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Default contagion and systemic risk in loan guarantee networks

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Abstract

This paper studies systemic risk in the Chinese debt market stemming from inter-corporate loan guarantees using field data from Zhejiang Province. We apply a weighted and directed network model to analyse the implications for default contagion and systemic risk under different stress testing scenarios. The empirical results indicate that the topology of the loan guarantee network is close to a ‘scale-free’ structure, which is known to be robust against accidental failures but vulnerable to coordinated attacks. Hence, the network is able to cope with idiosyncratic shocks resulting from single company failures, but can easily suffer from more widespread contagion if a group of systemically important companies are hit by a targeted shock. We further demonstrate that within our sample of small and medium-sized enterprise (SME) companies, increasing leverage reduces network stability and exacerbates the effects of contagion. More lenient bank lending policies increase the survival rate of sample companies and thereby reduce the losses from default contagion.

Key words: Loan guarantee network; SMEs financing; Default contagion; Systemic risk; Stress testing

JEL classification: G18, G23, G28, G33, G38

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1. Introduction

Several textile manufacturers in the city of Shaoxing defaulted on their debt payments in the wake of the global financial crisis in 2008. The resulting domino effect eventually spread to the entire Zhejiang Province underscoring the relevance of network effects for the overall impact of debtor default (Zhang, 2011; Wang and Yi, 2012). In this particular case, so-called loan guarantees played an important role, i.e., the promise given by the guarantor to assume the debt obligation of a borrower in case of default. These contractual commitments are widely used in many countries to alleviate the borrowing constraints facing small and medium-sized enterprises (SMEs) including China (EBCI, 2014). In this article, we are using unique field data from the city of Wenzhou in Zhejiang Province to study risk contagion of company defaults within such a loan guarantee network.

SMEs are often limited in their capacity to access bank credit due to insufficient collateral, lack of credit history, and sometimes even an inadequate professionalisation of the finance function. The information asymmetry that exists between companies and financial institutions, in the absence of adequate collateral, can explain negative responses to loan requests (Cusmano, 2012). Many Chinese SMEs find themselves in this predicament and therefore use loan guarantees as alternative means of accessing bank finance. Moreover, due to the lack of government guarantee schemes, bilateral or multilateral loan guarantees are commonly arranged among companies to support private lending.

Figure 1 depicts a typical loan guarantee structure between two companies A and B, with B providing the loan guarantee to A so that the latter can access a bank loan. The graph also highlights the potential paths for loss propagation in case of default. It is well documented that many Chinese SMEs are tied up in such loan guarantee schemes resulting in a highly interconnected network (Zhang *et al.*, 2012; Niu *et al.*, 2017). Each linkage forms a path for shock propagation among companies in case of default. High connectivity entails the potential of cascading failure that can lead to the breakdown of the entire loan guarantee network (Allen *et al.*, 2010). Network disintegration ultimately represents a systemic risk for the banking sector as a whole which can also spill over into the real economy. Hence, central banks and financial oversight bodies have the task of addressing this issue at the source.

In this article, we apply network analysis to analyse the risk implication of default. We model inter-corporate loan guarantees using a weighted directed network,[1] based on which stress testing is performed to evaluate network

[1]In a weighted directed network, edges are associated with directions and weights. For the loan guarantee network, the direction and weight of each arrow represent the corresponding direction of loss transmission and the size of the contingent loan guarantee liability, respectively.

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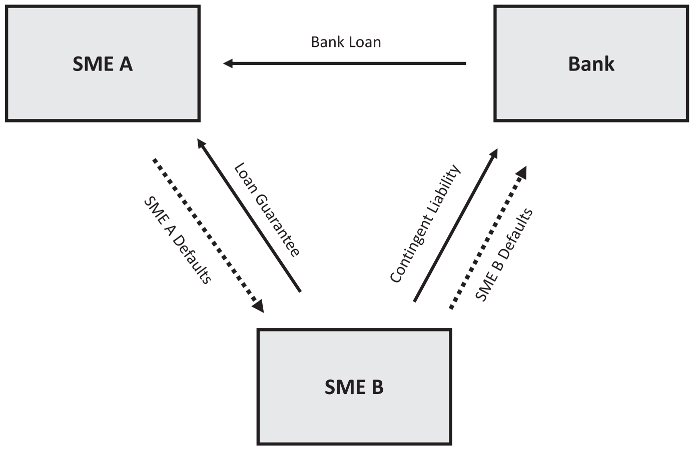

Figure 1 Example of a simple loan guarantee between companies A and B (black lines) and the potential loss propagation paths in case of default (dash lines).

stability under various scenarios. Our findings suggest that the topology of the loan guarantee network is close to a scale-free network structure, in which there exists a small number of nodes acting as ‘hubs’, while the majority are at the ‘periphery’. As shown by Barabási (2009), the scale-free property implies that it is robust in case of random attacks, but fragile when it comes to targeted attacks aimed at highly interconnected nodes. Our stress testing analysis confirms the robustness to idiosyncratic shocks and the fragility when a group of companies are hit, especially when it affects those with high centrality. As an extension to Modigliani and Miller (1958), we find that rising debt levels not only increase the likelihood of financial distress of individual companies, they also augment systemic risk in the network. Finally, our simulation results demonstrate that the provision of credit support during a crisis period is a vital ‘safety net’ that helps more companies to survive and also reduces the aggregate losses caused by default contagion.

The remainder of this paper is organised as follows. Sections 2 and 3 respectively describe the related literature and dataset. Section 4 presents the analytical construction of the loan guarantee network. Section 5 introduces the network topology and Section 6 the construction of debt contagion for the subsequent simulation analysis. Section 7 discusses the results of the stress testing analysis and Section 8 concludes.

2. Related literature

After the 2008 global financial crisis and the subsequent European sovereign debt crisis in 2011, the application of network theory to finance has attracted more attention than ever before. A series of theoretical contributions have

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focused on the relationship between the structural properties of financial networks and their resilience to systemic risk. A number of earlier works are still milestones in the field. Diamond and Dybvig (1983) study liquidity shortage in interbank deposits and claim that cross-holding of deposits helps to share liquidity risk across different banks. In the case of a bank default, cross-holdings will, however, turn into the most likely channels for loss propagation. Similar insights are discussed in Bhattacharya and Gale (1985) who examine the effect of liquidity shocks on interbank borrowing and lending.

The seminal work of Allen and Gale (2000) analyses contagion in a simplified four-bank network to confirm that the stability of the interbank market depends on its network topology. The authors argue that diversification, measured by the number of linkages between nodes (financial institutions), enhances system stability. Complete networks, where all nodes are equal to one another (all have the same bilateral obligations), are more robust than incomplete ones with a more sparse structure. Freixas *et al*. (2000) reach a similar conclusion and argue that complete networks embed the smallest risk of contagion, while the failure of a highly interconnected node is likely to trigger a systemic event. Hence, a credit chain structure of the type found in our data renders the banking system more fragile. Just like Allen and Gale (2000), Castiglionesi and Navarro (2008) study contagion in the interbank market using a four bank model and incorporate moral hazard into the analysis. The interbank network thereby acts as an insurance mechanism for banks with liquidity needs. The authors claim that a high level of connectivity increases systemic risk, because banks tend to seek more risky investments given the greater insurance effects derived from the network.

Gai and Kapadia (2010) develop an analytical model of contagion in financial networks with arbitrary structure and explore how the probability and potential impact of contagion is influenced by aggregate vs. idiosyncratic shocks, as well as changes in network structure and asset market liquidity. The authors claim that financial systems exhibit a robust-yet-fragile tendency: while the probability of contagion may be low, the effects can be extremely widespread when problems occur. This is confirmed by our work. Acemoglu *et al*. (2013) point out the robust-yet-fragile nature of complete networks, which tend to be considerably more fragile than sparse ones. In line with this insight, Eboli (2019) reach the conclusion that both complete and star-shaped networks, show the 'robust-yet-fragile' property, while the incomplete regular and cycle-shaped networks are found to be less robust than the more complete ones.

In recent years, simulation-based studies have also gained in popularity. As one of the seminal contributions, Eisenberg and Noe (2001) develop an algorithm to quantify systemic risk in financial market clearing and the implied default risk faced by each participant. Rogers and Veraart (2013) extend this framework by introducing the cost of default through a recovery function that drops discontinuously at the default boundary and then decreases linearly with

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the amount of assets available. Along similar lines as our study, they discuss the extent to which institutional consortia may have the means and incentives to rescue failing banks.

Furfine (2003) introduces a sequential default algorithm, which has been widely applied in many studies, to simulate risk contagion. The algorithm defines a default cascade in which the contagion is triggered by the failure of a randomly selected bank, and then the credit loss is passed on to other banks through the directed linkages. Once a bank has reached negative capital, it is considered in default. The contagion process terminates, if no additional bank fails in the current round. Our study employs the same logic.

Cifuentes *et al*. (2005) introduce a model which takes the effects of 'fire-sales' of illiquid assets into consideration. They show that if the demand for illiquid assets is less than perfectly elastic, forced sale may depress the market prices of such assets, and marking-to-market of the asset book can induce a further round of endogenously generated sales of assets, depressing prices further and inducing even more sales. Battiston *et al*. (2012) introduce a simulation algorithm to compute the DebtRank, which is a measure of systemic risk. The DebtRank, similar to the Google PageRank, measures the fraction of the total economic value in the network that is potentially affected by the default of a given company. Data limitations have prevented us from linking our analysis to these contributions more explicitly.

While banking networks have been widely explored, the examination of inter-corporate lending networks is still in its infancy, largely due to the limited availability of data. Yang *et al*. (2014) investigate Chinese credit linkage networks and show in their simulation that contagion spreads in a linear form, i.e., as the scale of the initial shock grows, the total number of firms in default and the volume of bad loans both increase linearly. Our study does not confirm this result. Niu *et al*. (2017) propose a hybrid representation of guarantee networks by applying a gradient boosting model for credit risk assessment. They find that often hundreds or thousands of enterprises back each other and constitute a sparse complex network. This study builds on this insight with a unique data set.

This study contributes to the existing literature in several ways. First, we present the first in-depth empirical analysis of contagion and systemic risk in the Chinese inter-corporate loan guarantee market based on real-world data from a field research study. By means of a sequential default algorithm, we develop an analytical framework to simulate the paths of default contagion and to evaluate its consequences. Second, while so far most of the studies on systemic risk have focused on interbank networks, our analysis provides one of the first attempts to explore the question from a corporate perspective, with a special focus on SMEs. Third, when modelling the loss cascade process, distinct from other studies on interbank networks (e.g. Furfine, 2003; Upper and Worms, 2004), in which interbank assets and liabilities are used to compute the contagion threshold, we propose a new capital threshold measure which better

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captures the capital structure and financing capability of SMEs by taking into consideration both the off-balance sheet private lending debt and the unused bank credit line.

3. Data

The dataset used in this study consists of the loan guarantee and other financial data of 575 local private companies based in the city of Wenzhou in Zhejiang Province. Effective date is 31 May 2015. Wenzhou is well known for its private economic and financial activities in China and is therefore a representative case for studying the effects of debt contagion. The data has been supplied by the Customer Risk Monitoring and Early Warning System of China Banking Regulatory Commission (CBRC) and has subsequently been augmented by our own calculations using the results of the empirical analysis. Supplementary surveys of selected sample companies confirmed the accuracy of the data. Confidentiality requirements prevent us from reporting sector identities and company names. See Table 1 for an overview.

Table 2 shows the descriptive statistics of our sample. The dataset consists mostly of SMEs with a size of assets ranging from CNY 3.03 million up to CNY 2291.20 million. Mean and median of the total assets are CNY 210.98 million and CNY 155.10 million respectively, while average net assets are CNY 119.59 million. The average loan guarantee exposure of each company is CNY 29.43 million. Unused bank credit lines represent the most important refinancing source for many Chinese SMEs; their aggregate availability is substantial for our sample. Overdue loans signal deteriorating liquidity, while non-performing loans deliver a much stronger message of potential insolvency.

Companies are categorised into three different risk classes based on whether bank loan payments are overdue for < 90 days and whether bank loans are non-performing (payments overdue for more than 90 days). The classification follows international norms. For our sample, 39 percent of the companies have been struggling to service their debt according to the contractual schedule and 26 percent of them were in a state of financial distress at the cutoff date of 31 May 2015, implying a significant probability of default.

(1) Risk class 1 (Low risk): no overdue or non-performing bank loan (61 percent of sample companies).
(2) Risk class 2 (Medium risk): overdue bank loan, no non-performing bank loan (13 percent of sample companies).
(3) Risk class 3 (High risk): non-performing bank loan (26 percent of sample companies).

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Table 1
List of available data and sources

Name	Symbol	Description	Source
Total assets	TA_i	In-balance sheet total asset	CBRC
Total liabilities	TL_i	In-balance sheet total liability	CBRC
Net assets	NA_i	Total asset - Total liability	CBRC
Loan guarantee	L_i	Contingent loan guarantee liability	CBRC
Unused credit lines	LOC_i	Unused credit lines of the year	CBRC
Bank loan	BL_i	Total amount of bank loan	CBRC
Overdue bank loan	OBL_i	Total amount of overdue bank loan	CBRC
Non-performing bank loan	NBL_i	Total amount of non-performing bank loan	CBRC
Debt ratio	δ_i	Total liability/Total asset	own cal.
Private lending ratio	β_i	Total private lending debt/total in-B.S. liability	own cal.
Recovery rate	θ_i	% of loss recovered	own cal.
Bank lending policy parameter	γ_i	% of unused bank credit line granted	own cal.
Capital buffer	K_i	Capital reserve of company i	own cal.
Defaulted company	D	A set of companies in default	own cal.
Default impact	DI_i	Capital losses due to contagion	own cal.
Edge weight	w_{ij}	Weight of each edge, $w_{ij} = L_{ij}$	own cal.
(In-/Out-) degree	k_i^-, k_i^+, k_i	(In-/out-) degree	own cal.
Rounds of contagion	m	Rounds of contagion	own cal.

Table 2
Descriptive statistics of variables (CNY million)

Variable	Symbol	Max	Min	Mean	Median
Total assets	TA_i	2291.29	3.03	210.98	155.10
Total liabilities	TL_i	1325.47	0.44	91.39	59.67
Net assets	NA_i	1156.51	–105.17	119.59	92.24
Loan guarantee	L_i	827.70	0.00	29.43	7.00
Unused credit lines	LOC_i	972.97	0.00	28.91	10.61
Bank loan	BL_i	637.05	0.20	57.00	35.00
Overdue loan	OBL_i	367.54	0.00	11.95	0.00
Non-performing bank loan	$NBLi$	324.74	0.00	8.00	0.00

4. Loan guarantee network

Loan guarantees connect companies through the implied set of contingent claims. It functions similarly to interbank networks on the basis of the banks' asset and liabilities (Boss *et al.*, 2004) or payment networks implied in the flow

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of interbank payments (Soramäki *et al.*, 2007). Let all loan guarantees be represented by the matrix $L \in \mathbb{R}^{n \times n}$, in which each element L_{ij} represents a bilateral contingent guarantee commitment of company j to company i (i.e., company i is guaranteed by company j). We assume $L_{ij} \geq 0$ (if $i \neq j$), and $L_{ij} = 0$ (if $i = j$). In later sections of this article, we will use the company identifier in a similar fashion: i represents a company triggering contagion, while j is a guarantor receiving claims due to i's default.

The resulting loan guarantee network can be depicted with a weighted directed graph $G = (V,E)$. $V = \{1, \ldots n\}$ represents the set of companies that are the nodes (vertices) of G; E are the edges of G that depict the links between companies i and j based on loan guarantees. Figure 2 presents the loan guarantee network G for our sample of 575 companies from Zhejiang Province as of 31 May 2015.

A is defined to be the adjacency matrix of G in which each element a_{ij} indicates whether company j has a loan guarantee liability to company i (i.e. $a_{ij} = 1$ if $L_{ij} > 0$, otherwise $a_{ij} = 0$). Finally, W is the corresponding matrix of edge weights, in which the weight of the edge from node i to j equals the amount of contingent guarantee liability of company j to company i ($w_{ij} = L_{ij}$).

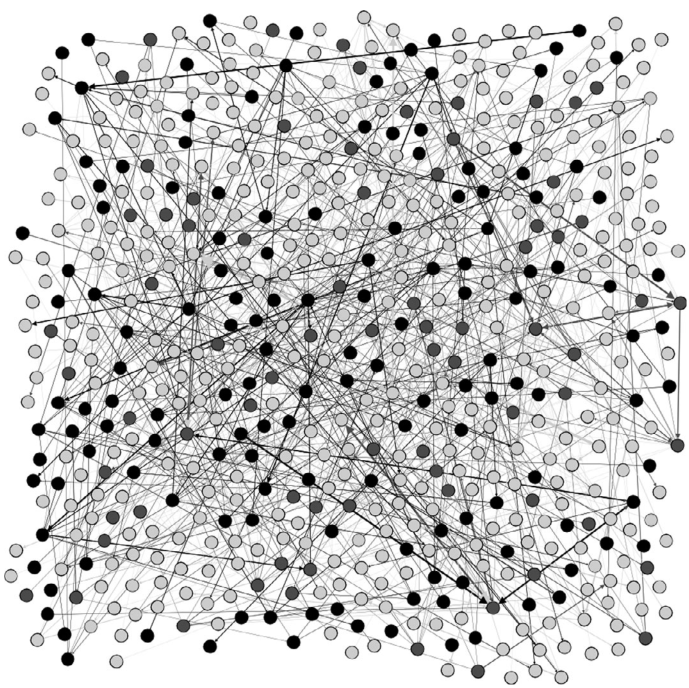

Figure 2 Loan guarantee network G consisting of 575 companies from Zhejiang Province as of 31 May 2015. Nodes are coloured according to their risk classes: light gray for risk class 1, gray for risk class 2 and black for risk class 3. The colour of each edge represents the risk class of the source node.

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5. Network topology

5.1. Degree

Degree measures the connectivity of a node in a network. A node is considered to be more influential or systemically important to others if it has a higher degree value (Freeman, 1977). Define the in-degree (k_i^-) of node i as the number of inward edges adjacent to it; correspondingly, the out-degree (k_i^+) is the number of outward edges.

$$k_i^- = \sum_j a_{ji} \quad k_i^+ = \sum_j a_{ij} \tag{1}$$

where a_{ij} and a_{ji} are the elements from the adjacency matrix A. They represent the inward and outward edges linked to node i. For a directed network, the degree (k_i) is the sum of number of in-degree and out-degree connections of a node.

$$k_i = k_i^- + k_i^+ \tag{2}$$

Figure 2 reveals the presence of nodes with widely differing connectivity. This observation is further confirmed by analysis of the in-degrees and out-degrees of nodes as shown in Figure 3, in which the size of nodes represents the corresponding (i) in-degree and (ii) out-degree values of the nodes (i.e., the larger the size of the node, the higher the in-degree or out-degree value). In sum, only a few companies have very high connectivity, thereby acting as the ‘hubs’ of the loan guarantee network.

Figure 4 display the degree distribution $P(k)$ for the sample. We notice that the distributions of k_i, k_i^- and k_i^+) are all skewed to the right and follow a power law distribution. This indicates that the topological structure of G is close to ‘scale-free’, which implies that it is robust in the case of accidental failures but vulnerable to coordinated attacks (Barabási, 2009). This property invites the scrutiny of regulatory bodies and financial market watchdogs as cascading losses can spill over into the banking sector and may even affect the real economy.

5.2. Small world

Another important property often found in real-world networks is the small world effect, which refers to the phenomenon that the distance between any two nodes in a network is very small, even though the network size is large. Boss *et al.* (2004), for example, find that the Austrian interbank network has an average shortest path length of 2.26, meaning that it takes less than three steps to go from any one node of the network to another. In a small world network,

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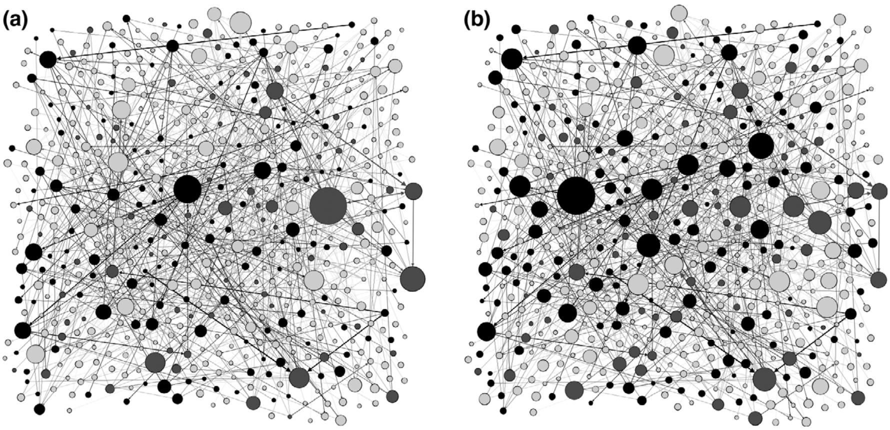

Figure 3 Illustration of (a) in-degree (k_i^-) and (b) out-degree (k_i^+) of the loan guarantee network; size and colour of the nodes represent the corresponding in-degree or out-degree values and risk classes respectively.

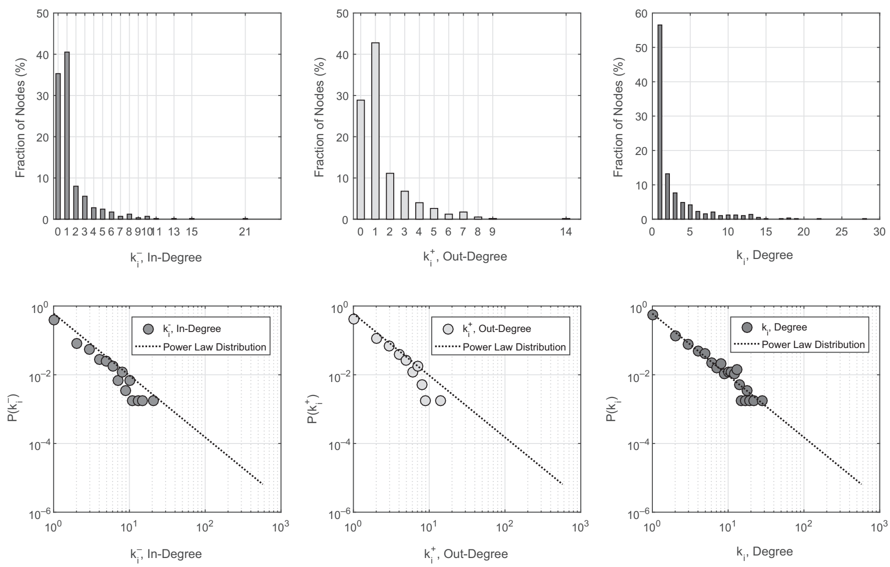

Figure 4 Distribution of frequency of In-Degree (k_i^-), out-degree (k_i^+), degree (k_i) (first row from left to right). Power law log-log plot of in-degree (k_i^-), out-degree (k_i^+), degree (k_i) (second row from left to right).

several highly interconnected 'hubs' are acting as the 'bridges' linking different parts of the network. As the shortest path length shrinks, economic or financial shocks travel much more quickly throughout the network, implying a greater exposure to systemic risk.

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Our loan guarantee network G has an average shortest path length of 5.13, suggesting the presence of a small world effect with about 5 degrees of separation. When considering its diameter, i.e., the length of the longest geodesic path between any two nodes in terms of number of edges, it is 19 for our sample and therefore about four times as large.

5.3. Clustering coefficient

The statistical method for measuring the clustering of a node i in a network is the (local) clustering coefficient (Watts and Strogatz, 1998). It measures how close a node's neighbours are to being a fully connected (or complete) network.

For loan guarantee network $G = (V,E)$, we define N_i as the neighbouring nodes which are directly connected to node i:

$$N_i = \left\{ \upsilon_j : e_{ij} \in E \vee e_{ji} \in E \right\} \tag{3}$$

The local clustering coefficient c_i for node v_i is then defined as the proportion of linkages between the number of linkages that could possibly exist between them. For a directed graph, e_{ij} is different from e_{ji}, and therefore for each neighbourhood N_i there are p_i (p_i −1) links that could exist among the vertices within the neighbourhood (p_i is the number of neighbours of a vertex). Thus, the local clustering coefficient for directed graphs is given as.

$$c_i = \frac{\left|\left\{ e_{jp} : \upsilon_j, \upsilon_p \in N_i, e_{jp} \in E \right\}\right|}{p_i(p_i - 1)} \tag{4}$$

where e_{jp} is the number of connected pairs between all neighbours of node v_i. c_i is between 0 and 1, and measures how interconnected among themselves the neighbours of a node are.

Figure 5 reports the relationship between the clustering coefficient c_i and the degree k_i. The negative slope of the plots suggests that companies with a low number of linkages (small degree value) are more likely to connect to neighbours that are highly interconnected with each other (large clusters), whereas companies with a high number of linkages are more likely to connect to sparsely connected neighbours. The average local clustering coefficient $\overline{c}_i$ is 0.0258, which is relatively small compared to other real-world networks.

5.4. Assortativity

We further investigate the network assortativity by examining the rich-club coefficient. A rich club effect emerges when nodes with high centrality tend to connect with each other (Alstott *et al.*, 2014). The existence of a rich club effect has an important impact on the stability of the network, as through these

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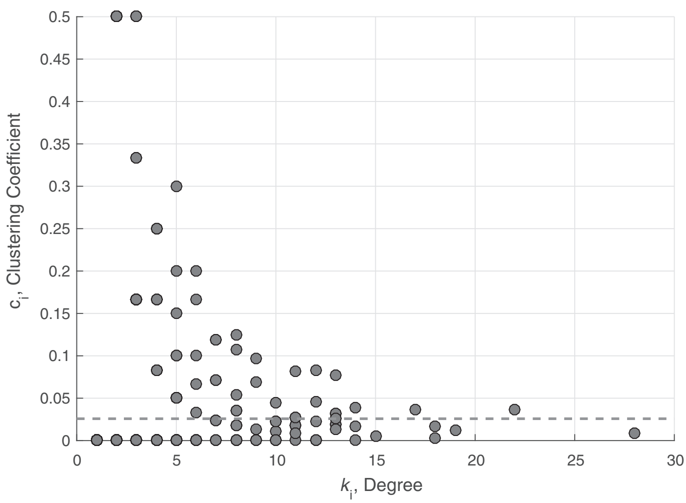

Figure 5 Clustering coefficient (c_i) vs. degree (k_i). The dashed line represents the average clustering coefficient.

highly interconnected 'hubs', disruptions can be transmitted within the network much more easily.

For the loan guarantee network $G = (V,E)$, we define $V_{>k}$ as the set of nodes with degree larger than k, $N_{>k}$ as the number of nodes with degree larger than k, and $E_{>k}$ as the number of edges connecting these nodes (Colizza *et al.*, 2006). The rich-club coefficient $\phi(k)$ is then given by:

$$\phi(k) = \frac{2E_{>k}}{N_{>k}(N_{>k} - 1)} \tag{5}$$

We further normalise this measure to account for the fact that nodes with higher degrees naturally tend to be more densely connected given that they have more incident edges (McAuley *et al.*, 2007).

$$\rho(k) = \frac{\phi(k)}{\phi_{unc}(k)} \tag{6}$$

where $\phi_{unc}(k)$ is the rich club coefficient of a maximally random network with the same degree distribution as the network under study. For a certain degree k, $\rho(k)> 1$ indicates the presence of a rich club effect.

Figure 6 depicts how the normalised rich club coefficient $\rho(k)$ is linked to the degree k. The results suggest the presence of a rich club effect for a considerable degree range. It emerges at around 4, peaks at $k = 13$ and continues to persist until around 19. Hence, nodes with 13 linkages are most likely to connect to each other.

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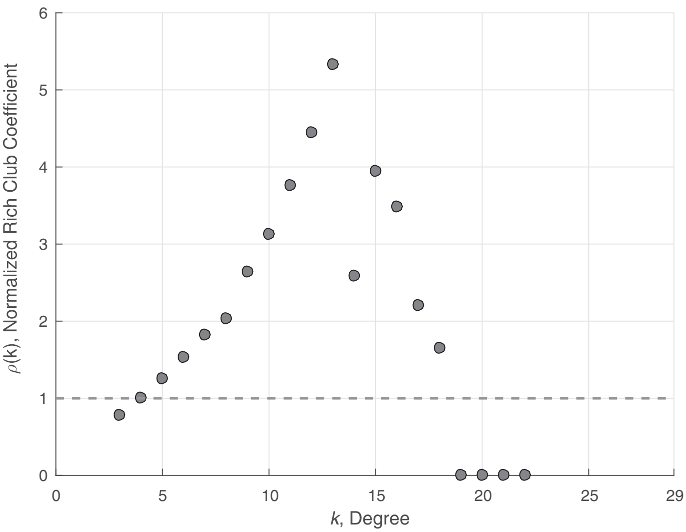

Figure 6 Normalised rich club coefficient $\rho(k)$ vs. degree k. The dashed line is the threshold line $\rho(k) = 1$.

6. Modeling default contagion

In this section, we develop the theoretical framework for the subsequent network stress testing simulation. Loan guarantees are assumed to get called upon as soon as they are 'in the money' and then cascade through the network without the legal process injecting time buffers to slow down contagion. The subsequent discussion relaxes these restrictions. The theoretical setup is divided into three parts: the definition of the capital threshold beyond which loan guarantees can be executed as well as the state of default and, finally, the characterisation of the loss cascade process and the role of bank lending policies in containing the loss spillovers.

6.1. Capital threshold and default

The balance sheet of a company in the loan guarantee network is described with its three main components: total assets (TA_i), total liabilities (TL_i) and net assets (NA_i). Off-balance-sheet financing consists of private lending (PL_i) and loan guarantees (L_i). Figure 7 shows the stylised balance sheet for a sample company.

Since we lack data on actual private lending, we introduce the private lending ratio β_i which describes the relationship between the total on-balance-sheet liabilities TL_i and the off-balance-sheet private lending TL_i for each company i.

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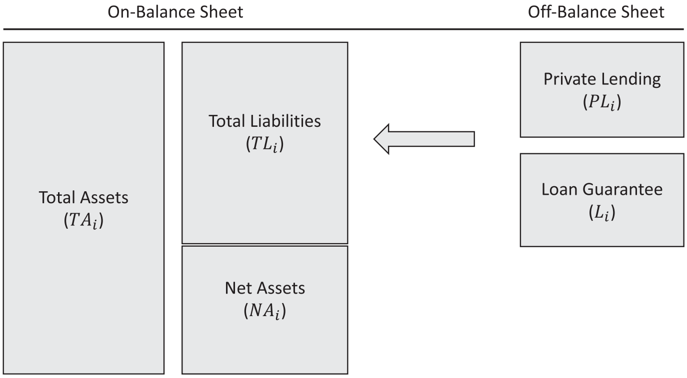

Figure 7 On-balance sheet and off-balance sheet items of company *i*.

$$\beta_i = \frac{PL_i}{TL_i} \tag{7}$$

The adjusted net asset position NA_i of company *i* defines the actual capital reserve once private lending is taken into account.

$$NA_i = TA_i - (1 + \beta_i) \times TL_i \tag{8}$$

Bank credit lines represent the most important refinancing source for many Chinese SMEs. They establish a maximum loan balance permitted by the lender and serve as an indication of the availability of new debt. A company's financing potential may, however, be negatively affected by risk concerns triggering the (partial) withdrawal of existing credit lines (as well as the rejection of new loan applications). Define LOC_i as the unused bank credit line of company *i* and $\gamma_i \in [0, 1]$ as the corresponding lending policy parameter. NL_i describes the availability of new loans to company *i*.

$$NL_i = \gamma_i \times LOG_i \tag{9}$$

If $\gamma_i = 0$, then banks are not willing to issue any new loans, whereas $\gamma_i = 1$ corresponds to full lending support in line with previous commitments. The combination of adjusted net assets and available new loans signifies the maximum shock that the company can cope with. We refer to it as the capital threshold.

Definition 1 (Capital Threshold)

The capital threshold (K_i) of company *i* is the sum of its net asset (NA_i) and available new loans (NL_i).

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$$K_i = TA_i - (1 + \beta_i) \times TL_i + \gamma_i \times LOC_i \tag{10}$$

A company is technically in default when it fails to fulfil its interest and debt repayment obligations. Default arises either from the lack of liquidity or from over-indebtedness (Ross *et al.*, 2012). Both require credit workout, either in pre-bankruptcy proceedings or during legal bankruptcy administration. While liquidity problems can be temporary in nature, a negative net worth is often an operational issue as well, requiring more fundamental restructuring. Following (Lo, 2011), we argue that over-indebtedness is the more relevant issue for predicting default. For the purposes of our study, we define default as follows:

Definition 2 (Default from Contagion)

A company defaults, if the losses from the loan guarantee liabilities exceed its own capital threshold.

We consider the case where defaults cascade through the network in an uninhibited fashion, meaning unsatisfied claims from one company's default lead to the immediate exercise of the loan guarantee (see Eisenberg and Noe, 2001; Upper, 2011; Rogers and Veraart, 2013). They are rolled over to other companies until all claims are satisfied. Thus, we are looking at the case where the legal process does not act as a potential buffer to slow down contagion. We further make the following simplifying assumptions.

Assumption 1 (Firm and Default Characteristics)

For the subsequent simulation analysis, we specify legal form, loan guarantee, and execution of guarantee commitment and default as:

(1) Each company has limited liability, i.e., the owners' wealth does not serve as collateral.
(2) The nominal value of the contingent loan guarantee liability equals the nominal value of the guaranteed debt (e.g. bank loan).
(3) Each company defaults on all of its debt indifferently; the repayment of existing debt during the liquidation process is also indifferent.
(4) After the default of one company, the net losses will immediately be passed on to its guarantors.

6.2. Loss cascade process

A loss cascade is a sequence of links through which a loss following default propagates in the network. Define m as the number of rounds of the cascade process, and $K^m(i)$ as the capital threshold of company i in round m. At the

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initial stage ($m = 0$), company i experiences a shock $\in_i > K^0(i)$ which results in its default. It leads to an immediate write-down of its debt and the exercise of the associated loan guarantees. Using the sequential default concept of Furfine (2003), we apply the following algorithm.

Algorithm 1 (Sequential Default Algorithm)

The algorithm simulates the loss contagion process based on the following steps:

(1) An initial shock (either targeted or random) is simulated to hit a company i or a group of companies, triggering the first round of contagion.
(2) For each round of contagion from 1 to m:

- the guarantee losses from round $m-1$ to any company j are subtracted from its capital threshold, and the new capital threshold after round m is recalculated. Any company with a negative capital threshold is then considered as defaulted.
- If at least one company defaults in round m, the algorithm repeats Step 2, otherwise goes to Step 3.

(3) The loss contagion stops, and the network is in a new equilibrium.

If $\theta_i \in [0, 1]$ represents the recovery rate for the company's debt, then i's default triggers losses of $(1-\theta_i) \times L_{ij}$ for each of its guarantors j. Due to the difficulty of determining the appropriate recovery rate in practice, we follow Furfine (2003) and test for different values for θ, which we, however, assume to be constant across companies. Without loss of generality, we ignore potential simultaneity problems. As pointed out in Upper (2011) and in contrast to Eisenberg and Noe (2001), the simulation does not account for higher-order defaults increasing losses at previously failed companies, which in turn may reduce the recovery rate on their liabilities.

The loss from the loan guarantee is imputed into the capital threshold of j. If it is smaller than its capital threshold, then the shock stops. Otherwise company j defaults as well, triggering a new round of losses to its guarantors. Company j's capital threshold after the first round of the cascade is computed as:

$$K^1(j) = \max\left\{K^0(j) - (1 - \theta_i)L_{ij}, 0\right\} \tag{11}$$

$K^1(j)$ is company j's capital threshold after the first round of contagion and $K^0(j)$ represents its initial capital threshold. In each subsequent round, we update the losses from the defaulted companies to the balance sheets of their guarantors and set the defaulted companies' capital thresholds to zero. The capital threshold of company j after m rounds of contagion is then given by:

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$$K^m(j) = \max\left\{K^0(j) - \sum_{c=0}^{m} \sum_{i \in D^{c-1}} (1-\theta_i)L_{ij}^c, 0\right\} \tag{12}$$

where $\sum_{c=0}^{m} \sum_{i \in D^{c-1}} (1-\theta_i)L_{ij}^c$ represents the total guarantee losses that company j has received during all m rounds and D^{c-1} is the set of defaulted companies in round $c-1$ or before (with $c = 1\ldots m$). At m, the set of defaulted companies D^m can also be characterised as a subset of the population of companies V; it represents the sum of initially defaulted companies and the companies not surviving one of the m rounds of contagion.

$$D^m = \left\{j \in V : K^0(j) = 0\right\} \cup \left\{j \in V : K^0(j) > 0, K^m(j) = 0\right\} \tag{13}$$

The loss cascade process is summarised in Figure 8 for an exemplary round m.

Following Cont *et al.* (2010), we can now define the default impact $DI(i)$ as the losses due to contagion from the default of company i alone.

Definition 3 (Default Impact)

We measure the impact caused by the default of company i with the default impact $DI(i)$, which is computed as the total loss of capital in the loss cascade process triggered by the default of company i:

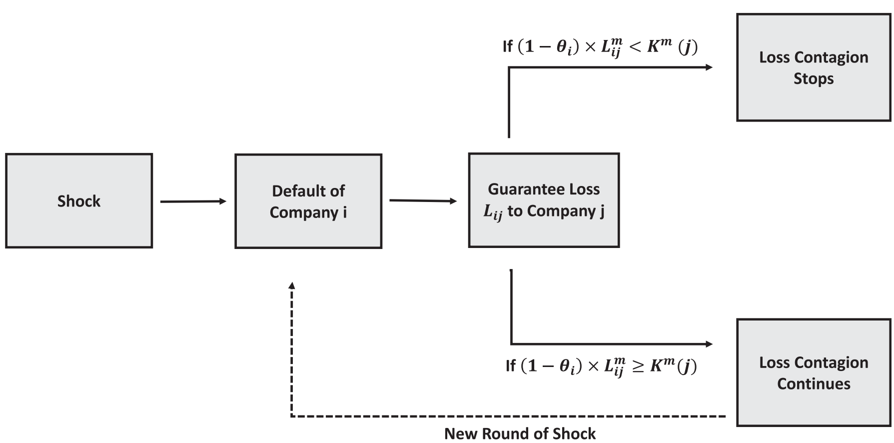

Figure 8 The loss cascade process in the loan guarantee network. θ_i is the recovery rate of guarantee losses of company i, L_{ij}^m is the guarantee loss of company j due to the default of company i, and $K^m(j)$ is the capital threshold of company j at an exemplary round m.

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$$DI(i) = \sum_{j \neq i} \left[K^0(j) - K^m(j) \right] \quad (14)$$

7. Stress testing analysis

This section presents the simulation-based stress testing analysis of the loan guarantee network G by applying the loss contagion algorithm proposed above. We start with a baseline scenario that reflects moderate market conditions. The focus of analysis is then shifted to how changes in the recovery rate will affect the outcome and how the system responds to random vs. targeted shocks.

7.1. Baseline scenario

In the baseline scenario, each company j starts out with an on-balance-sheet capital structure represented by $\delta_j^0 = TL_j^0/TA_j^0$ at the initial stage $m = 0$. Following, we illustrate the simulation results of a moderate case, in wich each company j in our sample ($j = 1, \ldots, 575$) is assumed to operate with a private lending ratio of $\beta_j = 0.3$ which represents the approximate average of the sample companies actually reporting this figure. We make the optimistic assumption that 50 percent of the bank loan can be recovered during the liquidation process, i.e., $\theta_j = 0.5 \forall j$.

Banks are believed to be risk averse and reluctant to take on high-risk projects. We select a moderate bank lending policy parameter of $\gamma_j = 0.5 \forall j$, i.e., 50 percent of the total unused bank credit line of the company can still be used. At the same time, we account for the fact than banks no longer issue new loans to companies with solvency issues by setting $\gamma_j = 0$ for any company j with an overdue or nonperforming loan (in risk class 2 or 3).

The baseline analysis assumes that one company fails at a time and then analyses its impact on the loan guarantee network. Table 3 reports results for the 20 firms with the highest default impact based on 575 simulation rounds, one for each sample company. The baseline analysis already delivers a concerning message regarding the potential impact of contagion. The default of company C0008 has the highest default impact with CNY 189.43 million capital loss, while the failure of B0020 triggers the default of 21 other companies. Company C0101 is found more prone to default than other companies, as it is more likely to be involved in the loss contagion process. Across the entire loan guarantee network, the failure of a single company triggers on average 1.8 rounds of loss contagion and 3.1 company defaults, causing an average default impact of CNY 112.35 million.

7.2. Sensitivity to recovery rate variations

The next step is to examine how variations of the recovery rate affect the stability of the loan guarantee network, while keeping the private lending ratio

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Table 3
Summary of the baseline scenario analysis with a static capital structure and with $\beta_j = 0.3$, $\theta_j = 0.5$ and $\gamma_j = 0.5\ \forall j$

		Default triggered by this company			Default triggered by other companies
No.	Company	No. of rounds of contagion	No. of defaulted companies	Default impact (CNY million)	No. of own defaults
1	C0008	4	14	189.43	0
2	A0038	3	12	185.71	2
3	C0017	3	17	177.81	4
4	C0043	3	9	177.39	4
5	A0099	3	15	172.16	0
6	A0063	3	4	166.30	1
7	B0020	4	21	165.85	0
8	C0101	3	6	164.32	8
9	C0041	3	11	156.30	1
10	A0004	2	7	156.28	1
11	A0056	2	5	154.49	1
12	A0039	2	9	153.88	1
13	C0107	2	2	151.75	1
14	B0007	2	2	150.81	1
15	B0011	2	3	150.55	1
16	A0054	2	8	148.13	1
17	B0016	2	5	147.29	1
18	B0010	2	7	145.50	1
19	A0035	2	4	143.75	4
20	C0039	2	6	142.11	2
Simulation Summary		No. of companies			575
		No. of simulations			575
		Avg. rounds of loss contagion			1.8
		Avg. no. of defaults due to contagion			3.1
		Avg. default impact (CNY million)			112.35

(β_j) and the bank lending policy parameter (γ_j) constant. Table 4 summarises the results. First of all, contagion occurs regardless of the choice of recovery rate other than in the unrealistic scenario of full loss recovery ($\theta_j = 1$). Second, and not surprisingly, we find that the contagion effect gets stronger as the recovery rate decreases. Third, and most remarkably, only few companies fail in our case due to contagion even if the recovery rate drops to zero. This can be explained by sample companies still having considerable capital reserves relative to their contingent loan guarantee liabilities. Thus, in contrast to evidence from interbank networks (e.g. Upper and Worms, 2004), the failure of a single company is unlikely to trigger a large-scale loss from contagion in this network. This is all the more noteworthy as our contagion algorithm is removing all the judicial buffers for slowing down network infection. The basic setup is therefore ideally suited to study the impact of crisis-triggered contagion.

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Table 4
Results of the sensitivity analysis with varying values of the recovery rate (θ_j). Other settings are $\beta_j = 0.3$ and $\gamma_j = 0.5$

	Recovery rate						
	$\theta_j = 1$	$\theta_j = 0.75$	$\theta_j = 0.5$	$\theta_j = 0.25$	$\theta_j = 0.1$	$\theta_j = 0.05$	$\theta_j = 0$
No. of companies	575	575	575	575	575	575	575
No. of simulations	575	575	575	575	575	575	575
Avg. round of contagion	0	1.4	1.8	1.8	2	2	2.4
Avg. no. of defaults due to contagion	0	1.7	3.1	3.8	4.3	4.3	4.6
Avg. default impact (CNY million)	0	78.31	112.35	137.46	139.80	145.95	162.23

7.3. Random and targeted shocks

Industrial specialisation renders a business community fragile by exposing companies to similar risk factors. Consequently, a highly concentrated network of industries/companies is more prone to systemic risk. The connections between companies in China are manifold and extend beyond industrial relatedness. They include family ties, friendship and, in particular, financing links via loan guarantees. These company linkages lead to the formation of risk clusters that may give contagion a much larger momentum. The next step of our analysis accounts for the possibility that groups of companies are hit by random or targeted attacks.

For the random shock scenario, the simulation starts with the failure of n randomly selected companies using a Poisson distribution. In contrast, the targeted shock scenario analyses the loss contagion triggered by the joint default of the n most systemically important companies at the initial stage (as measured by the adjusted out-degree). Table 5 shows the results for both scenarios. Average default impact increases with the number of companies in default and is considerably higher for targeted shocks. The latter can be taken as evidence that G has a scale-free topological structure that is comparatively robust under random shocks and fragile under the targeted shocks affecting highly interconnected nodes.

7.4. Lending policy constraints and contagion impact

Since the seminal work of Modigliani and Miller (1958), economists have devoted much effort to studying companies' financing policies. One of the consensus conclusions is that rising leverage increases the likelihood and the cost of financial distress (see Myers, 1984; Bradley *et al*., 1984; Hackbarth *et al*., 2006). In the final step of our analysis, we investigate how leniency vs. tightness of bank lending policies can help to cushion the effects of contagion.

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Table 5
Simulation results for random vs. targeted shocks with n representing the number of defaulting companies and the other parameters set at $\beta_j = 0.3$, $\gamma_j = 0.5$ and $\theta_j = 0.5$

	Random shock			Targeted shock		
No. of companies in the group	$n = 10$	$n = 20$	$n = 30$	$n = 10$	$n = 20$	$n = 30$
No. of simulations	100	100	100	100	100	100
Avg. round of contagion	2.1	2.9	3.5	3	3	4
Avg. no. of defaults due to contagion	13.8	19.2	32.1	20.4	24.5	36.9
Avg. default impact (CNY million)	764.42	1106.63	1988.39	815.48	1555.88	2714.46

Specifically, we compare the outcomes of three alternative lending regimes, $\gamma_j \in \{0, 0.5, 1\}$. As before, private lending ratio ($\beta_j = 0.3$) and recovery rate ($\theta_j = 0.5$) are set at moderate levels. We generate random shocks from a Poisson distribution to hit the loan guarantee network G, repeat the simulation 1000 times, and report the average results.

Several interesting findings are revealed by the simulation outcome presented in Figure 9. First, we notice that, as the level of debt (as described by debt ratio δ_j) in each company increases, the average survival ratio after a shock decreases from nearly 100 percent to slightly above 10 percent, together with a rising capital loss of up to CNY 1.70 billion. Notably, when the debt ratio exceeds 70 percent, more than 80 percent of the companies default. Second, rising levels of corporate debt cause larger contagion effects across the loan guarantee network. In particular, a jump is observed as the debt ratio starts to exceed 30 percent with as much as 70 percent of defaults caused by the contagion. In line with the findings of Upper and Worms (2004), this points to the existence of a critical threshold beyond which the effects of contagion become heavily accentuated within the loan guarantee network. After that, however, the contagion effects gradually attenuate, when the increasing leverage renders more and more companies insolvent at the initial stage. Moreover, bank lending support during the crisis also proves vital as a ‘safety net’ for SMEs. The results indicate that as much as 20 percent more companies can survive the shock under the full lending support setting compared to the other two scenarios.

8. Conclusion

In this article, we investigate the potential fragility of the inter-corporate loan guarantee market in China in terms of default contagion. Our analysis delivers a strong narrative regarding the usefulness of network theory for the detection of systemic risk. In particular, the simulation-based framework proposed in this article provides important insights for both regulatory authorities and financial institutions. By adopting a network focus, regulatory bodies can

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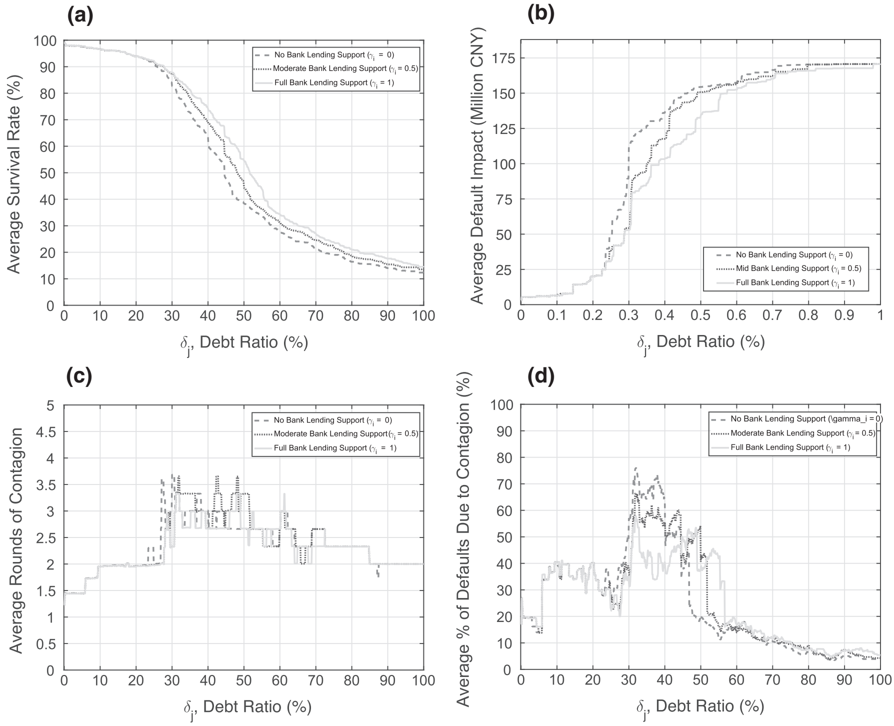

Figure 9 Summary of the simulation results for three alternative bank lending policy regimes ($\gamma_j = 0$, $\gamma_j = 0.5$, $\gamma_j = 1$) with $\theta_j = 0.5$ and $\beta_j = 0.3$. Plots (a) and (b) respectively display the average survival ratio (in percent) and the average default impact. Plots (c) and (d) respectively present the average rounds of contagion and the percentage of defaults due to contagion.

strengthen their early warning systems using simulation-based tools and network-analytic indicators. Along the same lines, financial institutions can develop a more robust understanding of their actual risk position.

Moreover, our analysis also suggests that it may be beneficial to establish a more centralised government guarantee programme or credit guarantee scheme (CGS), similar to the SBA's 7a loan program in the US and the Enterprise Finance Guarantee (EFG) programme in the UK, in which the government is acting as the lender of last resort (LOLR). Government intervention can help to dampen the strength of loss cascades and thereby help more companies to survive (targeted) shocks. Given the generally significant deadweight costs of financial distress and bankruptcy, we conjecture that such public policy actions will overall be welfare enhancing.

While our analysis delivers a strong narrative for more attention by oversight bodies, it comes with an important caveat which makes our research exploratory in nature. The sample used in this study is fairly small and, given

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the focus on a sub-region within Zhejiang Province, is likely to entail various biases. Follow-up work therefore needs to deliver a better understanding of geographical and sectoral differences. As an added benefit, it can help to clarify how supposedly contained crises can infect other sectors and geographies.

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