Credit Contagion in Financial Markets: A Network-Based Approach

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2013

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Received: date / Accepted: date

Abstract We propose a network-based model of credit contagion and examine the effects of idiosyncratic and systemic shocks to individual banks and the banking system. The banking system is built as a network in which banks are connected to each other through the interbank market. The microstructure captures the relation between debtors and creditors, and the macroeconomic events capture the sensitivity of the banks' financial strenght to macroeconomic events, such as housing. We have demonstrated that while idiosyncratic shocks do not have a potential to substantially disturb the banking system, macroeconomic events of higher magnitudes could be highly harmful, especially if they also spur contagion. In a concerted default of more banks, the stability of a banking system tends to decrease disproportionately. In addition, credit risk analysis is highly sensitive to the network topology and exhibits a nonlinear characteristic. Capital ratio and recovery rates are two additional factors that contribute to the stability of the financial system.

Keywords credit contagion · network models · credit risk · structural models · financial stability · alpha-criticality index

PACS 89.65.Gh

Mathematics Subject Classification (2000) 91G40 · 90C35

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1 Introduction

That information, where information is used in a very broad sense, propagates from its source to others is a well-known phenomenon that has been highlighted by many.[1] Viruses spread from infected individuals to susceptible, ideas spread among interacting individuals, rumors propagate across the community, people are affected by behavior of others etc. Schelling (1971) has demonstrated that interaction can spontaneously and unintentionally lead to some undesired outcomes, such as segregation. Similarly, if we link different financial institutions (or banks) through the interbank market of mutual claims into a financial network, then credit events spread from "infected" banks across the network, affecting the banks and the system.[2] Like many other network structures, not even the financial system is immune to highly extreme outcomes that are induced by events that seem unimportant at first. Many financial crises have been initiated by small events such as individual bank failures, drops in the housing market or sovereign debt etc. Kindleberger and Aliber (2011) provide a thorough historical overview of financial crises.[3]

In the paper, we develop an interaction-based model to examine the stability of a financial system under different circumstances. The banks are modeled through their balance sheets. They are represented by the nodes and linked to each other through the interbank market into a banking network. The model thus captures interdependency and leverage as the two prime micro-specifics of the banking system. Interdependency is reflected by the interbank market of mutual claims. Upper (2011) estimates that the interbank market represents approximately 20 percent of the banks' assets in developed countries. As to the second feature, the Basle Accord requires from the banks to have a minimum level of 4% of Tier 1 capital and a combined Tier 1 and Tier 2 capital ratio of at least 8%. A risk-adjusted Tier 1 capital ratio of at least 6% and a combined Tier 1 and Tier 2 ratio of at least 10% are required.

Banks possess various types of assets, while the liabilities part of the balance sheet is reduced down to the bank capital. Any loss directly reduces the level of the bank capital. Banks can incur losses either on the trading part of their assets or due to a shock or the interbank market. An idiosyncratic shock is represented as a sudden default of an individual bank, while the systemic shock is represented as a drop of housing by a certain proportion. A principal

[1] Testfatsion and Judd (2006), see Steinbacher et al. (2013) for the latest overview of interaction-based models in economics and finance.

[2] Methodologically, the network-based approach is similar to the epidemiological models in which the state of a node progresses between different types, from susceptible to infected and then to either recovered, immune or ceased (Pastor-Satorras and Vespignani, 2001). They differ in consequences that are induced by connectivity. In a financial network, connectivity can work either contagiously or as a channel of risk-sharing, while the epidemiological networks do not have the risk-sharing potential.

[3] In recent history, the default of Russian government debt in August 1998 sunk Long-Term Capital Management (LTCM), while the collapse of the subprime housing market in 2008 sunk Bear Stearns, Merrill Lynch and Lehman Brothers and many others, and continued into a sovereign debt crisis in Europe. Systemic events may take various forms, such as economic downturn, drops in the housing market or in sovereign debt etc.

characteristic of a systemic event is that it is widespread and not bound to a single bank. All shocks are one-time events and to banks unexpected events. A bank defaults when it runs out of capital. After a bank defaults, the counterparty banks are repaid the recovery rate (RR) proportion of the exposure at default (EAD). We assume that troubled banks cannot raise additional capital. An α-criticality index is constructed to evaluate the cost of single credit events to the banking system. The index measures the proportion of defaulted assets (capital) of the system caused by the shock.

We demonstrate that while idiosyncratic shocks do not have a potential to substantially affect the system, macroeconomic events of even moderate magnitudes can be very severe, especially if shocks become contagious which is very likely. In addition, credit risk analysis has proved to be sensitive to the network topology. Capital ratio and recovery rates are two additional factors that contribute to the stability of the financial system. The latter conclusion is similar to Furfine (2003), who argues that contagion is possible when RRs are low. Nier et al. (2007) find a negative and nonlinear relationship between contagion and the bank capital.

The early credit-risk literature includes structural and reduced-form models (Bielecki and Rutkowski 2002, Duffie and Singleton 2012). The first employ an asset value approach, in which the value of assets is assumed to follow a standard geometric Brownian motion, while the value of debtor's assets in relation to the debt determines its distance to default (Merton 1974, Leland 1994, Leland and Toft 1996, Collin-Dufresne et al. 2001, Giesecke and Weber 2004). In the reduced-form models, defaults are not linked to the debtor's capabilities to fulfill its obligations, but are considered the unexpected events whose probability follows an exogenously specified process for the migration of default probabilities which are calibrated either to historical or current market data (Vasicek 1977, Jarrow and Turnbull 1995). Alternative credit risk models were developed by Credit Suisse and J.P. Morgan (Boston 1997, Gupton et al. 1997). Some of the latest reduced-form models were proposed by Jorion and Zhang (2007) and Duffie et al. (2009). Furfine (2003) and van Lelyveld and Liedorp (2006) investigated the interbank market and contagion risk in the U.S. and the Dutch markets, respectively. In these models a default risk is associated with various types of continuous processes in a stochastic environment for which they fail to properly identify the risk threats which originate from the microstructure of the banking system (Colander et al., 2009). Hence, they cannot explain the large-size aggregate outcomes that are initiated by events of negligible sizes (Albert and Barabási 2002, Sornette 2009, Acemoglu et al. 2012). This is the fundamental drawback of these early credit-risk models.

Our paper differs from the existing literature in that we develop a network-based model in which the distance to default for a single bank is estimated from the bank's ability to fulfill its credit obligations. This follows an intuition of the structural models in which a bank defaults when the value of its assets falls below a certain level. In contrast to the previous structural models, we apply an interaction-based approach. Our paper thus relates to the growing field of the simulation-based experiments in economics and finance that are run on social networks. Haldane and May (2011) use networks to study contagion in financial markets. Boss et al. (2004) examine the network topology and stability of the Austrian interbank market. Degryse and Nguyen (2007) investigate the evolution and determinants of contagion risk in Belgian financial market. 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 and idiosyncratic shocks, changes in network structure and asset market liquidity. Although the probability of a contagion may be low in their model, the effects, when problems occur, can be extremely widespread. Nier et al. (2007) simulate financial stability of an artificial financial system and used a random network. They find a nonlinear relationship between contagion and interbank market. In addition, they show that contagion is a non-monotonic function of the banks' links to other banks, and also that more concentrated banking systems tend to be more prone to systemic breakdown. Dasgupta (2004) examines how crossholding of deposits can be a source of contagious breakdowns. Freixas et al. (2000) examine the contagion potential of single bank defaults. Battiston et al. (2012) and Beale et al. (2011) examine financial networks in connection to the level of homogeneity. Cifuentes et al. (2005) explore liquidity risk in a networked banking system. Leitner (2005) develops a model in which liquid banks bail out illiquid ones in order to prevent contagion and the collapse of the entire banking network. Similar to our work is a model of Egloff et al. (2007) which includes macro- and microstructural interdependencies among the debtors within a credit portfolio. Our model was extended by Steinbacher et al. (2014). See Upper (2011) for the recent overview of the credit contagion literature.

The remainder of the paper is organized as follows. The model is presented in Chapter 2 and the simulations design in Chapter 3. The results are presented in Chapter 4 and discussed in Chapter 5. Chapter 6 concludes.

2 The Model

2.1 The Bank

Individual banks are principal constituents of the banking network. They are represented through the balance sheet (Table 1).

Table 1 Bank balance sheet

Assets	Liabilities
Interbank assets	Capital
Mortgage loans	Interbank liabilities
Equity	Debt
Other non-trading assets	

We use a simplified structure of a balance sheet in which total assets $A_{i,t}$ of bank i in time t consist of mortgage loans $H_{i,t}$, portfolio of marketable assets $B_{i,t}$, non-trading and other assets $N_{i,t}$ and interbank assets $IB^j_{i,t}$.

$$A_{i,t} = H_{i,t} + B_{i,t} + N_{i,t} + \sum_{j \in N(g)} IB^j_{i,t} \tag{1}$$

$IB^j_{i,t}$ denotes the values of bank i holdings of interbank assets by banks j in time t, and the sum of these represents the entire exposure of bank i to the banking sector over time. The value of mortgage loans is randomly selected for each bank. The banks retain the same values of mortgage loans throughout the simulation runs and network topologies. The values can change only by the exogenous mortgage shock. Although the category of loans usually consists of those given to households and businesses, we did not make any distinction and simply assumed that it is only mortgage loans. Each bank is assigned a portfolio of marketable assets which consists of 6 stocks from the DJIA. Banks retain the same portfolio throughout the simulation runs. For this category, we apply a mark-to-market principle, which means that its dynamics is provided by the movements in the corresponding stock prices. We use daily closing prices. Other non-trading assets are included as a residual category so as to keep the value of each banks total assets the same and comparable between different network topologies. Initial values of other non-trading assets are calculated as the difference between the each bank's initial total assets and the sum of initial values of the bank's other assets. This category of assets usually includes the cash reserve, claims on banks and on customers, lending commitments, financial investments not assigned to any other balance sheet item, holdings in companies not accounted for using the equity method and in jointly controlled entities are reported as financial investments under equity holdings etc.

For simplicity we assume that the liabilities side of the balance sheet is confined to the level of the bank capital $C_{i,t}$. The capital stands as a cushion to absorb losses, which directly reduce its level for a full amount. According to the Basle Accord, capital is constituted of the core capital and retained earnings (Tier 1) and the supplementary capital (Tier 2). Supplementary capital includes undisclosed reserves, revaluation reserves, general provisions/general loan-loss reserves, hybrid debt capital instruments, and subordinated term debt. In the model, $C_{i,t}$ indicates the value of the Tier 1 capital of bank i in time t. Its initial value for each bank is calculated from the real data of Tier 1 capital ratio and the bank's total assets, while its dynamics promptly develops according to the bank's payoffs $\Pi_{i,t}$

$$C_{i,t+1} = C_{i,t} + \Pi_{i,t} \tag{2}$$

2.2 The Network

Now that the bank has been defined, let the banking system consist of a number of such banks. Banks are represented with a finite set of nodes $\mathcal{N} =$

$\{1, 2 \ldots, n\}$ and linked to each other with a finite set of links $\mathcal{L} = \{l_1, l_2, \ldots, l_L\}$, where $l_k = (i, j)$ links node i and j.[4] Links in the network are directed and weighted, indicating the exposure of j to i with strength given by the weight $\mathcal{W} = \{w_1, w_2, \ldots, w_L\}$. The links go strictly from the creditor to debtor. Hence, the banks can not be linked to themselves which means that there are no loops in the networks. An incoming link from bank i to j reflects the exposure of bank j to bank i and by definition represents an outgoing link from bank j to i. Each bank can have at most $(n-1)$ outgoing or incoming links. Such bank would be linked to every other bank. An isolated bank has no links and can not initiate contagion. The number of links terminating at particular node i is called the node's in-degree, while the number of links originating in particular node i is called the node's out-degree.

Distinction between the banks in-degrees and out-degrees is very significant for the risk propagation and, hence, for the stability of the banking system. In-degree nodes are potential sources of contagion, while out-degree nodes are recipients of credit events and potential sources of contagion in the subsequent stages. Banks with high out-degrees make their financial positions very sensitive to operations of other banks though they diversify the risks. On the other hand, default of a bank with high in-degree affects larger number of banks from the system and may provoke contagion if defaulted. However, when a bank defaults, its outgoing links may entail two opposing effects. They may work as a channel for the shock propagation or as a channel of risk-sharing. With low levels of diversification, the banks are very vulnerable to events by the small number of their counterparties. With such a constellation, the probability that a bank is affected by a default event of an arbitrary bank is smaller but if it is affected the cost for the bank is bigger. As the level of diversification increases, the probability that a single bank is affected by the shock increases, but the entire loss is distributed among many banks. In a complete network of four banks, Allen and Gale (2000) show that shock is absorbed by all banks and there is no contagion. Battiston et al. (2012) and Beale et al. (2011) have argued that individual banks can reduce the probability of a default by diversifying their exposure.

Some other significant node-related concepts from the network theory include centrality indices (Wasserman and Faust 1994; see also Ballester et al. 2006). They are related to the nodes positions in relation to other nodes. For instance, closeness centrality presents how close a node is to other nodes. In the banking network, the banks with the highest closeness centralities can be quickly infected by default events of other banks and can also quickly infect many others. The other measure, the betweenness centrality, relates to the banks presence on paths between other banks that are not directly linked. Banks with high betweenness centrality indices control the transmission of credit events in the financial network. As such they can be used to halt contagion and hence stabilize the banking system.

[4] For an overview of social networks, see Wasserman and Faust (1994) or Jackson (2010).

Although the centrality measures are compelling for estimating the node's importance in the graph theory, there are several reasons why they are very poor in determining the importance of single banks. The major critique is directed towards the fact that centrality measures do not properly assess the market microstructure, especially the magnitude of the links, the banks' capacities to absorb losses and the bank's ability to provoke contagion. Contagion is a deciesive element that determines the severity of an event. Small exposures may have a weak contagious potential, while a poorly connected bank could induce large effects if it is heavily exposed to a small number of potentially important banks and has the ability to collapse them. Generally, poorly capitalized small banks are much more vulnerable to defaults than the big and well-capitalized ones. In some cases, the banking system may face a too-many-to-fail problem (Acharya and Yorulmazer, 2007). Nier et al. (2007) demonstrate that the bank connectivity exhibits a nonlinear relation to contagion.

To consider for this, we impose an α-criticality index, which measures the importance of individual banks through the loss their defaults cause to the financial system. Analogically, the index could also be defined for events, such as a drop in housing. We say that a bank or an event is α-critical if its default, or the occurrence in the case of an event, leads to the collapse of α-part of a financial system.

The index is defined as

$$\alpha_{k,t} = \frac{C_{0,t} - C_{k,t}}{C_{0,t}} \tag{3}$$

C_0 and C_k represent the levels of total capital over time in a benchmark model and in the model with an event k. In the paper, an event refers to the drop in housing by the magnitude of k and default of bank i. The index measures the net loss of capital (or assets) over time that is due to a shock in relative terms. It is defined over $[0, 1]$ with $\alpha = 1$ indicating a default of the entire banking system. α-criticality index goes beyond the mere centrality indexes as it includes the micro specifics of individual banks and complexity of the banking system. Iori et al. (2008), Schweitzer et al. (2009) and Allen and Babus (2009) argue that the network of major international financial institutions is strongly interdependent, exhibiting an increasing scale-free characteristic.[5]

2.3 The default dynamics

Each simulation run starts from an initially specified system state and the rules of conduct. Banks' assets and capital levels then develop according to the changes on the trading part of the banks' assets, write-offs of the interbank exposures due to counterparty defaults or by losses on the mortgage due to the shock. Any change in the value of bank's assets is immediately reflected

[5] Such networks are resilient to the high rates of random failures, but very vulnerable to targeted attacks to the few of the most important nodes (Albert et al., 2000).

as the change of its capital. Banks in the model are not allowed to rebalance their balance sheets nor raise additional capital or be bailed-out.[6] If troubled banks were allowed to raise additional capital, there would be no bank defaults and, consequently, no contagion. For simplicity we assume that deterioration of banks balance sheet does not change its credit rating. We also assume that banks do not have information about the status of their counterparties or the network topologies.

Further, we assume that a bank defaults when $C_i \leq 0$ and not, as in reality, when its capital falls below the required Tier 1 ratio. A defaulted bank repays each of its creditors the recovery rate (RR) proportion of the exposure at default (EAD). Each creditor loses the loss given default (LGD) proportion of EAD.[7] RRs are not endogenous but are simulated for each bank. For each bank RR is randomly taken from the uniform distribution on an interval 0.3 to 0.6 and is fixed for all repetitions and network topologies. RRs are applied in the period after a default, while the amount a bank recovers from a defaulted bank increases its level of non-trading assets $N_{i,t}$. To keep things simple, we do not dissect the debt according to its seniority, although this defines the settlement priority in the case of a default. For instance, senior debt would be repaid before the junior debt, while the interbank money market is unsecured debt. We also do not consider the correlation between the economic downturn and the recovery rates, although a highly positive correlation between default rates and the GDP growth and the negative correlation between default rates and RR have been observed (Shleifer and Vishny 1992; Altman et al. 2005; Acharya et al. 2007). Shleifer and Vishny (2011) provide a discussion on fire sales in the perspective of the latest financial crisis.

After introducing RRs into the model, we can redefine Eq. 2 and provide the capital dynamics for each bank as

$$C_{i,t+1} = C_{i,t} + \Pi_{i,t} - \sum_{j \in N(g) | C_j < 0} \left[(1 - RR_j) \cdot IB_{i,t}^{j} \right] \tag{4}$$

Default of bank i deteriorates the balance sheet of an adjacent bank for the $(1 - RR)$ proportion of EAD and leads to a write-down of $(1 - RR) \cdot IB_{i,t}^{j}$ of the bank i's exposure at bank j. Implicitly we assume that credit events do not induce a general loss in confidence nor panics or bank runs, and that they do not affect the capital markets and the banks' portfolios.

2.4 A shock

The model is tested against an idiosyncratic and a systemic shock. The idiosyncratic shock is represented as a sudden default of either an individual bank or

[6] A government that wants to bail out a defaulted bank can either increase RR or provide the bank required capital. Governments usually do the latter. Rochet and Tirole (1996) argue that bailouts might stimulate moral hazard.

[7] Possible mutual exposures between the banks do not imply debt reconciliation.

simultaneous defaults of more banks. Generally, banks may default due to the failed business decisions, malpractice, fraud or any other bank specific event. In the paper, default events are exogenous and to banks unexpected events. The systemic shock is represented by a sudden drop in the value of mortgage by a certain percent. Systemic shock is different from the idiosyncratic in that it affects every bank whose assets includes mortgage loans. In our case this means every bank. In addition to its direct effects, a systemic shock can also become contagious if it induces bank defaults. Contagion is much more likely to occur in the case of a systemic shock because the shock itself reduces the capital of each bank, by which it reduces capabilities of banks to absorb additional writedowns due to the market risk and the counterparty risk.

3 Simulations

The banking network consists of $n = 40$ banks. Banks are numbered from 1 to 40 and retain the same number in all simulation runs. We use real data on the arbitrarily chosen banks' capital ratio and total assets as our initial data in $t = 0$. The data refers to December 31, 2011 and is acquired from the banks 2011 Annual Reports. This data is then used to compute initial values of the banks capital values (Table 2).

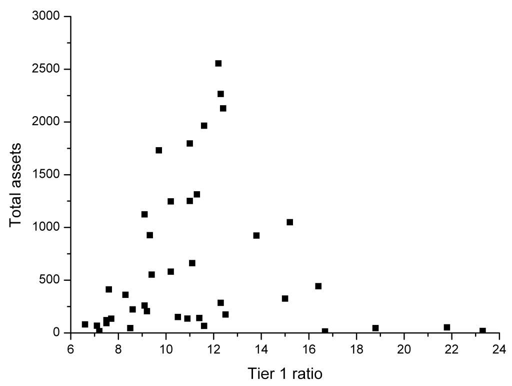


Fig. 1 Initial values of the banks' total assets against the banks' Tier 1 ratios

It is important to note that the structures of the banks' balance sheets from our simulation runs do not reflect the actual balance sheets structures of corresponding banks but are modified accordingly to meet the requirements of the network topologies, subject to the initial data on the bank capital and the total assets constraints.

The banks are heterogeneous in size and structure. The sample includes 13 big banks with total assets exceeding $900 bln each. Total assets of 17 banks

Table 2 Initial data for the banks

Bank	Tier 1 Ratio	Assets	Tier 1 capital	RR
1	12.40	2129.00	264.00	50.05
2	12.30	2265.80	278.70	55.02
3	11.00	1796.00	197.60	40.37
4	11.60	1965.00	227.90	34.80
5	11.00	1251.50	137.70	40.82
6	15.20	1049.20	159.50	46.01
7	9.32	926.77	86.40	56.69
8	11.10	661.80	73.50	35.82
9	16.40	443.00	72.70	44.24
10	12.30	285.40	35.10	43.85
11	23.30	18.70	4.40	38.08
12	11.40	141.70	16.20	48.66
13	21.80	53.00	11.60	35.25
14	7.20	16.45	1.20	45.46
15	10.50	151.00	15.90	39.13
16	9.40	552.70	52.00	33.10
17	10.20	580.80	59.20	39.79
18	9.10	260.00	23.70	30.36
19	8.50	45.70	3.90	49.60
20	10.20	1247.00	127.20	44.11
21	11.60	66.80	7.70	40.92
22	9.70	1731.00	167.90	51.81
23	7.60	412.80	31.40	51.34
24	12.20	2555.00	311.70	32.31
25	13.80	923.20	127.40	46.92
26	15.00	325.30	48.80	56.03
27	18.80	45.20	8.50	39.29
28	11.30	1313.90	148.50	49.95
29	12.50	174.60	21.80	54.77
30	16.68	13.80	2.30	36.80
31	10.90	135.80	14.80	48.74
32	9.10	1124.00	102.30	41.33
33	9.20	205.94	18.90	46.18
34	8.30	361.80	30.00	39.49
35	7.70	135.20	10.40	59.30
36	7.50	92.60	6.90	53.79
37	7.50	120.90	9.10	46.04
38	7.10	68.70	4.90	34.15
39	8.60	223.10	19.20	38.47
40	6.60	81.00	5.30	57.22

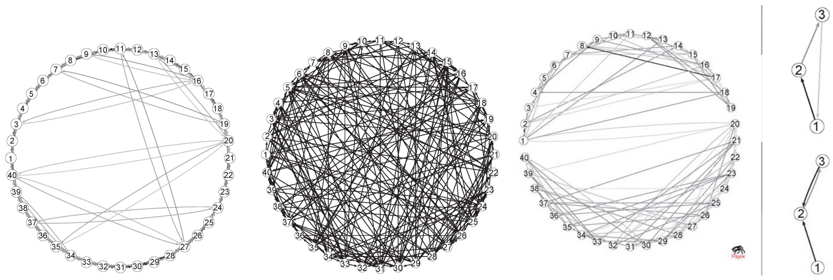
range from \$100 bln to \$700 bln each, while total assets of 10 small banks do not reach \$100 bln per bank. A cumulative initial value of banks total assets is \$25951.16 bln. The smallest banks from the sample have both the lowest and the highest capital ratios (Figure 1). On the average, the medium-sized and the largest banks have Tier 1 ratios above 9%. From the sample, seven banks have initial Tier 1 ratios below 8%. Bank number 40 has the lowest initial Tier 1 ratio of only 6.6%. Some descriptive statistics are reported in Table 3.

All simulation runs are iterated forward in time, using a synchronous update scheme. Time is discrete and defined over $t = 1, 2, \ldots, 252$, which should

Table 3 Descriptive statistics of banks' initial positions

	Assets	Capital	Tier 1 ratio
Mean	648.78	73.66	11.40
Median	305.35	30.70	10.95
Max	2,555.00	311.70	23.30
Min	13.80	1.20	6.60
Std. Dev	724.06	86.08	3.82
Skewness	1.17	1.30	1.39
Kurtosis	3.19	3.65	4.81
Obs.	40	40	40

resemble one business year. To get the effect of a shock, we first run the model without a shock to get baseline results and then subtract the baseline results from the shock runs.



(a) small-world network (b) complete network (c) cutpoint network

Fig. 2 The model is simulated on a small world network, complete network and two versions of a cutpoint network. In the first version of the cutpoint network node 3 is pointed to by node 1, in the second it is pointed to by node 2, while all other links are the same.

The model is run on two versions of a complex network, small world-alike network and a complete network. A complex network consists of two islands that are connected to each other with a cutpoint on each side (Figure 2). A node is a cutpoint if its elimination splits the network on more unconnected sub-networks. In a network, cutpoints are important not only because they retain connectivity, but foremost because of their abilities to transmit shocks from a distressed island to other islands which they connect. Cutpoints have the highest betweenness centralities and thus have a potential to become the most important nodes within the network. Banks number 1 and 20 that are cutpoints in our experiment. The two cutpoint banks are linked in both directions and the links are called bridges. In the first version of the model node 3 was pointed to by node 1, in the second it is pointed to by node 2 (Figure 2c). All other links are the same in both versions and are omitted in the two sub-figures. By using two versions of a cutpoint network we examine the effects of a negligible change in the network structure to the financial system. In a small world network each bank is linked to two the nearest banks on each side, while each link is rewired with a probability of $p = 0.1$ and preserved with probability $(1 - p)$ (Watts and Strogatz, 1998). We depart from the original small world network structure which is by definition undirected, in that we build the undirected network first and then transform the undirected links into directed links in both directions, although the weights are not of equal size. In a complete network, each bank is linked to all other banks and thus has a maximum number of $(n - 1)$ links. In a complete network of four banks, Allen and Gale (2000) demonstrate that a shock is absorbed by all banks and there is no contagion. The complete network from our paper could be referred to as a weighted complete network, because banks vary in size and the balance sheet structures, and hence, have asymmetric exposures to each other.

We first simulate the model against a systemic event and then against an idiosyncratic. A systemic event is characterized by a drop in the mortgage values by a specified percent. We start with a drop in the mortgage value of 1%, while the magnitude progresses at an increment of a percentage point up to the magnitude of 50%. An idiosyncratic event is characterized by a default of a single bank and of simultaneous defaults of three random banks. In the latter case, we do 100 independent repetitions, designating 100 different combinations of three defaulted banks. In each of the network topologies the same three banks default in a given repetition. All shocks are applied in $t = 10$.

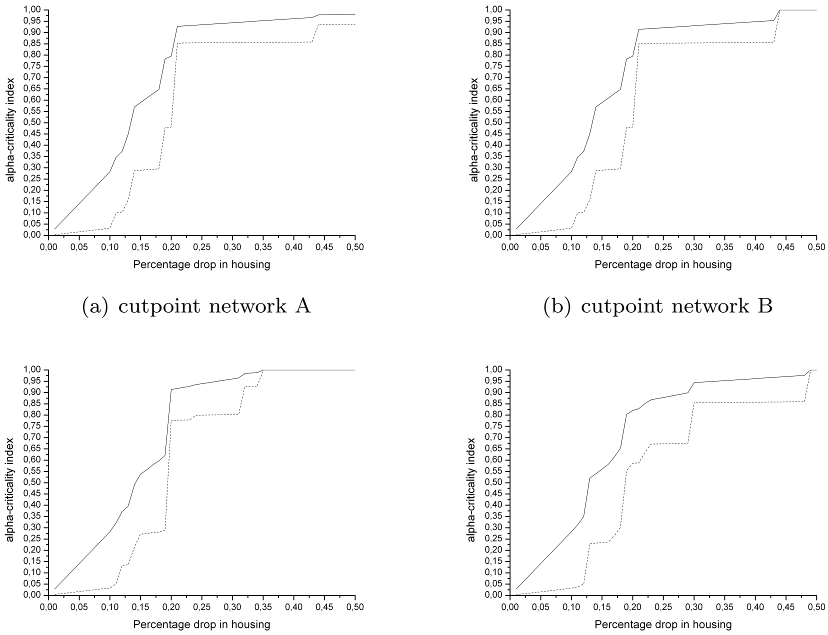
4 Results

There is no general answer which of the four network topologies is more resilient to the systemic event, because the networks respond differently for different magnitudes (Figure 3).

Shocks of the magnitude below 11% do not induce bank defaults, which means that the effects to the system are proportional to the shock magnitude and the level of mortgage loans within the banks. Up to this magnitude, all networks behave the same.

From the perspective of the minimum magnitude which is needed to collapse the entire network, the small world network performs the worst. It defaults from the shock of 35% on and exhibits the largest α-criticality index from the shock of 26% on (Figure 3c). However, the network is much more resilient to the shocks of smaller magnitudes and by far outperforms the other three networks for shocks in the range of 13-19%. For instance, a 19% shock is considered a 0.62-critical event in terms of the banking capital in the small world network and 0.78 / 0.78 / 0.80-critical in the cutpoint A / B / and complete network.

The cutpoint B network defaults from the shock of 44% on, although it slightly outperforms other networks for the shocks in the range of 30-43% (Figure 3b). The complete network defaults from a shock of 49% on, while it outperforms the others for the shocks in the range of 21-29% (Figure 3d). Cutpoint A network is the only network that did not fully default for any shock magnitude with the shock of 50% being considered a 0.94-critical event



(a) cutpoint network A

(b) cutpoint network B

(c) small-world network

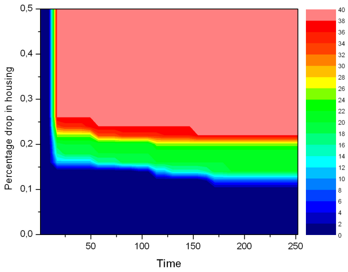
(d) complete network

Fig. 3 α-criticality indices for different percentage of a mortgage shock in $t = 252$. Doted line shows the values in terms of defaulted assets and the solid line in terms of defaulted capital.

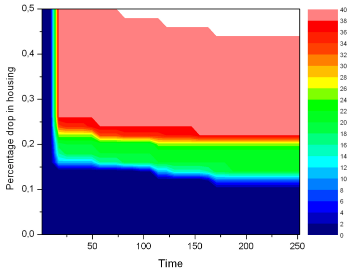
in terms of defaulted assets and 0.98-critical event in terms of defaulted capital (Figure 3a). The only bank which does not default is bank 3, which is the fifth largest from the sample with initial assets of \$1796 bln and Tier 1 capital ratio of 11 percent. Interestingly, the network outperforms the other three networks only for the last two shock magnitudes when they all default. However, for the shock magnitudes that do not exceed 17%, both cutpoint networks perform substantially poorer than the rest.

The figures exhibit some substantial discrete jumps in α-criticality values, indicating a nonlinear nature in the shock consequences. In a complete network, 12% shock sinks only 2 banks and is referred to a 0.05-critical event in terms of banking assets, while a shock of 13% sinks 19 banks, hence being referred a 0.23-critical event in terms of banking assets. The small world network exhibits a similar jump for the shock of 20%, while the two cutpoint networks for the shock of 21%. In each of the cutpoint networks, a shock by the additional percent sinks 37 banks, 12 more than the shock of 20%. Clearly, when the critical point is reached, a small additional increase in the shock level provokes contagion which may induce extremely large additional consequences.

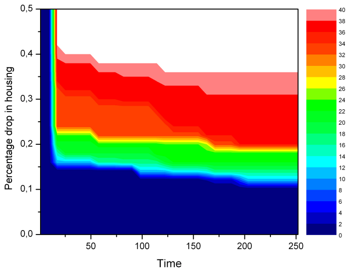
In Figure 4, we use a heat-map visualization to present the cumulative number of defaulted banks for different shock magnitudes. In all frameworks,



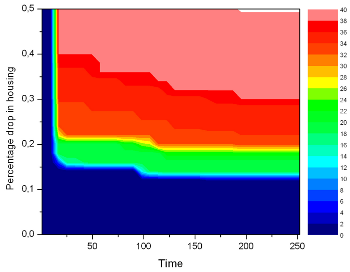
(a) cutpoint network A



(b) cutpoint network B



(c) small-world network



(d) complete network

Fig. 4 The number of defaulted banks over time for different magnitudes of a mortgage shock. The color palette propagates from blue to white which signifies a default of all 40 banks. The shock propagates at an increment of a percentage point up to the magnitude of 50%.

bank 40 is the first that defaults due to the combination of a mortgage shock of 11% that reflects a systemic event and the developments on the markets. Its default induces contagion in three frameworks. In the small world network, the bank sinks bank 39, whose default collapses bank 38. In the two cutpoint networks, the collapse of 40 induces 7 additional bankruptcies. Bank 39 is the first counterparty bank that collapses, while its default induces additional defaults of banks 33 and 34, both banks to which it is linked which makes risk-sharing too weak against the contagion. The contagion propagates to banks 23 and 31 and from these two banks to banks 29 and 35.

Default of the first bank is always induced by the systemic event. The banks that default first are those with the lowest capital ratio and whose significant portion of assets is comprised of the types that were hit by the shock. Then, subsequent defaults are induced by the interplay of many factors. The shock deteriorates the banks capital levels, which may, together with the additional writedowns due to the counterparty risk and the unfavorable developments on the equity markets, initiate defaults of counterparty banks. This increases the risk of contagion. The contagious dynamics is positively correlated to the shock magnitude but is nonlinear in nature. In addition, the larger the shock, the less time the counterparty banks have to avoid the consequences. A shock of 50% immediately collapses 24 banks in each of the four network topologies, while these defaulted banks collapse 36 / 36 / 38 / 37 banks in of the cutpoint A / B / complete / small world network, respectively. Although the subsequent defaults are highly concentrated within the very short post-default periods, they can be present over the entire time span. In a small world network, the last default occurs in $t = 195$.

Table 4 shows statistical results on α-criticality indices after single bank defaults. The number of observations denotes the number of banks.

Table 4 α-criticality index after single bank defaults

	Cutpoint A		Cutpoint B		Complete		Small World	
	Capital	Assets	Capital	Assets	Capital	Assets	Capital	Assets
Mean	5.17	3.46	5.16	3.46	4.55	2.73	4.76	3.11
Median	2.73	1.92	2.73	1.92	2.05	1.25	2.11	1.28
Max	20.47	15.77	20.47	15.77	19.85	10.89	20.60	12.74
Min	0.10	0.06	0.10	0.06	0.09	0.08	0.10	0.06
Std. Dev	5.60	3.87	5.58	3.86	5.21	3.04	5.49	3.50
Skewness	1.04	1.34	1.04	1.34	1.27	1.16	1.35	1.19
Kurtosis	2.94	4.25	2.96	4.25	3.71	3.18	3.97	3.06
Obs.	40	40	40	40	40	40	40	40

Single bank defaults are at most 0.2-critical events in terms of defaulted capital and 0.16-critical events in termsn of defaulted assets.

A complete network is the only network which does not induce contagion for any of the single bank defaults, even though a default of bank 24 induces only slightly smaller aggregate loss in terms of defaulted capital than it does in other three network topologies. Bank 24 is the largest within the system and has very small RR, though risk-sharing prevails in a complete network. The rule according to which a defaulted bank sinks a counterparty bank is that the capital of the latter is lower than the loss it suffers on its exposure at the first, hence $C_{i,t} \leq (RR_j \cdot IB^j_{i,t})$. In a complete network, the entire destructive potential of each defaulted bank is distributed among all banks, for which even the smallest ones are capable of absorbing the losses on the exposure to the biggest banks. In other three network topologies the losses are not wide spread but are concentrated to the few of the adjacent banks. For instance, in each of the cutpoint networks, bank 24 is linked to six banks and its default directly sinks 4 of them. From these, a default of bank 34 substantially reduced capital of banks 23 and 31, which default on the poor market developments later on. Default of bank 23 sinks bank 35, while default of bank 31 reduces the capital of bank 29 which defaults on the poor market development shortly after. These last four defaulted banks are second degree links to bank 24. Because of the smaller destructive potential of the smaller banks that default later on, these subsequent defaults do not induce further defaults. Overall, defaults of single banks do not induce further defaults in 27 cases of a small world network and in 21 cases in each of the two cutpoint networks. In a small world network, bank 32 is the most critical in terms of the number of additional defaults, while bank 24 is the most critical in terms of α-criticality indices in all four cases.

When three banks simultaneously default, the consequences are much more severe than in the case of a single bank default (Table 5). The shock as such reflects a sort of a systemic failure and could be considered a semi-systemic event. We do 100 simulation runs, in each of which a different combination of three random banks are initially sent into default. Notice that in all network topologies the same three banks default in the same repetition, hence we can directly compare the results.

Table 5 α-criticality index after simultaneous defaults of 3 random banks

	Cutpoint A		Cutpoint B		Complete		Small World	
	Capital	Assets	Capital	Assets	Capital	Assets	Capital	Assets
Mean	16.16	11.29	16.10	11.21	14.85	9.45	15.13	10.24
Median	15.18	10.27	15.18	10.27	13.84	8.59	13.89	9.75
Max	45.87	35.83	45.90	33.49	48.19	33.09	45.04	31.81
Min	0.90	0.69	0.90	0.69	0.79	0.67	0.90	0.69
Std. Dev	8.84	6.66	8.79	6.42	9.01	6.01	9.01	5.95
Skewness	0.68	0.97	0.67	0.75	0.96	1.16	0.70	0.79
Kurtosis	3.88	4.61	3.80	3.75	4.29	4.91	3.26	4.02
Obs.	100	100	100	100	100	100	100	100

The impact of a shock to the system crucially depends upon the combination of defaulted banks, with the consequences ranging from negligible to substantial. The most critical event in terms of the banking capital (0.48-critical) has been achieved after initial defaults of banks 1, 2 and 24 in a complete network.[8] The result may seem surprising given the risk sharing character of a complete network, yet it highlights the weaknesses of such a topology. Recall first that we have a weighted complete network. Secondly, given that no bank can avoid the default of any bank, the small and poorly capitalized banks that are heavily exposed to the banks with small RR have the poorest absorption capabilities on the one side and risk large writedowns, on the other. Hence, they are likely to fail to the large shocks and thus spur a new wave of additional defaults due to the counterparty risk. If big banks are linked to the failing big banks, they may be able to absorb the losses and thus prevent contagion. Intuitively, the behavior of a complete network to the shocks is similar to the systemic event as in both cases any event diminishes capital levels of every bank. It is just that for an idiosyncratic event the extent to each bank depends upon the combination of defaulted banks and may be smaller than in the presence of a systemic event. In cutpoint A network, the maximum

[8] These banks are the biggest three and amount to \$6949.8 bln in banking assets and \$854.4 bln in capital.

α-criticality index of 0.46 was achieved after defaults of banks 2, 4 and 20, while combination 1, 2, 24 was 0.43-critical event. The result seems surprising, given that combination 2, 4, 20 sums up to \$5477.8 bln in banking assets and \$633.8 bln in capital. In the B version of the cutpoint network, combination 2, 4, 20 was 0.42-critical event in terms of banking capital while combination 1, 2, 24 was 0.46-critical event. Why the difference? In the cutpoint A network, defaults of banks 2, 4, 20 substantially reduced the capital of bank 1 which defaults in $t = 160$ on the unfavorable equity market dynamics. Although the bank 1 default does not induce further defaults, it lowers capital levels of its counterparty banks, which contributed to the level of the event criticality. On the other hand, the loss due to the bank 2 default is distributed between banks 1 and 3 in the cutpoint B network for which none of them defaulted. In a small world network, combination 1, 2, 24 was 0.45-critical event, while combination 2, 4, 20 was 0.38-critical event. This suggests that not only the size of initially defaulted banks determine the criticality level of a certain credit event but also the banks microstructure together with the network topology.

Although these two combinations were considered the most critical events in terms of defaulted assets and capital, the most critical event in terms of the number of defaulted banks was combination of defaulted banks 20, 24 and 25. The combination that sums to only \$4725.2 bln in banking assets and \$566.3 bln in banking capital collapsed 12 additional banks in each of the cutpoint networks, 11 in a small world network and 10 in a complete network. Despite being considered the most critical event terms of the number of defaulted banks, this combination was perceived a 0.36-critical event in each of the cutpoint networks, 0.35 in a complete network and 0.30 in a small world network, all in terms of defaulted capital. The apparent mismatch in the number of defaulted banks and the criticality level is a consequence of the fact that this combination collapsed smaller banks with initial capital of less than \$31.4 bln.

We now turn to the question of the number of bank defaults over 100 repetitions of the model in different network topologies. First we examine the level of contagion in different network topologies and then also the frequency of individual bank defaults.

There was no contagion in 80 cases in a complete network, in 16 cases in a small world network and in 12 cases in each of the cutpoint networks (Figure 5). On the average, 1.4 (3.03) additional banks defaulted in a complete network, 2.68 (2.26) in a small world network and 3.52 (2.67 / 2.65) in each of the cutpoint networks; corresponding standard deviations are reported in the brackets. A complete network has proved to be the least contagious of the four. Yet, the network included a run which was the most critical from all. However, except for the extreme cases which may be very harmful, simultaneous defaults of three banks produce consequences of small-to-moderate magnitudes.

The smallest and poorly capitalized banks failed the most frequently (Figure 6). Bank 19 performed the worst in this respect, defaulting in 54 runs in each of the cutpoint networks and 33 times in the small world network. The bank is among the smallest. In each of the cutpoint networks, it is linked

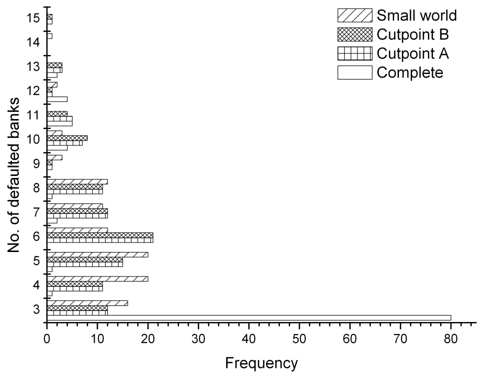
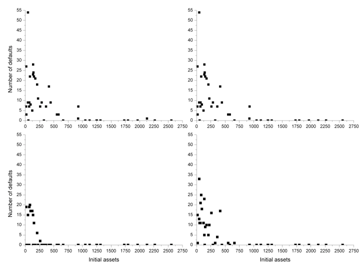
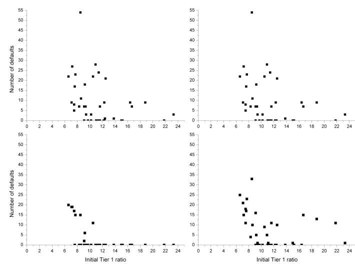


Fig. 5 Frequency of defaulted banks after a simultaneous default of 3 random banks over 100 repetitions in a complete network, cutpoint A network, cutpoint B network and small world network



(a)



(b)

Fig. 6 The number of bank defaults against the banks' initial level of assets (Figure 6a) and Tier 1 ratios (Figure 6b) in a cutpoint A (II quadrant), cutpoint B (I quadrant), complete network (III quadrant) and small world network (IV quadrant). Only additional defaults are used in the figures, while not also those in which individual banks defaulted as a part of a shock.

to only two banks, 12 and 15. In a complete netwok, bank 40 defaulted 20 times and banks 14 and 38 nineteen times each. Following the figures, we can conclude that the bank size and the capital ratio are two the most important factors of a bank default. Capital ratio is much more relevant factor in a complete network than in other three network topologies, because each default reduces the capital of each bank.

5 Discussion

Questions of stability of a financial system are complex and there is no clear answer which system is more stable, because different systems behave differently under different circumstances. The two cutpoint networks demonstrate that even a negligible modification in the network topology can induce sizable aggregate consequences.

The results indicate that banking networks may be highly vulnerable to systemic credit events and much less to idiosyncratic. Generally, if EAD is large enough and RR low, default of a bank can induce the subsequent failures of adjacent banks and hence become contagious. Even more so, if a defaulted bank is adjacent to poorly capitalized banks or if a substantially bigger bank is exposed to smaller banks. An event that induces contagion makes the effects of a shock nonlinear and elongated. A nonlinear nature of the shock consequences is rooted in heterogeneity of the banks. Since the banks differ in size and connectivity, they contribute differently to the stability of the entire system. For instance, small banks do not possess such a contagious potential than the big ones. On the other side, a default of a more important bank may trigger a new wave of subsequent defaults. When banks write down some of their assets, they lose some of the capacity to absorb additional losses on some other larger positions, such as the equity portfolio. Any unfavorable developments on other relevant markets can promulgate contagion and increase the likelihood of additional bank defaults in the latter stages. Banks can reduce their credit risk by implying a match funded balance sheet in which assets and liabilities consist of positions with similar characteristics.

In an idiosyncratic event, risk-sharing prevails over credit contagion. This is particularly the case in a complete network, where the single bank defaults do not induce additional defaults. The bank can avoid its default on the counterparty risk if its capital level exceeds its exposure to the counterparty banks for the given RRs and $C_{i,t} > \sum_j \left((1 - RR_j) \cdot IB^j_{i,t}\right)$ holds. This rule could be referred a safety shield rule.[9] If this rule does not hold, idiosyncratic events can induce bank defaults and become contagious. In the simulation runs, contagion due to the idiosyncratic event has collapsed smaller and at most the medium-sized banks. Generally, big banks are at risk only under very unfavorable combination of the network topology, the structure of an idiosyncratic shock and the post-shock developments on equity markets. However, the bank size alone does not imply the bank importance, as it has been the prevailing belief, but only in a combination with its balance sheet structure and the position within the banking network. A policy implication of the rule is that diversification across many banks lowers the probability of a bank default, but can not eliminate it.

A systemic shock propagates differently than the idiosyncratic. It develops in two stages. The shock as such reduces capital levels of each bank, which makes the banks more vulnerable to the counterparty risk. It is important to

[9] The notion of a risk-adjusted capital takes the spirit of this safety shield rule.

note that no RR are applied in the systemic event. When the banking system is hit by a systemic event, the factors that induce bank defaults are Tier 1 ratio and the proportion of the bank assets that were hit by the shock. Banks with the unfavorable combination in the two factors default first. Following the first defaults, the systemic shock may get contagious and can easily turn into a self-feeding system of subsequent defaults. Subsequent defaults are even more likely, given that the shock reduces the capital of each bank. This represents a very critical moment for the stability of the financial system and can explain the severity of the crisis even at a moderate shock magnitude.

As already mentioned, smaller banks are more likely to default due to the contagion than the bigger ones, particularly if they are poorly capitalized. In addition, if the level of bank capital is low and further reduced by the shock, even a small disruption on any other markets can collapse the bank. In the paper, the biggest banks were the most stable and among the last that failed. The biggest banks collapsed only after a combination of a systemic event of larger magnitude and contagion. If they are properly capitalized, the big banks represent a protective shield to the system. If not, they may spur contagion of additional defaults. In the paper, big banks have enough of capital to overcome defaults of smaller and medium-sized banks. However, the imbalanced balance sheet and unfavorable connectivity can make also the biggest banks vulnerable to defaults. The results also indicate that the failure of some of the medium-sized banks can cause contagion, but of the limited extend. Although, on the average, highly connected networks are more resilient to the shocks than other networks, they can not overcome very severe credit events, either.

Our results are similar to those of Upper and Worms (2004) who find that defaults of single banks in Germany can induce a contraction of 15% of the banking assets. Similar to implications of our paper are Battiston et al. (2012) and Beale et al. (2011) who have argued that individual banks can reduce the probability of a default by diversifying their exposure. Given that systemic events are much more critical events than the idoosyncratic, a stable banking system would consist of banks that not only diversify their exposure to different banks but also to different systemic events.[10] Systemic interdependences in different external events may limit the benefits of the balance sheet diversification. The latest financial turmoil was after all induced by a systemic event; i.e. drop in the housing.

In the model, credit events do not exacerbate uncertainty or loss of confidence or panics, while banks default when they run out of capital and not when the capital falls below the required level. We assume that credit events do not affect the investors' sentiments, although a bank default can spur the individuals to reassess their priors and reformulate their expectations of other institutions with similar characteristics or from similar environments.[11] In addition, the model does not include correlation or co-integration in different credit events and markets, e.g. mortgage market, equity and commodities mar-

[10] A portfolio principle of Markowitz (1952) could well be applied here.

[11] Hirshleifer (2001) provides an extensive overview of behavioral finance.

kets, sovereign debt, economic process, etc. Yet, disruptions in financial and capital markets have regurarly affected each other and have been followed by a period of an economic slowdown (Gilchrist et al. 2009). We also do not impose the liquidity condition (see Acharya and Merrouche (2013) and references therein.).[12]

6 Conclusion

A network-based model of credit risk was developed and simulated to examine the effects of idiosyncratic and systemic shocks to the financial system.

It has been demonstrated that the credit risk analysis exhibits a nonlinear behavior. The analysis is highly sensitive to the structure of the interbank market and the bank microstructure, particularly the banks' capital levels, the balance sheet structures and recovery rates. Type of the shock and its magnitude are two highly significant external factors.

In the simulation runs, idiosyncratic shocks do not induce large consequences on the average, not even for a simultaneous default of three random banks. Systemic shocks are far more costly to the system than the idiosyncratic and can induce extremely large consequences even for the moderate magnitudes. Successive bank defaults are much more probable after a systemic shock because the shock reduces the capital level of each bank that possesses an asset that was hit by the shock. The bank that overcomes the shock with barely any capital and has very unfavorable portfolio is highly vulnerable to the negative market developments and the counterparty defaults and, hence, has limited chances to avoid its default in the post-shock period. Any bank default in the post-shock period can spur a new wave of subsequent defaults due to the combination of the counterparty and the market risk.

Big banks have proved to be systemically more important than the smaller ones, although the level of importance depends also upon the network structure. Big banks have also been much more resilient to the shocks than the smaller and can, if capitalized enough, serve as stabilizing entities that can stop contagion. This is especially significant when a bank serves as a cutpoint.

An implication of the paper is that diversification reduces the probability that single events will cause huge disruptions to individual banks and, consequently, to the banking system. In addition to diversification, match funded balance sheets can improve the bank stability and that of the system.

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[12] See Brunnermeier (2009) and Tirole (2011) on the role of liquidity in the latest financial crisis.

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