk diffusion within the system. The cascade will lead to the default of a bank following the default of its counterparty

(Amini *et al.*, 2016). Elliott *et al.* (2014) used diversification and integration to describe the network structure. They found that diversification connects the network initially, permitting cascades to travel, but as it increases further, organizations are better insured against one another's failures. Integration also faces trade-offs: increased dependence on other organizations versus less sensitivity to own investments. Other cascade properties (network structures) also effect stability and risk contagion in the financial network. Acemoglu *et al.* (2015) showed that financial contagion exhibits a form of phase transition as interbank connections increase: as long as the magnitude and the number of negative shocks affecting financial institutions are sufficiently small, more "complete" interbank claims enhance the stability of the system. But the management of systematic risk is quite different in the real-time gross settlement system and the net settlement system. Chen and Wu (2019) provide an integrated analysis of the effect of connectivity and netting on systematic risk in financial systems by considering more detailed network structures of pure creditors and pure debtors.

In recent years, the need for regulatory practice and the expansion of analytical tools have made the complex network theory more rigorous in the study of financial risk issues. Academia find that the network connection in the financial system is not limited to direct financial transactions, but also the impact of information dissemination and asset price fluctuations (Paltalidis, 2015). Therefore, the single-layer network model is difficult to reflect multiple micro-risk contagion mechanisms, and the financial system has multi-level network attributes (Teteryatnikova, 2010; Poledna *et al.*, 2015; Ding *et al.*, 2017; Xu, 2019). Focusing on the real economy, the current research on systematic risk focuses on the level of financial institutions, but the two aspects of real economic debt and financial systematic risk are mutually integrated (Gou *et al.*, 2016; Paligorova and Joao, 2017; Lundqvist and Vilhelmsson, 2018), based on risk interconnectivity. From the perspective of the lack of research on the debt risk of non-financial corporation, this article proposes a two-tier risk contagion networks analysis for non-financial corporation debt risk to carry out innovative work on the limitations of the above two aspects. First, we focus on the non-financial corporation sector and use the guarantee circle in the bond market as a bridge to connect corporate debt with risk contagion. Our work provides a new perspective for analyzing systematic risks in financial markets. Secondly, it is more and more practical to study the network structure of the financial market based on the perspective of information interconnection and then the multi-level network analysis in this article can better describe this risk contagion mechanism. For non-financial corporation, the information interconnection channels are complex, including equity relationships, guarantee relationships, and being in the same industry cycle. In such a background, rationally utilizing the multi-level network analysis paradigm developed in recent years, and adding the information interconnection structure of the credit bond issuer guarantee circle to the establishment of the network structure, can accurately depict the actual risk contagion mechanism and path.

3. Construction of the two-tier counterparty risk contagion networks model

This article uses complex networks to analyze the risk associated with debt in a non-financial corporation.

3.1 Definition of two-tier counterparty risk contagion networks

In a common complex network, nodes and their connected edges are in the same layer, which is a single-layer complex network. In social network research, the academic community found that the relationship between people may have different attributes or categories. The portrayal of complex social systems with a simple network is an extremely simplified way of showing situations in which participants are connected by only one type of association.

Between social economic organizations, when an organization goes bankrupt or defaults, the organization's risks will spread through different levels of infection, such as debt and debt relations, equity guarantee relationships, information spillover relationships, and so on. This article will construct a network of two-level structure to portray the risk contagion mechanism between economic organizations.

Diversified networks are a special type of multi-layer network. The number of nodes in each layer is the same, and there is only one type of connection between layers. That is, a given node is only connected to its corresponding node in other network layers.

G is a two-layer complex network. The two layers of the G are G_h and G_m, respectively.

V is a set of all nodes in the graph, assuming the total number of nodes is N.

B is a set of all edges in graph G, where H is the set of all edges in the G_h layer, and M is the set of all edges in G_m layer. For the nodes i and j in the graph G, the edge formed by i pointing to j in the G_h layer is denoted as h_{ij}, and in the same way, the edge is denoted m_{ij} in the G_m layer.

In actual network modeling, since the edges between different nodes may have different weights, $w^{y}{}_{ij}$ is the weight of the node i pointing to the edge of node j, where the upper corner y is the layer, $y = \{h,m\}$.

3.2 Division of two-tier risk contagion networks

In the construction of the first layer of complex networks, we consider the actual guarantee relationship and the equity relationship as edges. Because of the directional guarantees for the company and the holding of shares (such as i to j guarantee, or i holds shares of j), the first-tier counterparty network is directional.

Some variables in a complex network system are defined as follows:

V is the set of all bond issuers, which is the set of nodes in the network, and the total number is N.

The guarantee relationship network matrix is $L(l_{ij})$, where l_{ij} represents the guarantee behavior of node i to node j, which is directional.

The equity relationship network matrix is $F(f_{ij})$, where the f_{ij} equal to 1 represents i and j belong to an enterprise group.

3.3 Measurement of the risk contagion of two-tier networks

3.3.1 Organization's external risk exposure. When a credit risk event occurs in a node in the network, the risk transmission of the node to other nodes can be divided into three ways. (1) The organization defaults and cannot repay the debt, so the creditor faces the loss of net assets; the organization guarantees this default organization will face responsibility for its debt repayment, resulting in liquidity output and a portion of net asset losses. (2) The default organization's external guarantee will be invalidated, which makes the potential solvency of the guarantee organization decline, and may lead to the early resale clause due to the failure of the relevant guarantee treaty, resulting in a large-scale liquidity shock. (3) When an organization falls into bankruptcy, the value of shares held by external organizations is lost to zero and face the risk of compensating part of the debt.

Therefore, when a credit risk event such as debt default occurs at a certain node, its potential external risk exposure (ERE) can be expressed as follows:

$$RiskExpo_i = (G_{iO} + G_{iI}) + (D_i - A_{iL}) + (E_i * P_{iO}) \tag{1}$$

$RiskExpo_i$ is the potential external exposure of the organization when it defaults, G_{iO} is the total external guarantee of the organization, G_{iI} is the external guarantee for the organization, D_i is the total liabilities of the organization, A_{iL} is the total current assets of the organization, E_i is the owner's equity and P_{iO} is other external organization' shareholding ratio.

3.3.2 Risk contagion channel – node degree. In a complex network, the number of connected edges of a node is defined as the degree of the node, and the degree k_i of the node i is the sum of the edges connected to the node i. In the undirected complex network, the attributes of each side are the same, and in the directional complex network structure, the in-degree and out-degree are the two parts of the node degree. The in-degree of node i represents the number of edges of other nodes in the network pointing to node i, and the out-degree of node i refers to the sum of the sides of node i pointing to other nodes.

3.3.3 Distribution of risk contagion channel – degree distribution. To describe the differences in the topological properties of each types of networks, the concept of degree distribution can be used. The average degree is defined as the expectation of all node degrees. $P(k)$ is commonly used to represent the distribution function of the degree of a node, that is, the ratio of the node with degree k to the number of all nodes, that is, the probability that any node in the network is exactly k. In this two-tier risk contagion networks model, node degrees in the network represents the number of risk contagion channels connected to other organizations in the network.

3.3.4 Risk contagion path – average shortest path. The path length refers to the number of connected edges in the path, and the average shortest path length is the expectation of the minimum number of edges between any two points in the graph. In a network with N nodes, d_{ij} is defined as the shortest path between node i and node j.

3.3.5 Aggregation of the risk contagion network – clustering coefficient. The clustering coefficients can be divided into two types. The first is the global clustering coefficient proposed by Watts (1998). This index reflects the probability that any connected node of j is also connected to i when i and j are connected nodes. The second is the local clustering coefficient, which is a kind of transitivity calculation. The number of connections of the node i in the network is k_i. The maximum number of connected edges is calculated as $k_i(k_i - 1)$, between the k_i nodes connected to i, and then the number of connected edges between the k_i nodes are obtained from the actual network as L_{i}i. Then the clustering coefficient of the node i is:

$$C_i = \frac{2L_i}{(k_i(k_i - 1))} \tag{2}$$

When the total number of nodes in the network is N, the global clustering coefficient is:

$$C = \frac{1}{N}\sum_i C_i \tag{3}$$

This article completes the construction of a two-tier counterparty risk contagion networks model using four dimensions: concept definition, data structure, risk-contagion network construction, and risk measurement indicator construction. Starting from the market multivariate data, according to the two-tier networks model, we can get the first layer contagion network (based on equity and guarantee) and the second layer contagion network (based on information spillover). Theoretically, the debt, equity, and guarantee relationships will constitute a two-way information spillover effect between the two organizations, so in the actual modeling, the second layer network tends to have a higher nodes degree than the first layer network. Finally, through a series of network topology calculations and network category identification, we can further assess the systematic risk level of a region and identify the key risk contagion nodes.

3.4 Regression model

Obviously, ERE can be used to measure the risk spillover level of a corporate bankruptcy to the regional economy. From the perspective of macro-prudential supervision, a meaningful question is whether the company's ERE is related to factors such as industry, region, listed company and ownership. In addition, ERE is based on information in the financial statements, which is a static indicator. It is difficult to reflect the complexity of the actual business activities of a company associated with the socio-economic system and the systematic importance in the economic system. From the perspective of complex networks, we can observe and evaluate the importance of a company in the regional economic system. From the perspective of risk-contagion networks, we can measure the risk spillover level of a company's bankruptcy in the regional economic system. Therefore, we hope to study two problems through a set of regression models: (1) what factors are related to ERE, whether it is affected by factors such as industry, region, listed company, and corporate ownership? (2) whether the company's ERE can cover the indicators in the risk contagion network?

We estimate multiple linear regressions of risk exposures on two types of variables, the first type is the complex network measurement indicators such as node degree and clustering coefficient, and the second type is the enterprise's own attributes and financial indicators. The balance of ERE is affected by several factors, the most significant one is the size of a company. In order to rule out the impact of this factor, we use three variables, revenue, net asset, and bond balance, to control the effect of company size.

Besides company size, there is substantial evidence that idiosyncratic company factors affect ERE. Specifically, idiosyncratic factors include ownership, industry, and listing or not. After controlling the size, we use the empirical model to examine whether ERE was affected by these idiosyncratic factors.

The structure of the risk contagion network is the focus of our research. After building an inter-enterprise risk-contagion network, we found that different nodes have a heterogeneous location and status in this network, which affects the role of enterprises in the risk contagion process. An important question is whether the role of enterprises in regional risk contagion could be reflected only by the ERE. and whether network analysis can provide a new perspective of risk contagion analysis. We selected two indicators, including node degrees and local aggregation coefficients, to represent the attributes of nodes in the risk contagion network; we then try to clear their relationship with ERE through empirical models.

$$
\begin{aligned}
\ln RiskExpo_i &= \beta_0 + \sum_{j=1}^{9} \beta_j \cdot x_{ij} + u_i \\
\ln RiskExpo_i &= \beta_0 + \beta_1 \cdot DegNet_i + \beta_2 \cdot ClusCoef_i + \beta_3 \cdot \ln Reve_i + \beta_4 \cdot \ln BondBal_i \\
&\quad + \ln \beta_5 \cdot NetAsset_i + \beta_6 \cdot PropFirm_i + \beta_7 \cdot Indust_i + \beta_8 \cdot ListedCom_i \\
&\quad + \beta_9 \cdot Reg_i \qquad (4)
\end{aligned}
$$

where $RiskExpo_i$ is ERE. $DegNet_i$ and $ClusCoef_i$ are nodes degree and clustering coefficient of networks, respectively. $Reve_i$ and $NetAsset_i$ are total revenue and net asset in balance sheets, respectively. $BondBal_i$ is the balance of the company's unpaid bonds. $PropFirm_i$, $Indust_i$, $ListedCom_i$, and Reg_i are dummy variables. $PropFirm_i$ represents the ownership of enterprise i, the value equal to 1 represents a state-owned enterprise while the value equal to 0 represents a private enterprise. $Indust_i$ represents the industry of enterprise i, the value equal to 1 represents manufacturing industry while the value equal to 0 represents service industry. In our sample, manufacturing includes industry, daily consumption, information technology, healthcare, and materials; the service industry includes optional consumption and real estate. $ListedCom_i$ represents whether enterprise i is a listed company, the value equal to 1 represents a listed company while the value equal to 0 represents a non-listed company. Reg_i represents the location of enterprise i.

ERE is based on information in the financial statements, which is a static indicator. Therefore, we make the following inference: ERE cannot cover the node degree, local clustering coefficient, and other indicators obtained through the complex network modeling.

In this section, we complete the construction of a two-tier counterparty risk contagion networks model using four dimensions: concept definition, data structure, risk-contagion network construction and risk measurement indicator construction. Compared with the existing risk contagion network model, the proposed model overcomes several shortcomings and is innovative. In terms of concept definition, the model proposed in this article comprehensively considers various types of risk communication mechanisms and defines risk communication networks in two dimensions: financial channels and information channels. In terms of data structure, the proposed model does not use simulation data in methods such as "maximum entropy," and not only uses financial data, but uses a combination of qualitative and quantitative data sources. The construction of risk contagion networks is based on innovative work in both conceptual definition and data structure. Finally, in the construction of risk measurement indicators, we propose a new indicator of ERE for empirical analysis.

4. Empirical study on non-financial corporate debt risk contagion

From the debt risk analysis of the government, residents, and non-financial corporation, it can be seen that the non-financial corporation debt accounts for 60 percent of China's total real economy debt, and the leverage ratio is 151.82 percent, much higher than the other two departments. The large repayment pressure makes the half of the new credit bond issuance funds used for repayment of interest in the current year. Therefore, this article will focus on the debt risk of the non-financial corporate sector and analyze the potential systematic risk issues in the non-financial corporate sector by using a regional sample.

4.1 Sample area

At present, small and medium-sized bond issuers are facing difficulties in financing. Some enterprises in Shandong, Jiangsu, Fujian, and other regions have adopted mutual guarantees and joint guarantees to improve credit qualifications and facilitate financing. This has led to the development of systematic risk management practices with Chinese characteristics. In order to obtain higher bond issuance quotas or lower financing costs, small and medium enterprises (SMEs) use mutual guarantees and joint guarantees to help their financing, which makes the inter-firm guarantee relationship and equity relationship between enterprises intertwined, and it is easy to form a regional risk contagion network.

The credit bond guarantee circle network often has a strong regional character. This regionality is reflected in two aspects. First, the scale and characteristics of the external guarantees of issuers in different regions are often different. The average external guarantee ratio between different provinces varies above 30 percent. In some provinces, industrial bond issuers have a high proportion of external guarantees, and some provinces have a high proportion of external guarantees. Second, due to the "acquaintance society" – the origin of the guarantee circle, the guarantee circle is often confined to a certain area. The guarantee circle originated from the "acquaintance society." For industrial bonds, the guarantee network usually originated from the same industry in the same region, or the owner of the upstream and downstream industries. For city investment bonds' issuers, the guarantee objects are mostly under the control of the same State-owned Assets Supervision and Administration Commission of the State Council (SASAC), or the city investment platform of the neighboring city.

The regional nature of the credit bond guarantee circle indicates that we should make our empirical analysis in a certain region. However, if the sample is confined to a city, the guarantee network cannot be fully developed, and the representativeness of its network structure is not strong enough. Therefore, we construct the guarantee network in a province.

We select the area of the study sample before the empirical study. We first pay attention to the scale of non-financial corporate debt in each province, including credit bonds and loans. The provinces with large debts have systemic importance in the process of debt risk identification, control, and prevention. Non-financial corporate debt can be divided into direct financing debt and indirect financing debt. The former mainly involves credit bond financing, and the latter mainly involves bank credit. According to the bank credit and credit bond market data as of December 2018, which was provided by The People's Bank Of China, shown in Table I, the non-financial corporate debts in Guangdong and Jiangsu are among the top two.

The risk-infected network proposed in our article incorporates information on external guarantees between enterprises, and it is reasonable to use the provinces with a higher proportion of external guarantees as samples. We use "external guarantee/net assets" to describe the proportion of external guarantees issued by credit bond issuers. The results of the provinces are shown in Table II, data is from wind, as of December 2017. Judging from the proportion of external guarantees issued by credit bond issuers, Jiangsu and Zhejiang rank among the top two.

Based on the information in Tables I and II, it can be found that non-financial corporations in Jiangsu Province have two characteristics: large debt scale and high external guarantee ratio. Further, Jiangsu's GDP in 2018 ranks second among the all provinces in China, and is an important economic engine in the Yangtze River Delta. From the perspective of economic scale, the real economic sector of Jiangsu Province has an outstanding position in China's economic system. With strong systemic importance, comprehensive debt scale, external guarantee, ratio, and economic volume, this article selects Jiangsu Province as the sample selection area.

China's credit bond market can be divided into industrial bonds and city investment bonds. Our work chooses industrial bond issuers as research objects. There are two main reasons: first, non-city investment platform debt accounts for about 78 percent of non-financial corporate debt, and city investment platform debt accounts for only 22 percent; up to

Province	Guang Dong	Jiang Su	Zhe Jiang	Shan Dong	Bei Jing
Bank credit	79,302.41	78,488.50	62,698.98	50,507.64	50,042.80
Credit bond	42,915.41	40,681.62	29,416.02	25,516.06	252,609.18

Table I. Top five provinces of credit bond and bank loan scale

Province	External guarantee ratio (%)	Province	External guarantee ratio (%)
Jiang Su	37.49	Chong Qin	14.42
Zhe Jiang	31.99	Fu Jian	13.60
Tian Jing	23.80	Gui Zhou	13.50
Qing Hai	23.23	Ji Lin	12.77
Xi Zang	22.68	He Bei	11.42
Shan Xi	22.48	Xin Jiang	11.33
Shan Dong	19.58	Nei Meng	11.23
He Nan	18.42	Yun Nan	10.80
Bei Jing	18.19	Hu Bei	10.75
Si Chuan	15.66	Shang Hai	10.28
An Hui	14.56	Jiang Xi	9.57

Table II. Statistics on the external guarantee ratio of bond issuers now, default enterprises are all industrial bond issuers. Second, the issuer of city investment bonds has a certain gap with the industrial bond issuer in the authenticity, completeness, and availability of information disclosure. The annual report, audit report, and prospectus and other information of the industrial bond issuer not only follow the regular disclosure process, but the content is more realistic. Relatively speaking, the city investment platform has more irregular expressions in the information disclosed regularly, and the contents of the financial statements are not detailed. Therefore, in the subject of research, increasing the proportion of industrial bond issuers will help improve the availability of data and data quality. From the above two points, the industrial bond issuers can be mapped to the majority of the non-financial corporate sector debt (78 percent), while taking into account the data quality. In the end, we selected the financing guarantee circle of the Jiangsu industrial bond issuer as the research object.

4.2 Construction of the first layer network

This section establishes the first-tier counterparty network of industrial bond issuer guarantee circles in Jiangsu Province.

We first collected 518 credit bond issuers in Jiangsu Province as of September 2018 as the main node samples. The companies covered by the whole network include provincial bond issuers related to the main nodes through the guarantee relationship and equity relationship. Among them, there are 330 main nodes in the city investment platform and 188 major industrial bond issuers. The external guarantee relationship of all enterprises uses the latest external guarantee information disclosed by the company in the third quarter of 2018, and does not include the historical information of the company's external guarantee. All corporate financial data are based on financial data for the third quarter of 2018. All data comes from wind.

We aim to build a network based on the real regional credit bond guarantee information. The construction of the actual network is divided into the following steps. Firstly, selecting 188 major industrial bond issuers in the overall sample. Secondly, collecting data for each bond issuer, including external guarantees, acceptance of guarantees and equity relationships, ending in the third quarter of 2018. Lastly, according to the above relationship, setting the issuer as the node, using guarantee and equity relationship as the edges, a directed network is then constructed. In the network graph, each node corresponds to a credit bond issuer. We use the serial numbers "A1, A2, B1, . . .Z9" to randomly mark the issuer's enterprise. In the construction of the network, some of the nodes connected to A1 may not be bond issuers. For non-bond issuer companies, such as A2, we make the following treatment. If A2 can establish the above connection with the second issuer enterprise B1 in the network, it will be kept in the network, otherwise the network will be removed. This is because, when A2 can be connected to B1, it completes the connection between A1 and B1 as an intermediate bridge, that is, a path as a risk contagion channel between A1 and B1.

Figure 1 shows the first-level risk-contagion network of Jiangsu industrial bond issuers. In the figure, we eliminate the few points and edges independent of the main network and obtain the giant component. The node size in this network is weighted by node degrees. It can be seen from the figure that after the enterprises with large bond balance in Jiangsu Province are found out, they can form a large-scale network structure through the connection of the guarantee relationship and the equity relationship. From this initially constructed network, we can observe the following characteristics: First, although the industrial bond issuers are located in different cities and counties in the province and belong to different industries, but most of them can connect with each other through guarantee and equity relationship. Second, in this network, there are some nodes, such as G6, L6, K7, L9, N9, B7, D6, etc. These nodes are connected with many surrounding nodes, but most of the other nodes are only associated with a small number of nodes. Third, this network has a distinctly high degree of local

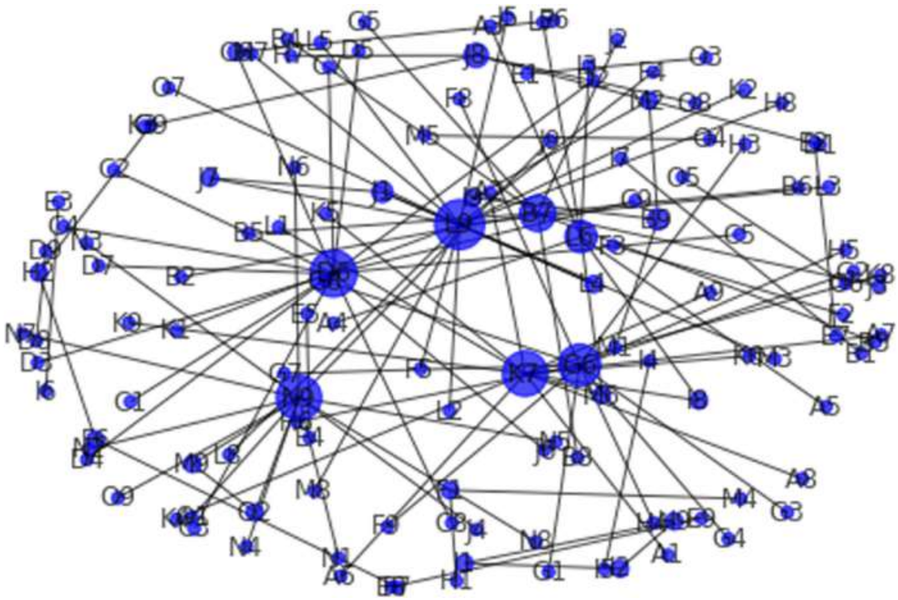

Figure 1.
The first network of industrial bond issuers in Jiangsu province

clustering. In smaller sub-networks, two-way or ring-shaped edges can be seen, which is the mutual security and joint security phenomenon.

As can be seen from Table III, the first layer network has 135 nodes and 128 edges, and the average shortest path is 4.4295. The between centrality of a node equal to 0 means that all the shortest paths do not pass this node. There are 11 nodes not equal to 0, which means that 11 issuers in the network are in the relative core position, which is the key node of the risk contagion path in the network.

The categories to which the complex network G_h belongs can be divided by graphical observation and network statistics as shown in Table III. First of all, we can see from Figure 1 that the overall connectivity of the first layer network is not high, many nodes are only connected to a nearby core node, and the network has the property of local clustering; it is presented around several nodes such as G6, L6, K7, L9, N9, B7, and D6. The number of connected edges of these core nodes is much higher than other nodes, which is consistent with this feature of scale-free networks. A few nodes in a scale-free network have a number of connections far beyond the average node. We call these nodes Hub nodes. The state of the Hub nodes directly determines whether the entire network system can operate normally. A few nodes in the network G_h have degrees far beyond other nodes. Figure 2 shows the degree distribution of G_h; it can be seen that the degree distribution of the network significantly matches the characteristics of the power law distribution.

The most important difference between a scale-free network and other networks (random network and small-world network) is that the former can describe the growth of the network and the preference connection mechanism of the new node. When the new nodes access the network, there is a characteristic of preferential connection to the original hub node (more

Node number	Edges	Average path length	Clustering coefficient	Between centrality not equal to 0
135	128	4.4295	0.0448	11

Table III.
Statistics of G_h

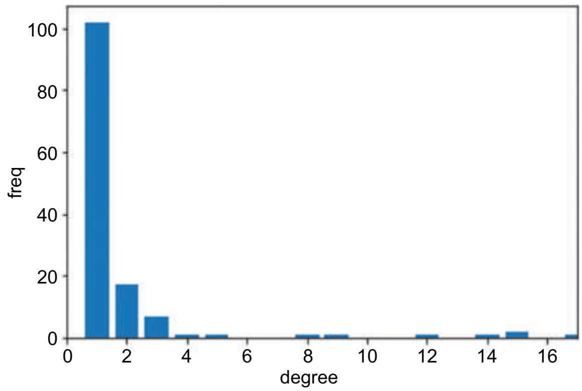

Figure 2.
Histogram of network degree distribution in the first layer

connected edges). From the statistical characteristics, the degree distribution of the scale-free network obeys the power law distribution, and the average shortest path length is small and the clustering coefficient is high. At the same time, according to the network statistics in Table III, it can be considered that the G_h network has certain characteristics of a scale-free network.

4.3 Construction of the second layer network

The second level is based on the interconnection of information between enterprises to establish a network. The information exchange between enterprises has the following meanings: when a private enterprise has a credit event, the credit level of other enterprises owned by the same actual controller will be affected. When a certain enterprise in a certain industry has a credit event, the credit level of other enterprises in the same industry in the same region will be affected. Those city investment platforms that under the same local SASAC or the Finance Bureau have a certain degree of information interconnection. For enterprises with guarantee relationships, there is information interconnection between them; for enterprises that are major suppliers or downstream customers, there is an information interconnection relationship between them. Based on the above principles, we establish a second layer of information interconnection network between the same nodes as the previous section. Since the direct information association between the two nodes i and j must be bidirectional, the information interconnection network at this level is an undirected and unweighted network.

Thus, an information internetwork G_m can be constructed as shown in Figure 3.

After the design of the information interconnection mechanism, we construct a second layer information network. The node size in this network is weighted by node degrees. From Figure 3, the following points can be observed: firstly, compared with the graph G_m, the overall connectivity of the G_h network is significantly enhanced, the maximum path length is significantly reduced, and the small world characteristics of the network are initially displayed. Secondly, the network still has a strong regional clustering effect, and several sub-networks can still be found from G_h. Some small-scale inter-enterprise information networks are still the basis of network G_m. By further analyzing the sub-networks, we find that it is easy to have direct information transmission between enterprises in the same industry chain in the same region. Finally, the number of key nodes in G_m has increased, and the difficulty of differentiation is higher than that of G_h.

Based on this, we can further calculate the complex network statistics of G_m.

It can be seen from Table IV that this layer network has 135 nodes, but the number of edges of the network rises to 169. Compared with the Between Centrality of G_h, the number of

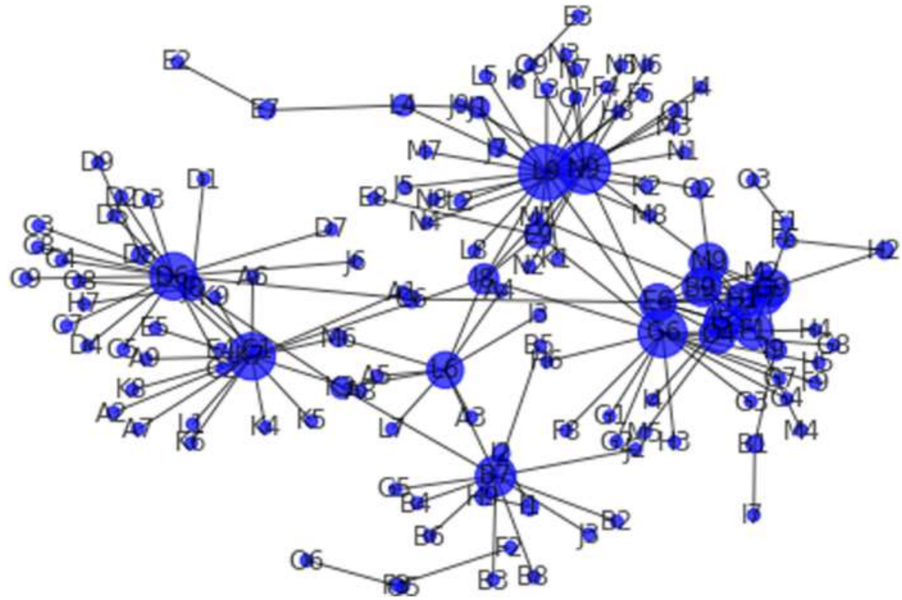

Figure 3.
The second layer of information internet

Node number	Edges	Average path length	Clustering coefficient	Between centrality not equal to 0
135	169	6.5262	0.1142	30

Table IV.
Statistics of G_m

key nodes in G_m has risen to 30. In general, the increase in the number of key nodes means that the channels of risk contagion are more diverse, but it may also lead to an increase in the stability of the network structure.

Figure 4 shows the degree distribution of G_m; we can find that the degree distribution of this network also has the characteristics of power-law distribution. However, combined with the significant increase of the clustering coefficient, the average shortest path length in the network drops significantly. We can think that the G_m has some characteristics of the small world network, and it should belong to the scale-free plus small-world complex network.

4.4 Identify key risk contagion nodes

We calculated the ERE of each node and reconstructed the G_h and G_m networks with the risk exposure as the weight, and compared it with the network graph in the previous section.

Figure 5 is the G_h weighted nodes size by ERE. On comparing to the G_h weighted nodes size by nodes degree in Figure 3, we can find that the position of the biggest nodes has changed. In Figure 1, K7, L9, and D6 are the biggest nodes; it means there is extensive equity and guarantee relationship between these nodes and other enterprises. That is to say, there are extensive micro risk contagion channels around these nodes; they are the key nodes in the risk contagion network. However, if we weigh the node size by the total potential infection intensity (ERE), we can find something different. In Figure 5, except for L9, which is still the largest node, the nodes such as K7 and D6 are no longer significant. They are replaced by I1 and E9, which become the nodes with the greatest potential risk contagion.

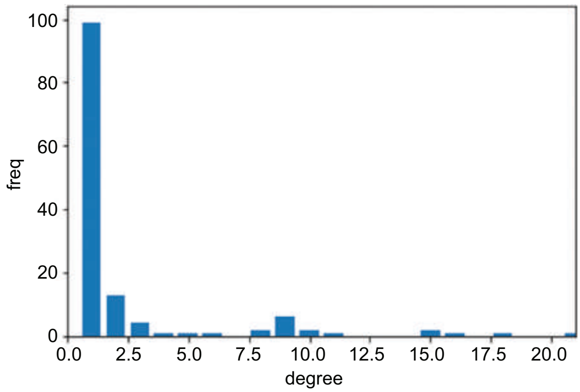

Figure 4.
Histogram of network degree distribution in the second layer

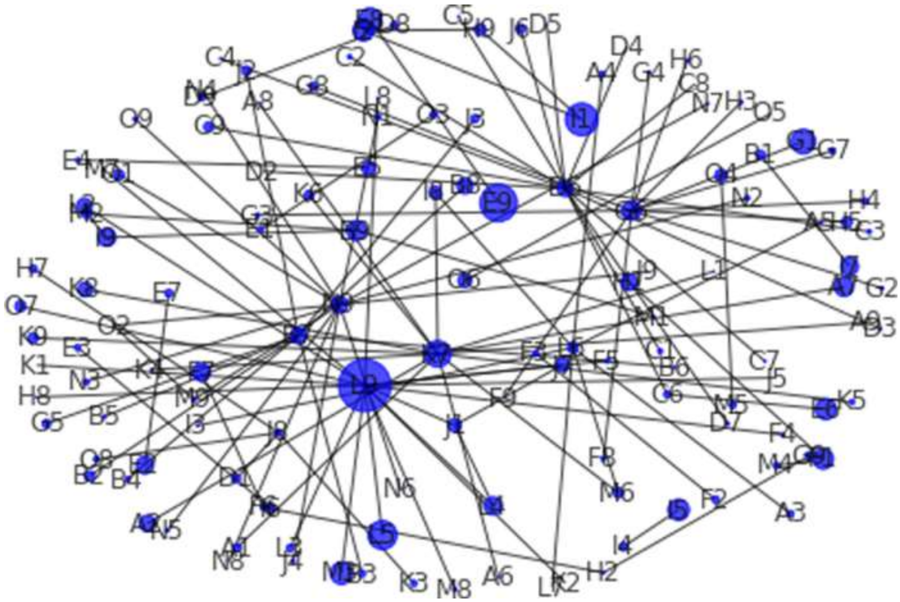

Figure 5.
Network diagram of G_h after assigning weight according to ERE

Figure 6 shows the information interconnection network G_m weight nodes size by ERE. Compared with Figure 3, the same conclusion can be drawn, that is, the key risk nodes are measured from the perspective of the micro risk contagion channel and the potential infection intensity, which will yield different results.

In fact, through the number of potential micro-risk contagion channels (node degree) around a specific node, it can be seen how many affiliates will be affected when an enterprise goes bankrupt or default, which is an important indicator to measure the potential systematic risk contribution of this enterprise. The ERE can measure the intensity of risk contagion; it is also an important indicator to measure the potential systematic risk contribution of this enterprise. When judging the key nodes in the risk contagion network, these two variables should be integrated to generate a more comprehensive indicator.

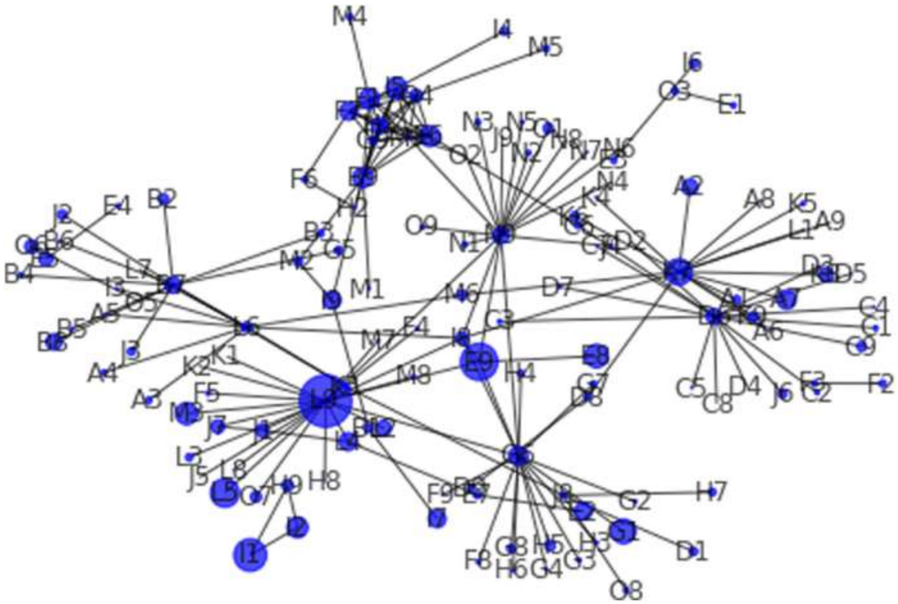

Figure 6.
Network diagram of G_m after assigning weight according to ERE

After identifying the key risk-contagion nodes in the network through the indicators of the two dimensions of node centrality and ERE, we obtained nodes such as B7, D6, E9, G6, I1, K7, L6, L9, and N9. A meaningful question that arises is what commonalities exist in such enterprise nodes. Obviously, if we can find the common attributes of these core nodes, it will be beneficial to the management and control of debt risk of the non-financial corporation.

From Figures 3 and 6, we can find that there are a series of sub-networks centered on nodes such as B7, D6, E9, K7, L9, and N9. Based on this, it can be speculated that these key nodes should be some important, regionally influential investment and financing groups. The correspondence between the node and the actual enterprise confirms our speculation.

It can be seen from Table V that the core nodes in the network are often the parent companies of large manufacturing groups. Compared with other companies in the group, these parent companies are intra-group investment platforms with many subsidiaries and grandchildren. They usually have better credit ratings and lower financing costs in the financial market, so they are the main financing entities within the group. Due to their high credit ratings and better ability to allocate funds, they are responsible for the large amount of interest-bearing debts guarantee of companies within and outside the group. The parent companies of such enterprise groups usually have large-scale fund allocation capabilities and better external financing capabilities (higher credit ratings) than other companies in the

Node code	Underlying enterprise	Whether a group company
B7	Xuzhou construction machinery group co., ltd	Yes
D6	Wuxi industry development group co., ltd	Yes
E9	Suning Electrical Appliance group co., ltd	Yes
I1	Pulp&Paper industry (China) investment co., ltd	Yes
K7	Jiangsu Shagang group co., ltd	Yes
L9	Jiangsu communications holding co., ltd	Yes
N9	Phoenix publishing & media group co., ltd	Yes

Table V.
Some core nodes corresponding to enterprises

group. However, when a local risk event breaks out, as an intermediary with the financial and credit transactions of the internal and external enterprises of the group, the micro-path of risk contagion is more extensive (higher node center degree); once a credit event occurs, it will often cause a greater risk shock.

4.5 Ownership and external guarantee scale

According to the previous analysis, small and medium-sized bond issuers are facing difficulties in financing. Some enterprises in some regions have adopted mutual guarantees and joint guarantees to increase credit ratings for each other in order to facilitate their financing process. In China, the financing environment faced by private enterprises and state-owned enterprises is different. In general, state-owned enterprises benefit from the government's implicit endorsement and high social visibility, which has a more relaxed external financing environment than private enterprises. Therefore, the use of mutual insurance and joint insurance to seek external financing opportunities, in more cases, is the passive choice of private enterprises. We divide enterprises into state-owned enterprises and private enterprises, and verify this phenomenon by comparing the scale of external guarantees with total assets, registered capital, and ERE.

As shown in Table VI, the proportion of external guarantees between state-owned enterprises and private enterprises varies widely. On average, the external guarantees/registered capital of private enterprises account for twice as much as state-owned enterprises, and the ratios of external guarantees to owner's equity and external exposure are also significantly higher than those of state-owned enterprises. This empirical result is consistent with the theoretical analysis of this article.

4.6 Determinants of external risk exposure

External risk exposure can be used to measure the risk spillover level of a corporate bankruptcy to the regional economy. From the perspective of macro-prudential supervision, a meaningful question that arises is whether the company's ERE is related to factors such as industry, region, listed company, and ownership. In addition, this indicator is based on information in the financial statements, which is a static indicator. It is difficult to reflect the complexity of the actual business activities of a company associated with the socio-economic system and the systematic importance in the economic system. From the comparison between Figures 3 and 6, it can be found that the obtained key risk contagion nodes are not identical by using external risk exposure and node degree as weights. We try to solve two problems through a set of regression models: (1) What factors are related to ERE? Is it affected by factors such as industry, region, listed company, and corporate ownership? (2) Whether the company's ERE can cover the indicators in the risk contagion network?

$Reve_i$ and $NetAsset_i$ indicate total revenue in balance sheets. $BondBal_i$ is the balance of the company's unpaid bonds. We use Model 2 to compare the effects of the three control variables, and then we find that revenue can control the size of the company effectively. In Models 3, 4, 5, and 6, we use the revenue as the control variable.

The result of the regression are shown in Table VII.

Table VII is the result of regression models. In Model 1, we use node degree and local clustering coefficient, which are obtained from the risk contagion network, as independent

Table VI.
Corporate ownership and external guarantee ratio

Ownership	External guarantee/registered capital (%)	External guarantee/owner's equity (%)	External guarantee/external exposure (%)
Private	342.35	20.69	25.77
Stata-owned	152.92	16.28	15.70

Table VII. The result of the regression on risk exposure

Dependent variable	Risk exposure Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	13.822***(0.346)	8.653***(1.216)	8.790***(0.931)	7.715***(1.150)	7.713***(1.161)	7.745***(1.242)
Degree	0.022(0.035)	−0.004(0.029)	0.004(0.024)	0.002(0.023)	0.006(0.027)	0.004(0.020)
Clustering coefficient	84.815(149.51)	−6.324(123.45)	–	–	−35.514(112.33)	–
Revenue	–	0.302***(0.082)	0.491***(0.078)	0.431***(0.698)	0.496***(0.081)	0.494***(0.078)
Bond balance	–	0.062*(0.034)	–	–	–	–
Net assets	–	0.055(0.062)	–	–	–	–
Property of firm	–	–	–	0.430(0.277)	0.443(0.283)	0.429(0.303)
Industry	–	–	−0.474*(0.271)	−0.493*(0.267)	−0.495*(0.269)	−0.511**(0.248)
Listed company	–	–	−1.079***(0.310)	−1.058***(0.306)	−1.065***(0.310)	−1.054***(0.375)
Region	–	–	–	–	–	−0.084(0.267)
Controls	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.03	0.39	0.49	0.51	0.52	0.52
Adjusted R-squared	−0.009	0.33	0.45	0.46	0.45	0.45

variables to regress the ERE. We can find that these two independent variables in Model 1 are not significant, and the R-squared is close to zero. We can make a preliminary judgment that ERE cannot cover the indicators in the risk contagion network. The ERE of enterprises has a positive relationship with the enterprise size. We choose revenue, net assets, and bond balance as the control variables of enterprise size. We use Model 2 to screen the control variables of enterprise size, and we find that revenue is the best controlling variables for enterprise size. After controlling the enterprise size, we found through Model 3 that the ERE is related to the industry and whether it is listed. The coefficient of *Indust* is negative, indicating that after controlling other factors, the average ERE of manufacturing enterprises is lower than that of service enterprises. The coefficient of *ListedCom* is negative, indicating that after controlling for other factors, the average external exposure of the listed company is lower than that of the non-listed company. This may be due to the high threshold of listed companies in China, and the higher regulatory norms make listed companies more stringent in external risk management. Through Model 4/5/6, we found that the *Indust* and *ListedCom* are always significant, but the *PropFirm* and *Reg* are not significant. This result indicated that ownership and location are not the main determinants of ERE. Through the Model 3/4/5/6, we found the coefficient of $DegNet_i$ and $ClusCoef_i$ are not significant. These empirical results confirm our inferences in the previous paragraph; ERE, which is a static indicator, cannot cover all the information of corporate's external risk spillover effects. From the perspective of complex networks, it has great significance to build an inter-enterprise risk contagion network. It is also consistent with the conclusions obtained in the previous comparison between Figures 3 and 6. From the perspectives of complex network topology and ERE, the identified key risk contagion enterprises are not completely consistent. Two types of indicators should be combined to find those enterprises with systemic importance.

5. Conclusion

The credit bond market not only has the individual risk of a single bond but is also a potential source of systematic risk. Specifically, bond issuers have mutual guarantees and joint guarantees for each other's debt; there are equity relations and transaction relationships between issuers; companies in the same geographical region and same industry are clearly relevant in the credit level and so on. When issuers form a guarantee circle through those guaranty relationship, local risks can spread through this network and become a potential source of systematic risk.

The empirical evidence in this article supplements the existing literature in the following aspects. First, when researching inter-agency risk-contagion networks, the maximum entropy method is often used to estimate the real inter-institutional risk-contagion path. This article uses the real financial transactions between enterprises, including guarantees, debts, and equity relationships. This article also innovatively adds mutual insurance and information spillover risks to the network construction. Second, this article constructs a first-tier risk-infected network that only includes financial funds and a second-tier risk-infected network that includes information spillover risks separately. Later, it was found that the information spillover effect could change the risk infection network structure, thereby changing the micro-mechanism of risk contagion and accelerating the transmission of risk. Third, existing research often uses structural hole theory when identifying systematic financial institutions based on complex networks. This method uses metrics to rank the relative importance of the financial institutions directly, and only the network topology attributes are considered. However, after adding ERE to the relative ranking of the importance of the institutions, the results would be more reasonable and effective.

Based on the above theoretical and empirical research, we have the following four points of recommendations in managing and controlling the risk correlation of non-financial corporation: (1) The expansion of the regional guarantee circle network should be controlled.

External guarantees should be supervised more prudentially than the internal guarantees within the group. Unlike many risk contagion channels within a group, external guarantee is an important way to make the cross-industry and cross-regional risk contagion. (2) When identifying and supervising key nodes in risk contagion network, the regulatory authorities should comprehensively consider the indicators of the two dimensions including ERE and external relevance. (3) When the government plans to intervene and control the regional risks of non-financial corporation, they should pay more attention to those key nodes, such as the group's investment and financing platform. Theoretical analysis shows that the regional credit bond issuers' guarantee circle is an important contagion path for potential regional systematic risk outbreaks, but external liquidity support can help the system to restore equilibrium. The government can resolve risk spread as soon as possible by coordinating with financial institutions to provide external assistance. The existing guarantee network has the topological characteristics of the scale-free network, and the connection degree of some nodes far beyond general nodes. Therefore, assistance to the above key nodes can effectively prevent the risk spreading in the system. (4) Supervising prudently the disorderly external guarantees of small and medium-sized issuers. The empirical analysis shows that the key nodes in the network are often the connection hub between one sub-network and another sub-network. It is more effective to rescue the key nodes when regional risk events occur. Once such a risk-contagion network with scale-free attributes evolves into a random network, the contagion mechanism will be more diverse and the efficiency of external assistance will drop significantly. Previous study show that the small-world bank network structure with the same number of nodes has the weakest stability in the face of external impact, while the scale-free network structure has the strongest stability. Therefore, it is necessary to prudently supervise the disorderly external guarantees of small and medium-sized issuers (non-key nodes with less connectivity within the system), preventing the existing guarantee circle from evolving into a random network structure.

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