Evolution of the Chinese Guarantee Network and Its Implication for Risk Management: Impacts from Financial Crisis and Stimulus Program

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Abstract: The guarantee relationship refers to the responsibility of a firm for another one’s financial obligation if that firm failed to meet its obligation, thus it might lead to potential risk contagion under negative market condition. Examining the topological properties of networks formed by such guarantee relationships is critical for an in-depth understanding and effective regulations of the financial risk. In this research, we analyzed the structure and evolution of the Chinese guarantee network with five years’ worth of real-world data from January 2007 to March 2012. We identified the scale-free and power-law properties of the guarantee network, and found the 2008 global financial crisis and economic policies in the aftermath (i.e., Chinese economic stimulus program and loose monetary policies, and latter adjustment) had significant influence on the evolution of guarantee network structure. In particular, the empirical and simulation results provide evidence that (a) before the stimulus program was implemented, the guarantee network became smaller because of the huge number of bankruptcies of small and medium firms caused by the global financial crisis; (b) the loose monetary policy along with the stimulus program increased the mutual guarantee behavior between firms, resulted in highly reciprocal and fragile network structure. The following adjustment of the monetary policy reduced the ratio of mutual guarantee relationships, and enhanced the resilience of the whole guarantee network.

1. Introduction

The guarantee relationship between two firms representing the responsibility of a firm (the guarantor) to assume the debt obligation of a borrower firm if that firm failed to meet its legal obligation of a loan (defaults) [1]. Through such interdependencies, firms are connected as a guarantee network. Loan guarantees could enhance the financing ability of firms, especially small and medium enterprises/firms (SME), thus facilitates the rapid growth in the economic upturn period. However, potential risks could emerge from the binding between firms in this guarantee network in the economic downturn period [2]. As a result, there is an elevating risk of cascading failures in the guarantee network during the economic recession period. Because of the interdependencies between these firms, the failure of one firm could cause successive failures of multiple firms, resulting in serious crisis of the system.

In 2008, with the breakout of global financial crisis, Chinese government announced the economic stimulus program worth of RMB ¥4 trillion (US $586 billion) on 9 November 2008 in order to reduce the impact of the global financial crisis on Chinese economy. This program aimed
to resist the negative impact from the financial crisis by investing hugely in infrastructure and social welfare by 2010. The credit condition was also loosen to help encourage loan application from firms [3]. This stimulus program, though successfully sustained China’s economic growth and largely stabilized the world economy [4], has resulted in a surge in debt in China, and dramatic structural change of China’s guarantee network. There was a huge amount of loans going to SMEs, many of which were not eligible for loans before the stimulus program. These SMEs could meet the new credit standard to get loans from banks through guaranteeing each other [5]. Although many of these SMEs were saved by these loans, economic studies and critics suspected that the stimulus program could cause explosion of credit debt and trigger future financial contagions because of failures of these SMEs. For example, Dr. Yifu Lin, the former chief economist and senior vice president of the World Bank, expressed his concern about the bad effect of stimulus program on China’s economy [6]. Other renowned economists, like Dr. Weiying Zhang and Dr. Zhiwu Chen, also warned that the stimulus program would lead to mal-investment, and might not be helpful in the long run [7, 8].

Decision makers also recognized such risk after the surge in debt in 2009, and took some actions to regulate the debt behavior. In March 2010, the central government’s work report delivered at the 11th National People’s Congress stated that the government planned to improve macro-control regulations in 2010. Since then, the People's Bank of China (the central bank of PRC) increased the reserve requirement ratio for five times in 2010 (from 15.5% to 18%). The major change of the monetary policy operations occurred on Oct 20th, 2010, when the People’s Bank of China raised the interest rates for the first time since the global financial crisis. These regulations and policy changes, to some extent, helped reduce the impact of the negative consequence of the stimulus program.

In the recent years, such risk led to a number of events of cascading failures among firms, due to the non-performing loans and high default rate of these SMEs [9, 10]. For example, Wenzhou, one of the richest economic hubs in China, has witnessed a debt crisis in 2012, and resulted hundreds of private companies went bankrupt like dominoes, leaving billions of bad debts to banks. The crisis was caused by banks collecting debts. Four big companies were unable to repay private loans, which were with a high interest rates (over 20%). The failure of these four companies affected 600 other companies through the mutual credit guarantee relationships among firms [http://www.scmp.com/business/banking-finance/article/2086186/debt-distress-shandong-province-illustrates-risks]. The incident dramatically increased the banks’ non-performing loans ratio to a decade high, and forced banks to more aggressively call in loans from all involved firms, leading to broader corporate collapses.

Despite the qualitative critics and studies on the stimulus program, little is known about the changes of the guarantee networks and how these changes are linked to the risk of cascading failures. There is a critical need for data-driven quantitative studies of the guarantee network and its associated risk. A good understanding of the guarantee network’s dynamic structure could enhance the decision-making process for economic policy through identifying the potential systemic risks such as the domino-like cascades of failures discussed above. However, how to leverage real-world guarantee data to model such behaviors and the overall structure of the guarantee network remains a challenge.

Network science presents a natural and promising way to address the challenge in modeling and analyzing guarantee networks. Network science focuses on the interactions between the elements of a complex system in order to discover the nature and underlying patterns of interaction relationships inside the system. It has been widely applied to model structure or dynamics of real-
world complex systems. Recently, network science has also been applied in finance research. For example, network science techniques have already been applied extensively to the global banking system [11], international financial network [12], interlocking boards of directors [13-15], corporate governance and corporate ownership links [16, 17]. The guarantee interdependencies between firms can be naturally represented as networks, in which each node represents a firm, and each (directed) edge represents the guarantee relationship between the two corresponding nodes. From such a guarantee network, we can capture the contagion path of obligations and failures. Using methods in network science to analyze the networks formed by guarantee relationships could fill the research gap in data-driven insights of how the topological structure of guarantee network is associated with economic policies and contagion risks, and help decision makers identify the potential systemic risks caused by firms’ failures (i.e. defaults) [18].

Existing research on guarantee networks mainly focused on analytics of small sampled data with only dozens or hundreds of firms, which led to useful insights for risk assessments with a high resolution. However, the results of small-scale network analysis were usually limited to the sample, and may not be consistent for other datasets. It is difficult to generalize the results for the entire guarantee system [2, 9, 19, 20]. Large-scale empirical studies of the state-wide guarantee networks are needed to understand the global topological properties of the guarantee system, and to inform effective risk management for decision makers. In this research, we use a comprehensive data provided by the China Banking Regulatory Commission (CBRC) ranging from January 2007 to March 2012 to investigate the structure and evolution of Chinese guarantee network, and examine how the changes of the guarantee network are associated with the potential risks of cascading failures. In particular, we aim to answer the following questions:

- What are the unique topological properties of the Chinese guarantee network?
- What is the influence of 2008 global financial crisis and China’s stimulus program in the topological structure of Chinese guarantee network?
- Does the change of topological structure of Chinese guarantee network influence the resilience of the system?

The contribution of this research is twofold. First, to the best of our knowledge, this is the first attempt to quantitatively characterize the evolution of the entire Chinese guarantee system as a complex network. Second, we quantitatively evaluate the relationship between economic policies and the structure of guarantee networks. The empirical and simulation studies provide evidence that the loose monetary policy along with the stimulus program led to the mutual guarantee behavior between SMEs, resulted in highly reciprocal and fragile network structure. The new angle gives the policy makers an in-depth understanding of national policy and provide instructions for the future policy-making.

The remainder of this paper is structured as follows. In section 2, we present the literature review. Section 3 describes the methodology, including data set, network construction and explanation of topological properties. Section 4 presents the dynamic analysis of topological and financial properties of guarantee network. In section 5, we do a simulation study to test the stability of guarantee network to verify the effects of economic policies. Section 6 summarizes the paper with implications, conclusions and opportunities for future research.

2. Related work
2.1 Network analytic perspective

In the past decade, complex network has emerged as an effective tool to model and study real-world complex systems of different domains, such as social networks [21, 22], biological networks [23-26], Internet [27-29], collaboration networks [30-32] and citation networks [33, 34] etc.

Recently, there has been a growing interest in applying network science to solve financial problems. For example, network analysis has already been applied extensively to investigating the global banking system [11], international financial network [12], interlocking boards of directors [13-15], corporate governance and corporate ownership links [16, 17]. These studies focused on characterizing the topological properties of the financial and business networks, and using these properties to interpret the individual and organizational behaviors.

Over the past decades, a great deal has been established about the links between topological characteristics and robustness of network. We classify these studies into three major types. The first one is the analysis of the “robust-yet-fragile” property of networks [35-38]. Within a certain range, connections serve as a shock absorber, and risk sharing prevails, so connectivity engenders robustness. However, beyond a certain range, the system can flip the wrong side of the knife-edge. Interconnections serve as shock-amplifiers, not dampeners, as losses cascade. The second one is the “fat-tailed distribution” of networks. In particular, fat-tailed distributions have been shown to be more robust to random disturbances, but more susceptible to targeted attacks [38, 39]. Because a targeted attack on a hub node can bring most part of the system into a crisis, whereas random attacks are most likely to fall on the periphery. The third one is the well-known “small world” property of networks [40]. In general, networks tend to exhibit local clustering or neighborhoods. So it will tend to increase the likelihood of local disturbances having global effects [41]. Either way, a small world is more likely to turn a local problem into a global one. Financial safety is a main concern of governments and banks. However, research on the robustness and resilience of financial networks is still rare. So our study about the association of topologies and robustness of guarantee network is meaningful.

2.2. Guarantee networks

In a guarantee relationship, the guarantor needs to assume the debt obligation of a debtor if that debtor defaults [42-44]. Therefore, such relationships represent the financial responsibilities and venues for potential risk contagion between firms [45]. The firms and their guarantee relationships form a dynamic complex guarantee network.

Guarantees make it easier for firms to acquire loans from banks, and could reduce the risk for banks [18, 46, 47]. Existing literature mainly focused on some small-scale guarantee networks [48]. The factors that determined if Chinese listed firms’ would participated in the guarantee network have been investigated [19]. Different methods have been developed by some researchers to assess the credit risk of individual firms with a small-scale guarantee network. For example, a contagion model was constructed to explore the risk among 13 SMEs[20]. A contagion model was established to modeled the critical conditions triggering infection [49]. With the loan guarantee data of 2007 from one Chinese commercial bank, NetRating based on the k-shell decomposition method is put forward to assess firms’ risk [48], and with a ten-year loan guarantee records from a major Chinese commercial bank, a boosting model [9] and visual analytics approaches have been used to assess firms’ credit risk [2]. Another question about the effect of guarantee on the guarantor was studied. An empirical study from Chinese listed firms from the Chinese stock market and bond market from
year 2007-2011 showed the role of guarantor didn’t have a significant effect on the firm’s default risk [50]. A study from Korean chaebol affiliates’ loan guarantees demonstrated the positive and negative effects of loan guarantee [46].

Research on the risk of a comprehensive nationwide guarantee network is yet to come. In addition, there is no research on the influence of economic situation and national economic policies on the topological structure of guarantee network. The 2008 financial crisis and the subsequent Chinese economic stimulus program are two perfect natural experiments to investigate the influence of economic situation and national economic policies on the structure of guarantee network, as well as the associated contagion risk in the system.

3. Methodology

3.1. Data

In this research, we acquired a comprehensive dataset from China Banking Regulatory Commission (CBRC), the official agency in China to regulate banking sectors. The data spans from January 2007 to March 2012, and contains the monthly information for all loans extended to the client firms, which have a credit line above 50 million RMBs. These loan guarantee data are from all the 19 nationwide Chinese commercial banks, which account for nearly 80% total loans in China. This data could represent almost entire loan guarantee relationships in China. In total, there are about 87900 firms and 84500 guarantee relationships from January 2007 to March 2012.

For each single loan guarantee, the data contains information of guarantor firm and borrower firm, and the time of the guarantee relationship. We also have detailed information, such as amount of loan, assets and liabilities of the firm.

Our dataset covers two important events in the global financial system: The global financial crisis caused by the bankruptcy of Lehman Brothers on September 2008, and the implementation of the Chinese economic stimulus program from January 2007 to March 2012. As two rare natural experiments, these events offer a good chance to investigate the change of guarantee network.

3.2. Network construction and analysis

To analyze the structure and dynamics of Chinese guarantee system, we constructed dynamic guarantee networks using the guarantee relationships between firms. Figure 1 illustrates the construction of the networks. Each node represents a firm, and each edge connecting two nodes represents the existence of guarantee relationships between the two corresponding firms in a specific month. An edge goes from the guarantor to the borrower. This dynamic guarantee network consists of 63 monthly loan guarantee data, enabling us to analyze the evolution and dynamics of the system over time.

Fig. 1. Illustration of the dynamic loan guarantee relationships in the guarantee network
In this research, we adopted a set of commonly used topological metrics to describe the structure and evolution of the guarantee network:

**Network connectivity** is measured by three metrics, number of connected components, ratio of the largest weakly connected component (giant component) in the whole network, and density [51, 52]. In each connected component, any node can reach another node through an undirected path. The giant component is the weakly connected component with the largest number of nodes. Network density is the ratio between the number of directed edge and the total number of possible directed edges, where E is the number of edges and N is the number of nodes in the network:

\[
\text{density} = \frac{E}{N(N-1)}
\]

**Degree** is the number of adjacent edges for a node. In the guarantee network, edges are with directions, from guarantor to borrower. Counting the degree of nodes could measure the extent to which they are connected within the system. In-degree measures the number of guarantors for the firm [53-55]. Out-degree measures the number of borrowers that received guarantee from the firm. In general, a higher value of average out/in-degree indicates more frequent guarantee relations among firms.

**Scale-free property** has been observed in many real-world networks [56-58]. In a scale-free network, degree distribution follows a power-law. Most nodes are only connected to a few edges, while there exist a few hub nodes that are densely connected with other nodes. To test the scale-free property of the guarantee network, we investigate both the in- and out-degree distributions, denoted by \( p_{in}(k) \) and \( p_{out}(k) \). In a scale-free network, both \( p_{in}(k) \) and \( p_{out}(k) \) follows a power-law distribution. The frequency of nodes with degree of k is proportional to k to the power of \( \lambda \), \( p_{in}(k) \sim k^{-\lambda} \) and \( p_{out}(k) \sim k^{-\lambda} \) [59].

**Clustering coefficient** measures the extent to which a node’s neighbors are also adjacent to each other. In real-world networks, nodes are likely to form such triads, resulting a higher average clustering coefficient of the networks. In social networks, it refers to the tendency that “friend of a friend is also a friend” [40, 60]. In the guarantee network, high clustering coefficient indicates that firms tend to form tightly guarantee clusters with high frequency of guarantees among them.

The **reciprocity (dyad; mutual guarantee relationship between two firms)** of a directed network is the ratio of the number of reciprocated edges to the total number of edges. Here, an edge is reciprocated if an edge is connected from node A to node B, and then there is also an edge from node B to node A [61]. In the guarantee network, it measures the ratio of mutual guarantee relationships to the total number of guarantee relationships in the network.

The **ratio of fully connected 3-node-subgraph (triad; mutual guarantee relationship among three firms)** of a directed network is the ratio of the number of edges forming a fully connected 3-node-subgraph to the total number of edges in the graph. In the guarantee network, it measures the extent to which the three firms provide mutually guarantees to each other.

The **ratio of isolated 2-node reciprocal component** indicates the level of isolated 2-node mutual component in the network, which is the number of isolated 2-node reciprocal component divided by the total number of weakly component in the network. This measure quantifies the extent to which two firms formed mutual guarantee relationships without any interaction with other firms.

We measure the efficiency and robustness of the guarantee network in transferring the risk by calculating the **average shortest path length** of the network. Average shortest path length is the
average number of edges along the shortest path connecting all possible pairs of nodes. Real-world networks usually exhibit a relative small average shortest path length, indicating the small-world property [62-64]. Because the guarantee network has multiple connected components, we calculate the average shortest path length of the giant component of the network (the largest weakly connected component) instead of the value for the whole network.

4. Results and discussion
4.1 Static topological and financial properties of guarantee network

In this section, we examined the static topological and financial properties of the guarantee network. Our dataset covers three important events in the global financial system: bankruptcy of New Century Financial Corporation on April 2007, bankruptcy of Lehman Brothers on September 2008, and implementation of the Chinese economic stimulus program from January 2007 to March 2012. As three rare natural experiments, these events offer a good chance to investigate the change of guarantee network from perspective of local subgraphs.

- Phase 1 (April 2007 to August 2008). Financial crisis period. Bankruptcy of New Century Financial Corporation on April 2007 can be considered as the beginning of subprime mortgage crisis.
- Phase 2 (September 2008 to November 2008). The most serious period of financial crisis. Lehman Brothers Holdings Inc. failed for bankruptcy on September 2008 and global financial crisis reached the summit.
- Phase 3 (December 2008 to December 2010). China has implemented the four-trillion economic stimulus program. The stimulus program ended at the end of 2010.
- Phase 4 (January 2011 to March 2012). This is the post-economic stimulus program period.

The topological properties of the guarantee network are presented in Table 1. Despite the increasing size of the guarantee network, there are a set of common static network features throughout the whole period (January 2007 to March 2012):

First, the average in-/out-degree is slightly lower than one, indicating that in general, firms had a small number of guarantors, and did not provide guarantees to others frequently. Both the in- and out-degrees exhibit a power-law distribution, with a slope ranging from 3.1962 to 3.4272, and 2.2574 to 2.7557, respectively, indicating that the guarantee network are scale-free, a property that commonly exists in real-world networks [3]. In such a scale-free network, most firms have a small number of guarantee relationships, while a few hub firms provide/obtain guarantees to/from many others. A closer examination of the loan guarantee data revealed that isolated mutual guarantee relationship displays in significantly higher frequencies than would be expected for a random network (p-value=0.0017). These isolated mutual guarantee couples are at the bottom of the whole system in terms of low assets and credit line and high default rate, indicating that high-risk SMEs are more likely to obtain loans with the guarantee from similar high-risk SMEs. Here, we define the two hubs: guarantor hubs and borrower hub. The guarantor hubs are those giving guarantees to others most frequently (top 1% out-degree). The borrower hubs are those obtaining guarantees from others most frequently (top 1% in-degree). We found that the guarantor hubs were usually firms with large assets, liabilities, and credit line. About 15% of them were listed firms, (compared with about 4.5 %, the average listed ratio of the whole network). On the other hand, the debtor hubs tended to have medium amount of asset and liability, but with high default rate and risk rating. The
overlap of guarantor and debtor hubs is rather small (around 15%) as compared with other real-world networks, which indicating guarantor hubs and borrower hubs have different characteristics.

Second, the giant component (largest WCC) stands for 27.97% of the nodes in the whole guarantee network, indicating that the network is more decentralized than most other complex networks like social networks [21, 22], biological networks [23-26], Internet [27-29], collaboration networks [30-32] and citation networks [33, 34] etc. Within the giant component, we observed the small-world effect as indicated by the small average shortest path length (14.55–18.40). In addition, the average clustering coefficient is also relatively large (0.57%–1.57%), indicating a strong “a friend’s friend is also a friend” effect throughout the guarantee network, implying guarantee is a strong trust relationship.

Third, we also summarized the basic financial characteristics in Table 1. In general, the average leverage ratio, as measured by total liabilities divided by total assets, has been maintained at around 60%, which is higher than the average leverage ratio for listed firms in the network (around 40%). The ratio of listed firms was relatively low (around 2-5%). The decrease of firms’ listed ratio, indicating more and more guarantees given by non-listed firms. This echoed the above findings of large portion of isolated mutual guarantee relationships. We will discuss this in detail in the following section of dynamic network analysis.

Table 1. The summary of the topological properties of the guarantee network in four phases

| Measure | Phase 1 (04/07-08/08) | Phase 1 (09/08-11/08) | Phase 2 (12/08-12/10) | Phase 4 (01/11-03/12) | Whole period (01/07-03/12) |
|---------|------------------------|-----------------------|-----------------------|-----------------------|-----------------------------|
| N       | 37685.24               | 39002.219.20          | 48062.35               | 6425.6                | 67130.87                    |
| E       | 36347.35               | 37436.208.6           | 46981.12               | 6372.16               | 65825.87                    |
| <d>     | 0.96                   | 0.96                  | 0.98                   | 0.98                  | 0.98                        |
| λ_in    | 3.39                   | 3.20                  | 3.23                   | 3.23                  | 3.23                        |
| λ_out   | 2.25                   | 2.35                  | 2.74                   | 2.76                  | 2.76                        |
| Δ       | 2.56E-05               | 2.46E-05              | 1.40E-07               | 2.80E-06              | 8.92E-07                    |
| C       | 0.01                   | 0.01                  | 0.01                   | 0.01                  | 0.01                        |
| WCC     | 10604.41               | 10563.77              | 13279.54               | 1726.95               | 18994.06                    |
| WCC (%) | 0.79%                  | 0.11%                 | 0.60%                  | 28.35%                | 0.71%                       |
| CN       | 12171.65 | 302.05  | 12431.62 | 9.19  | 15286.87 | 1897.23 | 21372.87 | 1698.35 | 15669.06 | 3871.35 |
|----------|----------|---------|----------|-------|----------|----------|----------|---------|----------|---------|
| r (%)    | 14.1%    | 0.25%   | 13.58%   | 0.12% | 14.80%   | 0.41%    | 14.36%   | 0.35%   | 14.37%   | 0.51%   |
| 2-node (%) | 3.49% | 0.09% | 3.62% | 0.10% | 3.82% | 0.17% | 3.56% | 0.25% | 3.65% | 0.22% |
| 3-node (%) | 1.14% | 0.10% | 1.16% | 0.08% | 1.34% | 0.11% | 1.34% | 0.05% | 1.26% | 0.14% |
| l        | 14.49    | 0.48    | 14.55    | 0.09  | 18.07    | 1.86     | 18.40    | 0.42   | 16.93    | 2.13    |
| AA (million) | 217527.56 | 122.34 | 2446.39 | 86.02 | 2446.23 | 60.65    | 2597.22  | 61.85  | 2387.25  | 194.79  |
| AL1(million) | 40131.08 | 16.56  | 427.10  | 3.50  | 452.61  | 12.61    | 407.71   | 9.94   | 423.40   | 28.48   |
| AL2      | 0.60     | 0.01    | 0.60     | 0.01  | 0.61     | 0.08     | 0.62     | 0.04   | 0.61     | 0.01    |

N: number of nodes; E: number of edges; <d>: average out/in-degree; λ_{in}: power-law index of in-degree distribution; λ_{out}: power-law index of out-degree distribution; Δ: density; C: average clustering coefficient (directed); WCC: size of the largest weakly connected component (giant component); WCC (%): ratio of giant component (%); CN: component number; r(%): Reciprocity (%); 2-node(%): ratio of isolated 2-node reciprocal component (%); 3-node(%): ratio of fully connected three nodes (%); l: average shortest path length; AA: average assets (million); AL1: average loans (million); AL2: average leverage ratio (total liabilities/total assets).

### 4.2 Dynamic analysis of guarantee networks

Analyzing the dynamics of the guarantee network could reveal the short- and long-term impact of economic conditions and policies on the evolution of the guarantee credit guarantee system. In this section, we depict the topological properties and financial characteristics of the guarantee network for 63 months (from January 2007 to March 2012) that cover the financial crisis in 2008 and the implementation of the Chinese economic stimulus package.
Fig. 2. Evolution of the guarantee network scale.
Fig. 3. Dynamics of the topological properties of the guarantee network.
Figure 4. Dynamics of financial characteristics of firms in the guarantee network.

Figure 2 presents the evolution of the guarantee network. Figure 3 presents the dynamics of different topological properties of the guarantee network. In general, the guarantee network exhibits distinguished dynamic patterns in the four phases (defined in 4.1). We found that after the financial crisis began (marked by the bankruptcy of Lehman Brothers), the network size decreased, resulting in a more densely connected network. In addition, although the size decreased, the average asset of the firms in the guarantee network increased, indicating that the failed firms were with a relatively lower asset as compared with those did not fail. This indicated that the financial crisis caused large-scale bankruptcy of small and less connected SMEs. The implementation of Chinese stimulus program immediately stopped the decrease. Since then, the network has been increasing (almost linearly), even after the end of the stimulus program. The Pearson correlation between the growth of network scale and the new loans data (retrieved from People’s Bank of China) also verified that the network size and amount of loan from banks are positively associated. The correlation coefficients between new loans and the counts of nodes and edges are 0.56 (p-value<0.001) and 0.58 (p-value<0.001), respectively. Similar pattern was also observed for the number of weakly connected components, and the size of the giant component. Interestingly, both the size of the network and the giant component, and the number of components, decreased a bit before the end of the stimulus package, and increased significantly right after it.

Furthermore, we observed clear turning points within Phase 3, when the stimulus program was being implemented. More interestingly, the turning points for most topological properties were the same, but different for a few properties. In the following, we focus on the description of these turning points, and the economic implications of them.

The average degree, the exponent of the power-law in-degree distributions, average reciprocity, average ratio of fully connected 3-node-subgraph, and average clustering coefficient were increasing rapidly after the initiation of the stimulus program. These values suddenly dropped in the
last quarter of 2009, and quickly resumed the increasing trend until April 2010. Since then, all these values kept decreasing until the end of 2011 except a snap surge right after the end of the stimulus program (December 2010). The exponent of the power-law out-degree distribution followed a similar pattern, expect that it did not drop significantly in April and May 2010.

These findings indicated that there were many new mutual guarantee relationships as a result of the stimulus program. This included both mutual guarantees between two firms (reciprocity), and among three firms (ratio of fully connected 3-node-subgraph). To compare the dynamics of the average assets and loans between the overall guarantee network and mutual guarantee network (Figure 4), we found that these newly mutual guarantee relationships were mainly formed by firms that are with low assets and loans (p-value < 0.001 in both chi-square tests). A closer look at these mutual guarantee firms revealed that they were mostly (around 70%) not part of the giant component, but in other smaller isolated components. After the initiation of the stimulus program, the inclusion of these small firms caused the surges of loans and the loans to assets ratio (as shown in Figure 4). This trend was turned over briefly in late 2009 because of the dynamic fine adjustment of the People’s Bank of China. However, the trend resumed in 2010, until the government and the People’s Bank of China started to improve the macro-control regulations by increasing the reserve requirement ratio for five times in 2010 (from 15.5% to 18%).

Different from the other properties, the average shortest path length of the giant component kept increasing after the initiation of the stimulus program until September 2010, after when the value kept decreasing. This pattern is the similar as the size of the giant component. These findings indicated that the core of the guarantee network was not influenced significantly by the changes in regulations, until September 2010, only one month before the People’s Bank of China (the central bank of PRC) increased the interest rate. This echoed the above finding that mutual guarantee relationships were mostly in smaller isolated components.

These turning points were well-aligned with the changes of monetary policies and the practice of the stimulus program.

At the beginning of the stimulus program, the monetary policy was ultra-loose, the People’s Bank of China started to take actions to tune the loose monetary policies in the second half of 2009. According to the central bank, these fine tuning did not change the monetary policy, but aimed to address the side-effect caused by the ultra-loose monetary policy by making it more targeted, flexible and forward-looking [http://www.pbc.gov.cn/zhengcehuobisi/125207/125227/125957/126003/2896353/index.html]. It was perceived as a signal to change the monetary policy.

In March 2010 (17 months since the initiation of stimulus program), the government work report delivered at the 11th National People’s Congress stated that the government planned to improve macro-control regulations in 2010.

Since then, the People’s Bank of China increased the required reserve ratio for five times in 2010 (from 15.5% to 18%). The major change of the monetary policy operations occurred on Oct 20th, 2010, when the People’s Bank of China raised the interest rates for the first time since the global financial crisis. These regulations and policy changes, to some extent, helped reduce the impact of the negative consequence of the stimulus program.

4.3 Dynamic changes of ERGM in guarantee networks

The network analysis showed that the guarantee network experienced dramatic changes during
financial crisis and the stimulus program. The burst of mutual guarantees could be the main factor driving the changes of the guarantee network. In this section, we used the Exponential Random Graph Model (ERGM) [65] to verify the significance of the formation of mutual guarantee relationships and further explore how the localized mutual guarantee relationships led to the dynamics of the whole guarantee network.

ERGM (also named as p* model) is a statistical model that can effectively predict the edges as a function of individual factors and network structure [66, 67]. In ERGM, \( \{e_i\} \) is a set of measurable properties of a network, such as those reported in Section 4.2. \( \{\beta_i\} \) is a set of field parameters to be estimated. We then define the ERGM to be the set of all possible networks of a certain number of nodes. In this set, each network \( g \) appears with probability [59]. For more details of ERGM, please refer to [66, 68, 69].

\[
Pr(g) = \frac{1}{Z} \exp(\sum \beta_i e_i).
\] (1)

In this study, we formulate an ERGM for the directed guarantee network with two properties:

\[
Pr(G = g) = \frac{1}{Z} \exp[\beta_1 D(g) + \beta_2 R(g)],
\] (2)

where \( D(g) \) denotes the number of edges, and \( R(g) \) denotes the number of pairs of nodes that mutually connected each other. Markov chain Monte Carlo (MCMC) method was adopted to estimate the parameters [66]. Essentially, \( D(g) \) and \( R(g) \) evaluate the density and reciprocity of the network given the fixed number of nodes in the network, respectively.

The empirical results of the ERGM model showed that both the density and reciprocity were significant (p-value<0.001) throughout the entire time period, as shown in Figure 5. In particular, the coefficient of density was negative, indicating that edges occurred relatively rarely, especially if an edge is not part of higher order structures such as reciprocity. The coefficient of density decreased almost linearly after the initiation of stimulus program, indicating that the network has been becoming sparser during that period. On the other hand, the positive coefficient for reciprocity provides evidence that the guarantee relationships tend to occur in a mutual form, indicating that if \( A \) provides guarantee for firm \( B \), the chance of \( B \) providing guarantee for \( A \) is significantly higher. In particular, the coefficient of reciprocity kept increasing after the initiation of the stimulus program until September 2009, and then kept decreasing until the end of the stimulus program. This turning point happened around the same time of the first turning point reported in previous section.
Fig. 5. Dynamic changes of coefficients in ERGM.

The results of ERGM indicated that, although the guarantee network became sparser after the implementation of the stimulus program, the chance of forming mutual/reciprocal guarantee relationships has been higher than forming non-reciprocal relationships. Such phenomenon was becoming more and more significant until the last quarter of 2009, when the People’s Bank of China started to adjust the monetary policies.

5. Simulation

The dynamic network analysis in Section 4 revealed that the stimulus program dramatically changed the topological properties of the guarantee network, and resulted in a surge of mutual guarantee relationships (both dyad and triad). The following adjustments of monetary policies constrained the guarantee behaviors, thus reverted the increasing trend of mutual guarantee relationships. Such mutual guarantee relationship, though helps low-quality SMEs obtain more loans, and reduce the risk of small-scale arbitrary risk events, could result in large-scale cascading failures/defaults because of the risk and failures propagates via the guarantee relationships among firms [18, 42, 70]. In this section, we examine the potential risk of cascading failures represented by the guarantee network using a simulation model.

We represent the assets and liabilities of a firm i at time t as $A_i(t)$ and $L_i(t)$, respectively. $G_i(t)$ denotes the amount of loan guarantee firm i provides for firm j at time t. Following the literature in economics and finance, we adopt the Fermi distribution model to characterize the probability of default failure. Fermi distribution is a logistic function that was originally from quantum statistics, and has been successfully applied to modeling failures of firms and banks in economics and finance [71, 72]. In our research, $P_i(t)$ is a Fermi logistic function that determines the probability that a firm defaults at time t:

$$P_i(t) = \frac{1}{1+e^{-k\left(\frac{L_i(t)+\sum_j G_{ij}(t)}{A_i(t)} - \delta\right)}}$$

(3)

where $k$ represents the influence of external environment, $\delta$ represents the mean value of the
leverage ratio (total liabilities/total assets), and \( w_j(t) \) represents whether firm \( j \) has failed. The leverage ratio is determined by the current assets and liabilities of a firm, as well as the assumed debt caused by the failure of the firms to which \( i \) provides guarantee. Intuitively, the higher the leverage ratio a firm has, the more likely it would fail.

The simulation is based on the aforementioned dynamic guarantee network and the financial characteristics obtained from real-world data. We simulated the failures of firms caused by random initial failures (random attack) in one month. In the simulation, \( k \) was empirically set to 1.5, and \( \delta \) was the average leverage ratio of firms from real-world monthly guarantee network data. In particular, for each month, the simulation runs as follows:

1) \textit{Initial failures.} At the beginning of each simulation (\( t=1 \)), 5\% of firms were randomly selected to be the initial failures. The selected firms default, and their liabilities will be assumed by the adjacent firms in the network.

2) \textit{Failure propagations.} At each time step \( t \), we determine whether a firm \( i \) fails or not at time \( t \) based on equation (1).

3) \textit{Finish.} The simulation keeps running until there is no firm fails at \( t_{\text{finish}} \), \( t_{\text{finish}} \geq 1 \).

We run procedure 1) to 3) for 10,000 times for each month from January 2007 to March 2012 (63 months), and take the average ratio of failed firms for each month. Figure 6 presents the simulation results. We found that the dynamic pattern of average ratio of failed firms was similar to the pattern of topological properties (average degree, the exponent of the power-law in-degree distributions, average reciprocity, average ratio of fully connected 3-node-subgraph, and average clustering coefficient). The correlation between the average ratio of failed firms and the average reciprocity was very high (correlation coefficient=0.83, \( p \)-value<0.001). The turning points were the same (September 2009 and April 2010). This result indicates that the more prevalent mutual guarantee relationships are, the more fragile the whole guarantee network is. The fragility of the guarantee network was strongly influenced by the stimulus program and changes of monetary policies. In general, the stimulus program caused an elevated risk of the banking system. The follow-up adjustment helped reduced such risk, but the risk was still higher than it was before the financial crisis.

![Fig6. Contagion in the guarantee network](image-url)

6. Implications and Conclusions
This research presents the first attempt to quantitatively characterize the evolution of the entire Chinese guarantee system as a complex network. The empirical and simulation studies provide evidence that (a) the financial crisis caused a huge number of bankruptcies of SMEs, making the guarantee network smaller, and (b) the loose monetary policy along with the stimulus program encouraged the mutual guarantee behavior between SMEs, resulted in highly reciprocal and fragile network structure. The latter adjustment of the monetary policy reduced the ratio of mutual guarantee relationships, and enhanced the resilience of the whole guarantee network.

Our study contributes to the literature through proposing a complex network approach to analyzing the guarantee relationships between firms in a whole country. The simulation model based on real-world guarantee network presents a novel network-based method to evaluate the fragility of the guarantee systems. The empirical and simulation results provide data-driven insights of how the stimulus program and following monetary policy adjustments influenced the guarantee behaviors of firms, and the fragility of the guarantee system.

In practice, this study indicates that although the mutual guarantee relationship could help low-quality SMEs obtain more loans, and reduce the risk of small-scale arbitrary risk events, it could be the cause of large-scale cascading failures/defaults for the whole system. This research suggests that decision makers (e.g., government, central bank, and other authorities) control the prevalence of mutual guarantee relationships through adjusting monetary policies. More data-driven research is needed to identify the optimal prevalence of mutual guarantee relationships, so that decision makers could develop proper economic policies to allow SMEs to take advantage of mutual guarantees to survive and grow without elevating the risk of cascading failures for the whole system.

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