

Research Article

Resilience of Interbank Market Networks to Shocks

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This paper first constructs a tiered network model of the interbank market. Then, from the perspective of contagion risk, it studies numerically the resilience of four types of interbank market network models to shocks, namely, tiered networks, random networks, small-world networks, and scale-free networks. This paper studies the interbank market with homogeneous and heterogeneous banks and analyzes random shocks and selective shocks. The study reveals that tiered interbank market networks and random interbank market networks are basically more vulnerable against selective shocks, while small-world interbank market networks and scale-free interbank market networks are generally more vulnerable against random shocks. Besides, the results indicate that, in the four types of interbank market networks, scale-free networks have the highest stability against shocks, while small-world networks are the most vulnerable. When banks are homogeneous, faced with selective shocks, the stability of the tiered interbank market networks is slightly lower than that of random interbank market networks, whereas, in other cases, the stability of the tiered interbank market networks is basically between that of random interbank market networks and that of scale-free interbank market networks.

1. Introduction

Interbank markets play an essential role in modern financial systems. In an interbank market, banks with liquidity shortages can borrow liquidity from banks with liquidity surpluses. This interconnection of the banking system can lead to an enhanced liquidity allocation, but it also contributes to risk sharing among banks. Interbank linkages in interbank markets might become a contagion channel through which solvency or liquidity problems of a single bank can spread to other banks. Direct interbank connections become a source of systemic risk, which has highlighted the importance of interbank markets for financial stability.

The importance of interbank linkages has been recognized in safeguarding overall financial stability. At the same time, there has been a lot of empirical research on the recognition of such linkages as a channel of contagion. These studies adopt data on interbank

exposures from a number of countries, namely, Switzerland, United States, Germany, the United Kingdom, Holand, Denmark, India, and Finland [1–8]. These researches are valuable in providing insights into the empirical significance of interbank contagion in real interbank markets. However, the empirical literature assumes maximum diversification or a complete interbank market structure, which is obviously not in accord with the actual situation. In addition, the use of maximum entropy techniques underestimates contagion risk relative to an approach that uses information on actual bilateral exposures, which is revealed in Mistrulli’s research on the Italian banking system [9].

A new approach to contagion risk in financial market originates from network theory. The connections between financial institutions, such as interbank linkages, make financial institutions form complex networks [10–18]. There are many applications of network analysis to financial systems. Most of the current research using network theory focuses on issues such as financial stability and contagion. Allen and Gale [19] demonstrate that the spread of contagion depends crucially on the pattern of interconnectedness among banks. When the network is complete, the impact of a shock is readily attenuated, and there is no contagion. However, when the network is incomplete, the system is more fragile. The initial impact of a shock is concentrated among neighboring banks. Under the assumption that the banking structure is, respectively, a local and global network, Cassar and Duffy [20] find that, when the banking network is a local one, the transmission speed of banking risk is relatively low, and interbank liquidity is inadequate; when the banking network is a global one, the transmission speed of banking risk is relatively high, and interbank liquidity is not seriously inadequate. Aleksiejuk et al. [21] study the effects of one bank’s failure on the nucleation of contagion phase in a financial market and discover the power law distribution of contagion sizes in 3D- and 4D-networks as an indicator of self-organized criticality behavior. However, the self-organized criticality dynamics is not detected in 2D-lattices. The difference between 2D- and 3D- or 4D-systems is explained in terms of the percolation theory. Dasgupta [22] discusses how linkages between banks represented by cross-holding of deposits can be a source of contagious breakdowns. De Vries [23] shows that there is interdependence between banks’ portfolios, given the fat tail property of the underlying assets, and this carries the potential of systemic breakdown.

Vivier-Lirimont [24] addresses the issue of optimal networks from a different perspective: he focuses on network architectures where transfers between banks promote depositors’ utility. He finds that only very dense networks, where banks are only a few links away from one another, are compatible with a Pareto optimal allocation. Babus [25] considers a model where banks form links with each other in order to reduce the risk of contagion. The network is formed endogenously and serves as an insurance mechanism. Gai and Kapadia [26] develop an analysis model of contagion in financial networks with arbitrary structure and find that financial systems exhibit a robust-yet-fragile tendency: while the probability of contagion might be very low, the effects could be extremely widespread should problems occur. The resilience of the system to strong shocks in the past is also unlikely to prove a reliable guide to future contagion. Allen and Babus [27] investigate the resilience of financial networks to shocks and the formation of financial networks.

As for random banking networks, Iori et al. [28] study banking systems with homogeneous banks, as well as systems in which banks are heterogeneous. With homogeneous banks, an interbank market unambiguously stabilizes the system. With heterogeneous banks, knock-on effects become possible, but the stabilizing role of interbank lending remains so that the interbank market can play an ambiguous role. In random interbank market network, Nier et al. [29] find that (i) the more capitalised banks are, the more resilient the banking

system against contagious defaults is, and this effect is nonlinear, (ii) the effect of the degree of connectivity is nonmonotonic, (iii) the size of interbank liabilities tends to increase the risk of knock-on default, and (iv) more concentrated banking systems are shown to be prone to larger systemic risk. Georg and Poschmann [30] also indicate that common shocks are not subordinate to contagion effects but are instead a greater threat to systemic stability.

Tiered banking systems are found in a many of countries such as the UK, Austria, Belgium and Germany, but the empirical evidence of contagion risk in these systems is mixed. Wells [4] and Harrison et al. [31] report that relatively limited scope for contagion exist among UK banks. Boss et al. [32] and Degryse and Nguyen [33] find that tiered banking systems in Austria and Belgium are stable, and systemic crises are unlikely to strike. On the contrast, Upper and Worms [3] suggest that, in the structurally similar banking system in German, the effects of the breakdown of a single bank could potentially be very strong, and system-wide bank failures are possible. In the theoretical studies of tiered banking system, Freixas et al. [34] show that tiered system with money-center banks, where banks on the periphery are linked to the center but not to each other, may also be susceptible to contagion. Nier et al. [29] model the tiered structure by classifying the banks in the network into large and small banks and find that tiered structures are not necessarily more prone to systemic risk and that whether they are or not depends on the degree of centrality, which is the number of connections to the central node. Such that, as the degree of centrality increases, contagious defaults first increase but then start to decrease, as the number of connections to the central node starts to lead to greater dissipation of the shock. Teteryatnikova [35] constructs tiered banking networks, where banks are linked by interbank exposures with a certain predefined probability. The tiered structure is represented either by a network with negative correlation in connectivity of neighboring banks, or alternatively, by a network with a scale-free distribution of connectivity across banks. The main findings of Teteryatnikova's paper highlight the advantages of tiering within the banking system in terms of both the resilience of the banking network to systemic shocks and the extent of necessary government intervention should a crisis evolve.

The literature mentioned above mostly investigates how different network structures respond to the breakdown of a single bank in order to identify which ones are more fragile. But we still cannot obtain a clear picture about whether there exists a certain network that can well withstand shocks, that is, the one that has a high stability against shocks. Motivated by these considerations, we construct in this paper a tiered network model and numerically analyze contagion risk on different types of networks and then study how resilient different network models are against shocks. In this paper, interbank market network models studied are random networks, small-world networks, scale-free networks, and tiered networks. The paper is organized as follows. Section 2 introduces the approach to construct tiered interbank networks and the way to describe contagion effect of shocks. Section 3 analyzes the effect of shocks on interbank market networks, and Section 4 provides a conclusion.

2. The Basic Model

2.1. Tiered Interbank Market Network Model

Tiered structure is detected in a range of countries' interbank markets, such as the Austrian interbank market and the German interbank market, and is commonly defined as an organization of lending-borrowing relations/linkages between banks, where relatively few first-tier

or head institutions have a large number of interbank linkages, whereas many second-tier or peripheral banks have only few links. First-tier banks are connected to second-tier banks and are also connected with each other, whereas second-tier banks are almost exclusively connected to first-tier banks [35]. In order to explain the formation of tiered structure, we suggest a setup for a network model of the interbank market, though in real life it is much more complex. In interbank market networks, each node represents a bank, and each edge signifies a directional credit lending relationship between two banks.

Generally, in the interbank market, the number of banks with large-scale assets is relatively small, and a bank with large-scale assets has a high bank credit degree, which leads to the phenomenon that a small number of banks in the interbank market have high credit degrees, while most banks have relatively low credit degrees. Here, bank credit degree represents trusted banks' capacity of obtaining funds without immediate payment. Therefore, this paper assumes that each bank in the interbank market has a certain amount of bank credit degree which follows a power law distribution at the interval $(0, 1)$. In the interbank market, banks with liquidity shortage will make credit lending from banks with liquidity surplus to meet their liquidity needs. Generally, there are no sponson or mortgages in the credit lending relationships. Therefore, bank credit degree is the main factor in determining credit lending transactions. Moreover, this paper assumes that a bank with liquidity surplus and a bank with liquidity shortage do their credit degree interaction to determine whether they could fulfill credit lending transactions. Inaoka et al. [36] use the mean-field interaction to build scale-free banking networks. However, the credit degree of the bank with liquidity shortage is a major consideration, and this paper assumes that the credit interaction between banks is nonmean field. Provided with the above postulates, the interbank network model in this paper is addressed as follows.

- (i) *Deciding Bank Credit Degrees in the Interbank Market.* Supposing that the number of banks in the interbank market is N , we let c_i denote the credit degree of bank i , where c_i follows a power law distribution and $0 < c_i < 1, i = 1, 2, \dots, N$.
- (ii) *Determining the Interaction between Banks.* In the interbank market, a bank with liquidity surplus is a potential creditor bank and a bank with liquidity shortage a potential debtor bank. Generally, there are no sponson or mortgages in the credit lending relationships. Whether there is a credit lending relationship between them is based on their credit degree interaction c_{ij} , which is defined as $c_i^\alpha \times c_j^\beta$, $0 < \alpha < 1 < \beta$.
- (iii) *Deciding Interbank Credit Relationships.* Based on the interaction, we decide interbank credit relationships using the threshold method. When the interaction c_{ij} is larger than or equal to c , we define an interbank credit lending relationship between node i and node j , where the value of the threshold is set by c , which is calculated as $\tau \times c_{\max} \times c_{\min}$, with τ being a positive parameter, c_{\max} and c_{\min} the maximum and the minimum values of the bank credit degrees, respectively.

With the above-mentioned steps, we can construct interbank market networks. Note if c_{ij} is larger than or equal to c , there is an interbank credit relationship between node i and j , where bank i is the debtor bank and j the creditor bank. At this time, the credit degree of bank i is mainly considered to decide the interbank credit relationship, so we set $0 < \alpha < 1 < \beta$ in step (ii). Next, we analyze whether the network model we constructed has the characteristic of a tiered structure. Based on the network model presented above, the result is showed in Figure 1 after performing a numerical simulation.

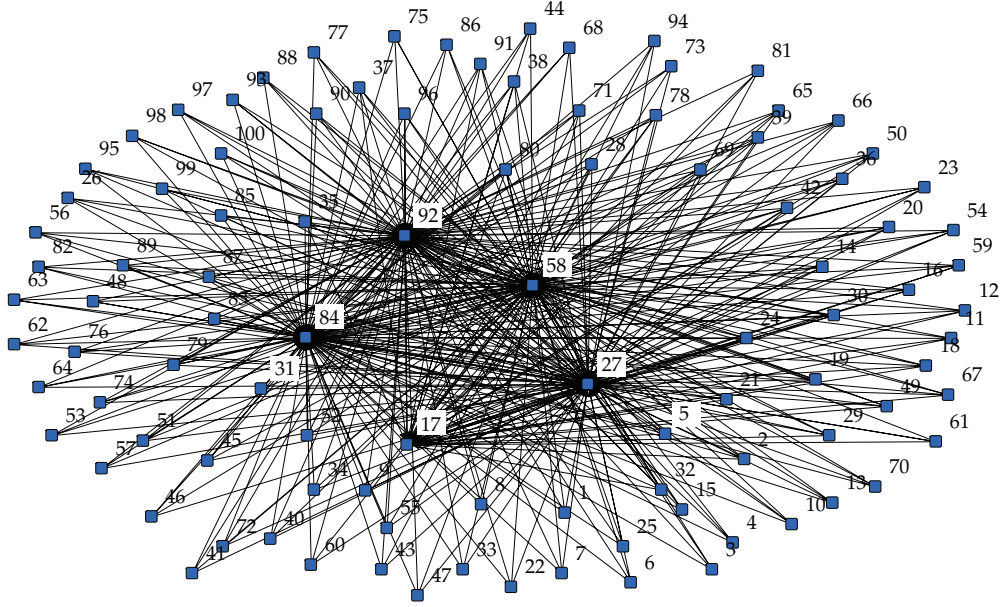


Figure 1: The graph of an interbank market network.

In the simulation, we choose the network size $N = 100$, and other parameters are chosen as follows: the power law index of the distribution that bank credit degrees follow, denoted by ρ , is equal to 0.2, and $\tau = 0.3$, $\alpha = 0.1$, and $\beta = 3$. From Figure 1, we can see that nodes 17, 27, 58, 84, and 92 are first-tier banks, and other nodes are second-tier banks. We also know that first-tier banks are connected to second-tier banks and are also connected with each other, whereas second-tier banks are exclusively connected to first-tier banks. This means that our simulation result suggests that tiered structure can be detected in the interbank market network model presented in this paper. It is worth pointing out that tiered structure is a critical phenomenon, because it can only be produced under special parameter values, rather than arbitrary parameter ones. Through many simulations, we find that the parameters of the model are sensitive to the formation of tiered formation except the network size N . In order to form tiered structure in the interbank market, the ranges and requirements for relevant parameter are as follows: $\rho \in [0.1, 2]$, $\tau \in [0.1, 1]$, $0 < \alpha < 1 < \beta < 5$, where the difference between α and β should be large.

2.2. Constructing Bank Balance Sheets

In order to study the resilience of the interbank market to shocks, in this section we develop a simplified model of a real-world interbank market, which allows us to analyze the process of shock transmission. The primary function of banks is to channel funds received from depositors towards productive investment. This makes bank balance sheets mainly consist of assets and liabilities. In this paper, we assume that an individual bank's assets, include investments, liquid assets, and interbank assets, denoted by V , I , and L , respectively, and that a bank's liabilities are composed of interbank loans, deposits, and net worths, denoted

by B , A , and M , respectively. We then construct bank balance sheets by deciding the following aspects.

- (i) *Bank Deposits.* For bank k , we set the ratio of its deposit A_k in its total assets TA_k to be η , that is, $A_k = \eta TA_k$. And then, we can generate the total assets of the interbank market, denoted by E , and $E = \sum A_k / \eta$.
- (ii) *Interbank Assets and Borrowing.* According to the total assets of interbank market E , we can obtain total interbank assets $TA = \theta \times E$, where θ is the ratio of total interbank assets in the total assets of the interbank market. Boss et al. [11] find that the size of interbank credit lending follows the power law distribution, so we assume that the credit lending size of bank i from bank j , denoted by x_{ij} , stem from a power law distribution, and $\sum \sum x_{ij} = TA$. Therefore, we can know the interbank assets L_k and the interbank borrowing B_k of bank k are equal to $\sum_i x_{ik}$ and $\sum_i x_{ki}$, respectively.
- (iii) *Liquid Assets.* Based on the total assets of bank k , we have the liquid assets V_k of bank k , which is equal to $\phi \times TA_k$, where ϕ is the percentage of liquid assets in the total assets of bank k . And, then, we know the total liquid assets of the interbank market, denoted by V , and $V = \phi \times E$. Moreover, we can figure out the size of the total interbank investment I , which is equal to $(1 - \phi - \theta)E$.
- (iv) *Bank Investments.* Borrowing in the interbank market is restricted to short-term solvency needs and does not cover long-term investments. Therefore, for any bank k , we require that its investments I_k be no less than its net interbank borrowing, that is, $I_k \geq B_k - L_k$. So we set I_k to be equal to $(B_k - L_k) + (1 - \phi - \theta)E/N$.
- (v) *Bank Net Worths.* According to steps (i)–(iv), we complete the asset part of the bank balance sheets as well as interbank borrowing and deposit in the liability. Noting that the bank assets are equal to bank liabilities, we can determine the remaining component, net worth M_k .

In short, we complete the construction of banks' balance sheets in light of the above steps. Note that, in step (ii), the determination of the interbank credit lending size is based on the interbank market network, that is, $x_{ij} > 0$, when there exists a link between bank i and bank j , or $x_{ij} = 0$.

2.3. Shocks and Shock Transmission

In this paper, we study the consequences of an idiosyncratic shock striking some banks in the interbank market and then analyze the contagion effect of shocks due to interbank exposures. Moreover, we study the resilience of different interbank market networks to shocks. Therefore, we first analyze the process of shock transmission.

For any given realization of the interbank market, let S_k be the size of shock on bank k , and let D_0 be the set of banks affected by initial shocks. For bank k in set D_0 , we assume shock S_k to be first absorbed by its net worth, then its interbank liabilities to be followed by its deposits, as the ultimate sink. If $S_k \leq M_k$, the shock is fully absorbed and if $S_k > M_k$, bank k defaults. When the bank defaults, if the residual shock $(S_k - M_k)$ is less than the interbank liabilities B_k of bank k , all the residual shock $(S_k - M_k)$ is transmitted to its creditor banks. However, if $(S_k - M_k) > B_k$, all the residual shocks cannot be transmitted to creditor banks, and depositors receive a loss of $(S_k - M_k - B_k)$.

Let D_1 be the set of creditor banks of default banks in D_0 ; that is, $D_1 = \{i \mid i : k, S_k > M_k, k \in D_0\}$, where $i : k$ denotes that bank i is the creditor bank of bank k . We assume that the residual shock of a default bank is divided into its creditor banks according to the respective proportions of its liabilities to creditor banks. All banks in D_1 receive a certain shock, which, in turn, is absorbed by their net worths, interbank liabilities, and deposits. If there are default banks in D_1 , the transmission continues flowing down the chains until the shocks are completely absorbed.

3. Impact of Shocks on Interbank Market Networks

3.1. Parameters of Models for Simulations

In this section, we determine the parameters for conducting simulation analysis to study how resilient different types of interbank market networks are against shocks. In this paper, we analyze four types of interbank market networks, which are, namely, tiered networks, random networks, small-world networks, and scale-free networks. These four network structures are revealed in real interbank markets by empirical analysis. In the simulation, we choose the network size $N = 20$. For the tiered interbank market network, we choose the parameters as follows: $\rho = 0.2$, $\tau = 0.3$, $\alpha = 0.1$, and $\beta = 3$. According to Erdos and Renyi's model [37], we connect every pair of nodes with probability $p = 0.2$ to create a random network. Based on the algorithm provided by Watts and Strogatz [38], we start with a ring lattice with 20 nodes in which every node is connected to its nearest two neighbors and randomly rewire each edge of the lattice with the probability 0.02 such that self-connections and duplicate edges are excluded. The scale-free network is generated by the algorithm [39]: starting with three nodes, at every step, we add a new node with two edges that link the new node to two different nodes already present in the system. When choosing the nodes to which the new node connects, we assume that the probability that a new node will be connected to node i depending on the degree of node i . After some steps, we can generate a scale-free network with 20 nodes. Note that the random interbank market network, the small-world interbank market network, and the scale-free interbank market network constructed based on the above methods are undirected, we adopt the following method to determine the direction of edges in the three networks: for arbitrary node i and node j , if there is an edge between node i and node j , the probability of the direction from i to j is 0.1, the probability of the direction from j to i is 0.3, and the probability of bidirectional connection between node i and node j is 0.6.

When constructing bank balance sheets, the exogenous parameters take the following values: $\eta = 50\%$, $\theta = 40\%$, $\phi = 5\%$. In the interbank market, we consider two kinds of banks, homogeneous banks and heterogeneous banks. In the homogeneous case, all banks are identical in deposits, and we let bank deposits be 1000 units; in the heterogeneous case, bank deposits stem from a normal distribution, which is set as $N(1000, 100)$.

3.2. Simulation Results

In this section, we investigate the impact of shocks on the interbank market networks through the simulation. Based on the realization of interbank market networks, in this paper, the shock applied to each bank is calibrated to wipe out all investments of the bank. For each shocked bank, we count the overall number of defaults and then adopt the number to measure the

impact of shock on the interbank market. In this paper, we consider two kinds of shocks, selective shocks and random ones, where selective shocks mean shocking the nodes in a certain order, namely, from the nodes with the largest degree to nodes with increasingly smaller degrees, and random shocks mean shocking some nodes from the network in a stochastic manner. For each set of parameters, we repeat this practice for 100 draws of the networks and report averages across realization.

Figure 2 reports the impact of selective shocks and random shocks on the interbank markets. For the tiered interbank market network, from Figures 2(a) and 2(b), we can see that in the homogeneous case the impact of selective shocks is larger than that of random shocks, because the number of defaults caused by selective shocks is larger than that caused by random shocks. However, in the heterogeneous case, the impact of selective shocks is the same as that of random shocks when the number of shocked banks f is small, while the impact of selective shocks is higher than that of random shocks with the increase of f after a certain threshold. In the random interbank market network, the impact of shocks is similar to that in the tiered interbank market network in the heterogeneous case. This can be revealed from Figures 2(b)–2(d). With regard to the small-world interbank market network, we learn that the impact of random shocks is larger than that of selective shocks from Figures 2(e) and 2(f). In the scale-free interbank market network, when f is less than 0.6, the impact of random shocks is larger than that of selective shocks; but, beyond the threshold 0.6, the impact of random shocks and selective shocks is identical. In short, from the perspective of shock transmission, we can figure out that the tiered interbank market network and the random interbank market network are basically more vulnerable against selective shocks, while the small-world interbank market network and the scale-free interbank market network are basically more vulnerable against random shocks.

Next, we analyze differences of the effect of shocks on four types of interbank market networks. The results are showed in Figure 3. As we observe from Figure 3, the number of defaults in the scale-free interbank market network is the smallest, and the number of defaults in the small-world interbank market network is the largest. This signifies that scale-free interbank market networks have the highest stability against shocks, while the small-world interbank market networks are most vulnerable against them. At the same time, we can find that, for tiered interbank market networks, when banks are homogeneous, faced with selective shocks, the stability of the tiered interbank market networks is slightly lower than that of random interbank market networks. In other cases, the stability of the tiered interbank market networks is basically between that of random interbank market networks and that of scale-free interbank market networks.

4. Conclusion

In this paper, we develop a model of shock transmission in the interbank market and analyze the resilience of four types of interbank market structures to shocks, namely, tiered networks, random networks, small-world networks, and scale-free networks. The interbank market network models are constructed based on network theory, where nodes represent banks and links represent interbank credit lending. Under this framework, the tiered network is modeled under two postulates, one being that interbank credit lending relationships are established by the interaction of bank credit degrees, and the second being that bank credit degrees follow a power law distribution on the interval $(0, 1)$. And random interbank market networks, small-world interbank market networks, and scale-free interbank market networks

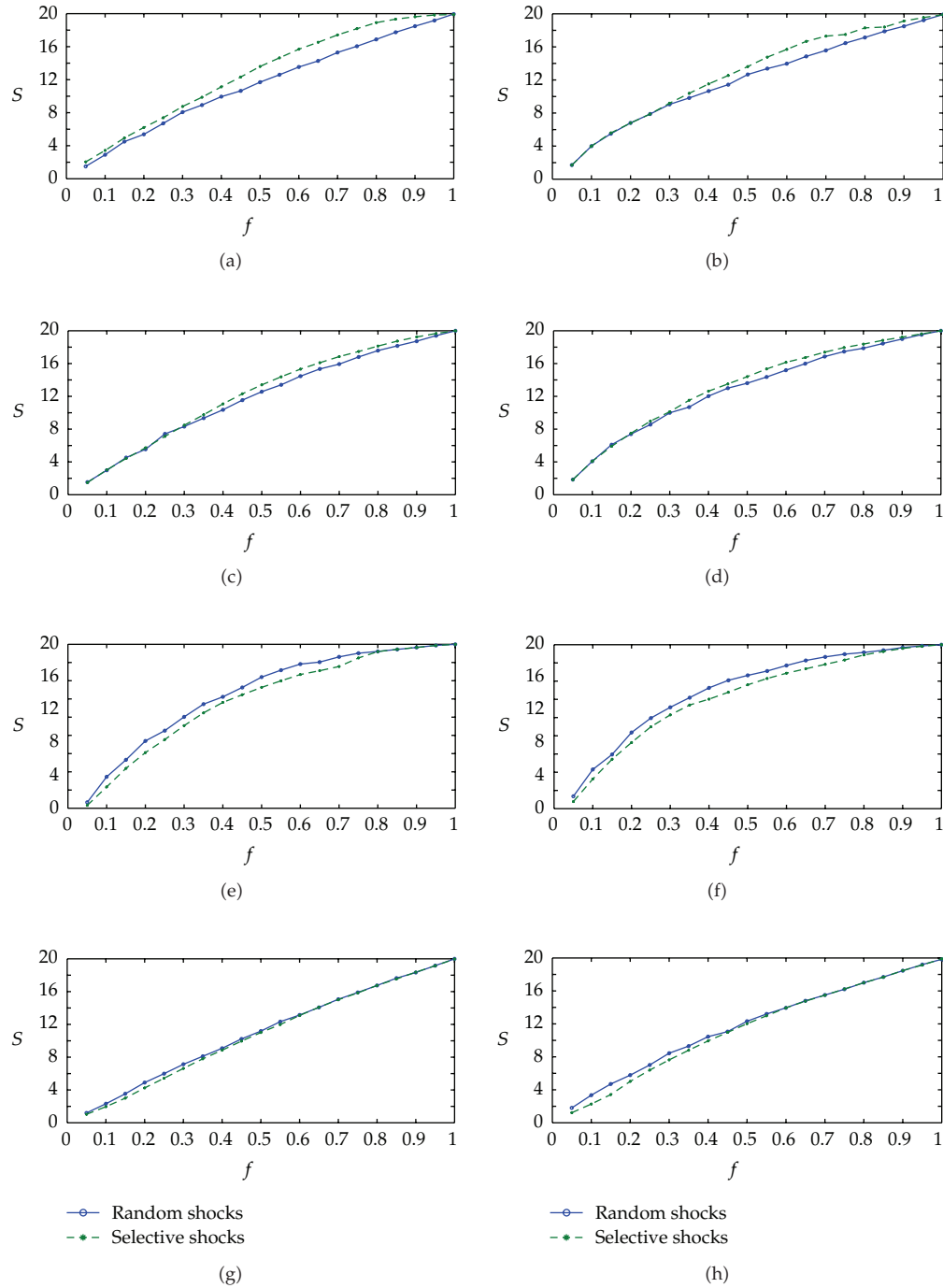


Figure 2: Number of defaults caused by random shocks and selective shocks. (a), (c), (e), and (g) correspond respectively to the results of tiered networks, random networks, small-world networks, and scale-free networks in the homogeneous case; (b), (d), (f), and (h) are, respectively, the results of tiered networks, random networks, small-world networks, and scale-free networks in the heterogeneous case. f denotes the number of shocked banks in the interbank market, and S represents the number of defaults.

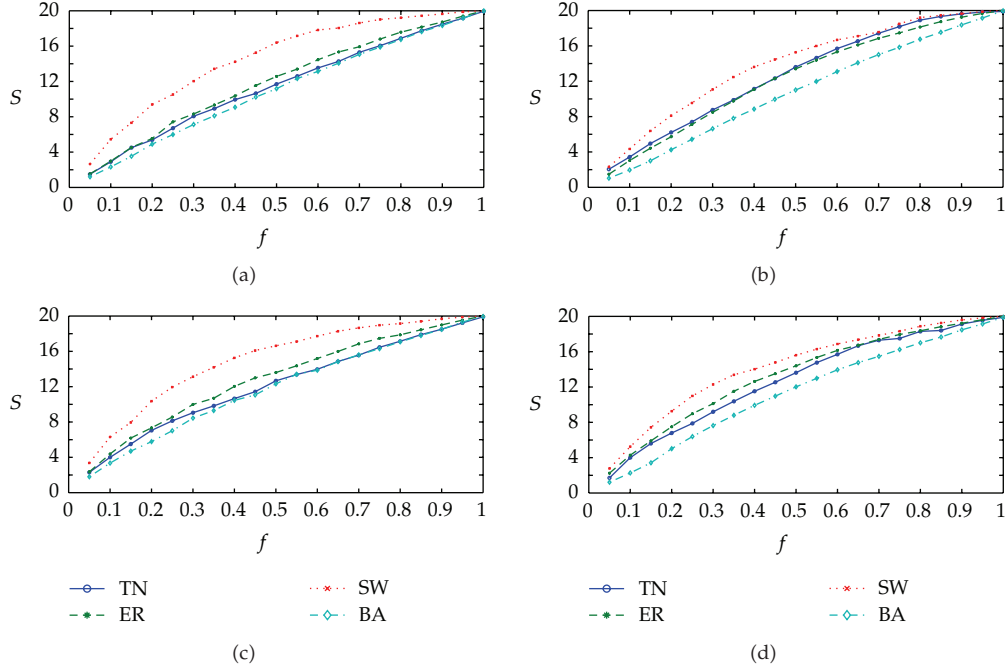


Figure 3: Differences of shocks on four types of networks. TN, ER, SW, and BA represent, respectively, the tiered networks, random networks, small-world networks, and scale-free networks. (a) and (b) are the respective results of random shocks and selective shocks in the homogeneous case, (c) and (d) random shocks and selective shocks in the heterogeneous case.

are constructed based on the algorithm [37–39], respectively, where the direction of edges are exogenous.

The network structure of the interbank market is important in determining the spread of contagion defaults and in deciding the resilience of the interbank market to shocks. Through the simulation analysis, we find that tiered interbank market networks and random interbank market networks are basically more vulnerable against selective shocks, while small-world interbank market networks and scale-free interbank market networks are basically more vulnerable against random shocks. In addition, scale-free interbank market networks have the highest stability against shocks, while the small-world interbank market networks are most vulnerable against them. And for tiered interbank market networks, when banks are homogeneous, faced with selective shocks, the stability of the tiered interbank market networks is slightly lower than that of random interbank market networks. In other cases, the stability of the tiered interbank market networks is basically between that of random interbank market networks and that of scale-free interbank market networks.

These findings highlight the importance of network structure in determining the spread of contagious defaults. While greater connectivity increases the spread of contagion in the interbank market network, it also improves risk sharing among neighboring banks and thereby reduces the susceptibility of banks to defaults. These opposing effects of risk sharing and risk spreading interact differently in varying structures. For example, in small-world interbank market network, there exist long-range edges, which make the default contagion easier, and, hence, small-world interbank market network become most vulnerable against

shocks. As a result, the resilience of an interbank market to shocks, and the optimal number of bank rescues depend on the features of the structure of an interbank market. These insights provide the basis for specific policy recommendations in order to maintain the stability of banking systems.

The models and results presented in this paper suggest some directions for future research. An interesting extension of the paper would focus on a model whose setup is even closer to the one in real life to demonstrate the tiered banking systems. Alternatively, one could think of creating dynamic models to analyze the resilience of interbank markets to shocks, that is, to consider the evolution of interbank market networks with time. These strands of research would add realism to the model and provide new, potentially valuable insights.

Acknowledgments

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