Systemic risk and heterogeneous leverage in banking networks☆

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Tolga Umut Kuzubaş [a], Burak Saltoğlu [a], Can Sever [b],*

[a] *Boğaziçi University, Department of Economics, Natuk Birkan Building, 34342 Bebek, Istanbul, Turkey*
[b] *University of Maryland, Department of Economics, Tydings Hall, 20742, College Park, MD, USA*

HIGHLIGHTS

- The systemic risk depends on the leverage dispersion across banks in a network.
- Heterogeneous leverage has implications in a banking network.
- The systemic risk implications of bank specific characteristics are explored.
- The relative significance of different types of borrowers is illustrated.
- A policy experiment related to the surcharge requirements is conducted.

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ABSTRACT

This study probes systemic risk implications of leverage heterogeneity in banking networks. We show that the presence of heterogeneous leverages drastically changes the systemic effects of defaults and the nature of the contagion in interbank markets. Using financial leverage data from the US banking system, through simulations, we analyze the systemic significance of different types of borrowers, the evolution of the network, the consequences of interbank market size and the impact of market segmentation. Our study is related to the recent Basel III regulations on systemic risk and the treatment of the Global Systemically Important Banks (GSIBs). We also assess the extent to which the recent capital surcharges on GSIBs may curb financial fragility. We show the effectiveness of surcharge policy for the most-levered banks vis-a-vis uniform capital injection.

1. Introduction

The global financial crisis of 2008 paved the way for a thorough consideration of systemic effects of bank defaults. Recent financial regulations, such as Basel III, placed special emphasis on the mitigation of systemic risk. In an interbank network, an idiosyncratic shock hitting a bank may spread via borrowing–lending linkages and may thereby impair the stability of the whole system. Bank balance sheets and network positions, and the connectivity of the network are crucial aspects of financial stability. In this paper, through simulations of banking networks, we study the systemic risk implications of leverage heterogeneity. We show that introducing leverage heterogeneity significantly changes systemic risk measures,

and reveals the significance of bank specific characteristics. We use financial leverage data of the US banking system from[1] to observe relative systemic significance of the biggest and the most-connected borrowers, the evolution of the network after a shock, systemic consequences of interbank market size and the impacts of market segmentation. We then discuss the potential implications of our results as they relate to Basel III regulations on systemic risk and to the treatment of the GSIBs. Our approach is useful for assessing to the extent to which recent capital surcharges on GSIBs may reduce the financial fragility in the banking system. We show that the surcharge for the most-levered banks reduces the total systemic risk.

Broadly, there are two strands of literature focusing on the implications and measurement of systemic risk. The first strand mainly relies on market based indicators to measure systemic risk, however these indicators do not allow for a detailed analysis of potential contagion effects or inference of risk prior to a crisis. Using a macroeconomic framework and employing data from the 2008 financial crisis, He and Krishnamurthy [1] provide evidence to support this observation.

The second strand uses network approach. There are several measures of systemic importance and systemic risk contributions of individual nodes, following the seminal papers of Erdos–Renyi [2], Bonancich [3] and Borgatti [4]. Recently, relying on earlier work on network topology, Soramaki and Cook [5] develop algorithms to identify the systemic importance of nodes in a network. Paltalidis et al. [6] model systemic risk using the Maximum Entropy approach for Eurozone. Kuzubaş et al. [7] compare the relative performance of risk measures, using interbank network data for 2001 Turkish banking crisis and observe the evolution of the network during the crisis. In another recent paper, Minoiu and Reyes [8] analyze the global interbank network, using a large dataset; they observe that the density of the global banking network as defined by these flows is pro-cyclical and find that country connectedness in the network tends to rise before crises and then to fall in their aftermath. Our results are in line with this finding. Hale et al. [9] examine the composition and drivers of cross-border banking and show that on-balance sheet syndicated loan exposures, which account for one third of total cross-border loan exposures, increased during 2008 financial crisis due to large drawdowns on credit lines growth before the crisis. Saltoglu and Yenilmez [10] discuss the role of connectivity in banking networks and its implications for systemic risk. There are several studies applying a network based analysis of systemic risk to different banking networks e.g. Ref. [11] for the US market, Benitez et al. (2014) for Mexican banking system, Puhr et al. [12] for the Austrian interbank market, and Caldarelli et al. [13] for the Italian overnight money market. Cont et al. [14] analyze how balance sheet sizes and network structure affect the systemic risk contribution of the institutions. They provide specific policy implications, targeting the most contagious banks in the system. Iyer and Pedró [15] conduct an econometric analysis of data from a natural experiment and conclude that a policy targeting the systemic risk should decrease excessive exposure of single institutions and limit the effect of shocks. Most of these studies, including that of Gai et al. [16], find that interbank networks consist of several central players and many institutions that are less connected. That is, links across banks in interbank borrowing and lending markets are not distributed evenly. In line with this evidence, we use geometric distribution in our study to form banking networks with a small number of central players, and many less-connected ones.

Simulation based studies investigate the role of interbank linkages in absorption and amplification of risk. Iori et al. [17] suggest that interbank market stabilizes the system for homogeneous banks case, whereas its role remains ambiguous in systems with heterogeneous banks. Gai et al. [16] offer policy recommendations for different network structures. Jo [18] extends Chan-Lau's [19] network analysis linking liquidity and solvency risks, and discusses how they are related to Basel III requirements. Haldane [20] discusses the role of concentration in risk amplification, and argues that interconnections among financial institutions may serve as shock amplifiers or absorbers, depending upon the degree of connectivity. We will discover this "knife-edge" property of the network in our analyses. Eisenberg and Noe [21] and Diamond and Dybvig [22] are network models including market dynamics. Eisenberg and Noe [21] reveal the existence and uniqueness of clearance vector for financial system in *fictitious default algorithm*, while Diamond and Dybvig [22] examine the effects of a bank run associated with policy issues. We employ a similar algorithm in our model. Gleeson et al. [23] propose a method for calculating the expected size of contagion cascades in the network, based the Nier et al. [24] and Gai and Kapadia [25]. Our theoretical framework adapt several features from these two models. Bluhm et al. [26] incorporate market equilibrium into a heterogeneous banking network, focusing on the microfoundation, including optimal portfolio decisions along with liquidity and capital constraints.

Despite a large body of literature on the linkages between the leverage and systemic risk, most of the existing network models mentioned above have been built on homogeneous leverages. On the other hand, Adrian and Shin [27,28], Danielsson et al. [29,30], and Brunnermeier (2009) reveal the importance of financial leverage in systemic risk. Thurner [31] shows that higher leverage gives rise to higher volatility in prices in the financial markets, and hence higher risk. Moreover, small random events, that are harmless at low levels of leverage, may have a severe effect on the system in the case of relatively high leverage. Brunnermeier and Sannikov [32], in a macroeconomic model, illustrate the relationship between high leverage positions and a more unstable system. Ramadan [33], employing a cross-sectional data analysis, concludes that leverage is a significant factor for risk, no matter which method is used in estimation. These findings give rise to the question about the role of leverage differentials in network analysis of banking systems.

Our paper contributes to this literature by using networks tool to analyze systemic risk in the case of heterogeneous leverages. We investigate systemic consequences of leverage differentials across banks. Our main concerns are fragility

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Table 1
Balance sheet representation.

Assets (A_i)	Liabilities (L_i)
External assets (A_i^E)	Unsecured interbank borrowing (L_i^I)
Unsecured interbank lending (A_i^I)	Equity (E_i)
	External deposits (L_i^E)

and systemic risk within the financial system. We note that our approach does not capture losses by creditors outside the financial system. That is, we keep track of losses within the banking system that arise from idiosyncratic shocks to the equity of banks. We introduce a balance sheet based network model with heterogeneous leverage levels, which is missing in the existing literature.[2] In the case of varying degrees of leverage across banks, we create a stress scenario. By performing simulations in Monte Carlo framework, we focus on the effects on stability of connectivity, the volume of interbank transactions, shock size, leverage distribution and liquidity. Network is formed exogenously and randomly, using a geometric distribution to capture the properties of real banking systems mentioned above. We also investigate the decrease in connectivity at the end of the shock spread process. We show that results are significantly different from those in the case of homogeneously levered banks. In essence, the main contribution of our study is the observation of the relative systemic significance of individual banks. Depending upon their initial lender–borrower positions, connectivity and leverage level, banks have different systemic significance for the system. In our model, even net borrowers are more open to first step shocks, and net lenders are more sensitive to losses due to counterparty defaults. Connectivity also affects the relative resilience of the net borrowers and lenders with these competing forces. In addition to the number of defaults, we propose various measures of systemic risk. First, we investigate the number of banks whose net worth falls below the capital adequacy ratio (CAR), i.e. banks deplete their required minimum capital which is 8% after the shock. This measure is more complete and sensitive than the number of defaults, since it allows us to observe all banks that are significantly affected.[3] As mentioned earlier, it is a challenge to predict systemic risk, an issue also raised in Ref. [1]. The main reason in using this measure is to signal the stress in the system, even when there is no default. We introduce different target banks for idiosyncratic shocks,[4] since the bank that is hit by initial shock is crucial in our analyses. We also study the impact of leverage dispersion.[5] Additionally, while looking at the impact of leverage dispersion, we compute the Gini coefficient of the shock spread process (calculated as percentage depletion of banks' net worths), where higher Gini coefficient implies that more banks are severely affected losing significant portions of their net worths. Total net worth loss (calculated as the sum of individual percentage losses) is also evaluated in order to measure the asymmetric impacts of shocks. Based on these measures, we show that bank identity and dispersion of the leverage sequence significantly affect the stability. Finally, we analyze how our results differ when we add liquidity effect (e.g. fire sale mechanism) that reduces the total value of assets in the case of a default in the system. This amplifies the effect of a shock, especially if a highly levered bank is hit. We provide policy implications about leverage distribution and surcharge, and discuss how these are related to Basel III regulations.

In Section 2, we introduce the model and define the environment. In Section 3, simulation results and related policy implications are illustrated and discussed. Finally, we conclude in Section 4.

2. Theoretical framework

We introduce a balance sheet-based network model where systemic risk arises from idiosyncratic shocks to bank assets. We construct an interbank money market with N institutions.

As shown in Table 1, balance sheet identity of bank i is

$$A_i^E + A_i^I = L_i^I + L_i^E + E_i \quad \forall i = 1 \ldots N \tag{1}$$

where A_i^E are the assets from outside of the interbank market.[6] External deposits are liabilities to external depositors. θ_i is defined as the liability composition of bank i:

$$\theta_i = \frac{L_i^E}{L_i}. \tag{2}$$

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[2] A recent study by Kapan and Minoiu [34] presents similar findings to ours. They examine the role of bank-specific balance sheet strength in the transmission of financial sector shocks to the real economy. They find that banks that were initially more dependent on market funding reduced the credit more than other banks, during 2008 crisis. Their key results suggest that strong bank balance sheets are crucial for the recovery of credit after a crisis. This is in line with our policy implications. Although Nier et al. [24] conducted a similar analysis of systemic risk, the model they propose does not capture the impact of heterogeneous leverages across banks, nor do they incorporate any relationship between size of bank-specific interbank transactions or leverage levels. We will discuss how our approach is able to capture these in Section 2.

[3] For completeness, we use the existing CAR regulation in our analysis. We use Tier 1 ratios from data, but we also note that this is not the exact measure used for 8% threshold. That is, Regulatory Capital Ratio employs a broader capital measure than Tier 1. Hence, our results for this measure may change quantitatively, whereas they are resistant to changes in CAR values in a qualitative manner.

[4] These targets in different experiments are the biggest borrower, the smallest borrower, a random bank and the most-connected borrower.

[5] That is, we create different leverage sequences which will be described in detail in Section 2.

[6] It consists of liquid assets, fixed assets and other long-term lending activities.

Table 2
Balance sheet values.

Parameter	Bank 1	Bank 2	Bank 3
A_i, L_i	10	10	10
θ_i	0.6	0.6	0.6
L_i^E	6	6	6
γ_i	3	4	5
E_i	≈3.33	2.5	2
L_i^I	≈0.67	1.5	2

Total assets are defined as $A_i = \gamma_i E_i$. Since, leverage is the ratio of total assets to equity (net worth),[7] γ_i is the leverage for bank i, and γ_{Nx1} is the leverage vector for the system. The model aims to capture the effect of varying degrees of leverages in an otherwise homogeneous system with a uniform balance sheet size across banks. We have initial lenders and borrowers, although the balance sheet size is uniform. We also introduce symmetry of liability compositions in terms of external deposits via identical θ_i values. We establish the negative relationship between interbank borrowing and the equity of the bank in the following way:

$$L_i^I + E_i = (1 - \theta_i)L_i \tag{3}$$

where θ_i and L_i values are the same across banks. In this regard, if a bank has higher leverage (and thus lower capital), it will participate in more interbank borrowing. It will become a bigger borrower than an average bank. A direct implication of Eq. (3) with identical (θ, L) pairs and $A_i = \gamma_i E_i$ is that highly levered banks borrow more in the market. Consequently, despite homogeneous sizes, asset compositions are different across banks. In this framework, we use a procedure to construct networks and balance sheets similar to the ones in Ref. [24] and Gai et al. (2010). We use realizations of network to determine initial positions of the banks in terms of whether they are a lender or borrower. Given the structure of the interbank network, A_i, θ_i and γ_{Nx1}; E_i, L_i^I, A_i^E and A_i^I are determined endogenously. That is, we distribute interbank borrowing uniformly among the lending links of any bank.[8] Thus, a bank with high leverage is more likely to be a net borrower.

We introduce balance sheet heterogeneity by allowing γ_i values to differ across banks.[9] Banks with low net worth, i.e. a lower equity buffer to absorb adverse shocks, are more sensitive to financial shocks; and they also transmit higher portions of a shock to the creditors via bilateral interbank claims. Lenders would lose their loans when a debtor defaults. On the other hand, banks with high capital would be stronger against adverse shocks. To specify the bottom line of our model, introducing heterogeneous leverage levels and Eq. (3) give rise to having some big lenders and big borrowers with initial market segmentation. Benchmark leverage levels are adapted from data for a sample of US banks from Forbes's listing.[10] We note that the leverage sequence affects the results quantitatively, whereas it is not important for the main focus of our paper. Moreover, we have experiments using a mean preserving spread for leverage sequence, and investigate further the effects of dispersion.

2.0.1. An example of network and balance formation

This example serves to illustrate the network and balance sheet formation mechanism above. We consider a 3-bank network with $A_i = L_i = 10$ and $\theta_i = 0.6$ for all banks. Following from definition (2), $L_i^E = 6$ for all banks. Let the leverage vector be $\gamma = [3, \ 4, \ 5]$ for banks 1, 2 and 3, respectively. Table 2 illustrates implied balance sheets.

Note that A_i^I and A_i^E values are missing above, and Bank 3 is the biggest borrower (i.e. highest leverage). We need to construct a network to complete balance sheets endogenously. Let the network be as follows (see Fig. 1):

Arrows indicate the direction of lending. Based on this network, remaining balance sheet values are constructed. Since, Bank 1 borrows 0.67 ($L_1^I = 0.67$), and Bank 2 and Bank 3 are the lenders, they both lend 0.335 and 0.335 to Bank 1. Since Bank 2 borrows 1.5 ($L_2^I = 1.5$), and the only lender is now Bank 1, Bank 1 lends 1.5 to Bank 2. Since Bank 3 borrows 2 ($L_3^I = 2$), and the only lender is Bank 2, Bank 2 lends 2 to Bank 3. Balance sheet is completed as follows (see Table 3):

2.0.2. Shock transmission

We introduce idiosyncratic shocks to the equity of the banks (e.g. decrease in housing prices). A shock (s_i) that wipes out a fraction (k) of the assets of bank i,[11] $s_i = kA_i$. We shock randomly chosen banks, and specifically targeted banks, depending

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[7] See Ref. [28].

[8] The interbank market clearing condition is expressed as $\sum_{i=1}^{N} A_i^I = \sum_{i=1}^{N} L_i^I$.

[9] Note, different γ_i values also imply different net worths.

[10] We choose $N = 25$, as in Ref. [24]. This number is reasonable by considering the evidence represented by Leaven et al. [35]. They show the trend in increasing banking concentration. That is, several banks own a large fraction of banking assets. We adapted 25 banks from Forbes's listing published on December 22, 2014, as mentioned above. Leverage ratios and the names of the banks used as benchmark sequence are available upon request.

[11] Note that shock size k means that k fraction of assets of the bank is wiped out.
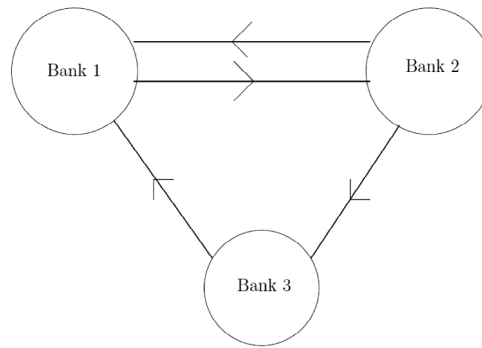
Fig. 1. Network example.

Table 3
Endogenous balance sheet items.

Value	Bank 1	Bank 2	Bank 3
A_i^I	1.5	2.335	0.335
A_i^E	8.5	7.665	9.665

upon their characteristics. In this way, we are able to reveal the relevance of bank-specific characteristics. We target the most-connected and the biggest borrowers in the system. Given that an initial shock spreads from borrower to lender via unpaid interbank claims, the most-connected and the biggest borrowers are expected to be systemically important. We investigate the effect of connectivity in their relative systemic significance. To see the impact of balance sheet position on the significance of a bank, we also target the smallest borrower. If net worth of a bank (E_i) is not sufficient to absorb the shock, the bank defaults, and residual shock is transmitted to the creditors of the bank. We define an event for bank i as default, if constraint shown below is breached:

$$A_i^E + A_i^I - L_i^I - L_i - s_i > 0 \qquad (4)$$

where s_i is the shock to assets of the bank. In case interbank liabilities are still not sufficient to absorb the residual shock, some of the losses are borne by depositors outside the system. A default borrower cannot pass an amount greater than its debt to a lender. By the condition (4), if $s_i < E_i$, bank does not default, but its net worth becomes $E_i' = (E_i - s_i)$. Thus, it becomes more vulnerable for the potential shocks arising from counterparty defaults during future rounds of the same process triggered by initial shock. In our model, highly levered banks are more vulnerable to the first step shocks, they have a greater capacity to pass on the residual shock to lenders. As a second source of vulnerability, although they have higher capital values, bigger lenders are more open to lose their interbank assets due to potential counterparty defaults. Thus, connectivity plays a role in relative significances of net lenders and borrowers for the rest of the system. In the case of a default, a shock that is not absorbed and is (potentially) transmitted through interbank borrowing links of the default bank is $(s_i - E_i)$. Transmitted shock is divided among lenders proportional to the lending amounts. The shock transmitted to bank u is calculated as a ratio of bank i's total borrowing to the number of its lenders, which is given as,[12]

$$s_u = \frac{s_i'}{H_i}$$

where H_i is the number of lenders of bank i and s_i' is the transmitted shock to the lenders after the default of bank i. As mentioned above, the residual shock, s_i', is defined as

$$s_i' = \begin{cases} L_i^I, & \text{if } (s_i - E_i) > L_i^I \\ s_i - E_i, & \text{otherwise.} \end{cases}$$

This definition of transmitted shock is in line with our main concern; losses within the banking system.[13] It imposes an upper limit to the transmitted shock so that a bank cannot transmit the part of shock that is higher than its existing debt to

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[12] While distributing the residual shock among the creditors of the default bank, we modify the weighting algorithm of the *proportionality* principle of Eisenberg and Noe [21] which is based on the weights of the borrowing links between banks. Defining a *relative liability matrix*, they introduce distinct weights of lenders in the total lending of default bank. As a result, if a default occurs, all claimant nodes are paid by the defaulting node in relation to the size of their claim on the defaulting bank's assets. We do not introduce different weights for borrowing linkages. It has a direct result in distributing the residual shock equally among creditors in this framework. In our benchmark model, because all lendings are given equally, if there are m lenders of default bank, each lender receives $\frac{s_i}{m}$.

[13] If $(s_i - E_i) < L_i^I$, creditor banks receive a total shock of $(s_i - E_i)$. If $(s_i - E_i) > L_i^I$, the whole amount cannot be transmitted, then the transmitted shock is L_i^I.

Table 4
Summary of benchmark parameters.

Parameter	Description	Benchmark value	Range of variation
A	Total assets in the system	125 000	Fixed
N	Number of banks in the network	25	Fixed
θ	Ratio of external liabilities to total liabilities	0.75	0.6–0.85
k	Shock size (fraction of A_i)	0.4	0–1
γ_{Nx1}	Leverage vector	Forbes's List $\mu \approx 18, \sigma \approx 5$	0–$2\sigma_\gamma$ around μ

other banks. In our procedure, *sequence of defaults* of Eisenberg and Noe [21] is used for modeling the domino effect. After this first transmission, if the creditor bank have a net worth sufficient to absorb the shock, $s_u < E_u$, it withstands the shock, but its net worth becomes $E'_u = (E_u - s_u)$. If the shock is not absorbed, $s_u \geq E_u$, it is transmitted by the same mechanism and rounds continue until no further defaults occur. The possible terminal points of this scenario are the failure of the whole system where no bank is left to transmit the remaining shock, or no further defaults occur, since the whole shock is absorbed.

2.0.3. Examples of shock transmission

This example illustrates the shock transmission mechanism. For a specific network realization, suppose Bank 1 lends $20 to Bank 3, and borrows $5 from Bank 2, $11 from Bank 4. Equities of Bank 1 and Bank 4 are $7 and $21, respectively. Bank 2 borrows $6 from Bank 4. When Bank 3 is hit by a shock, and violates the default constraint, Bank 3 will not be able to repay $20 to Bank 1. Hence, Bank 1 will lose $20, which causes it to violate its default constraint. Then Bank 1 defaults, and is unable to repay $5 to Bank 2 or $11 to Bank 4. Assume equity of Bank 2 is so low that Bank 2 defaults after a loss of $5. Next, Bank 4 will lave a loss of $11 (from Bank 1) and loss of $6 (from Bank 2). Since its net worth is high to bear these shocks and does not violate default constraint, it will lose $17 in total, but will survive. Hence, the domino effect ends. Three banks default, but the last bank is still alive (even if it lost from defaults of counterparties) due to its initially high equity.

Another example would help to show the relevance of transmitted shock and a more sensitive measure. Suppose Bank 5 defaults. The initial shock is $20, whereas Bank 5 initially owes $5 to Bank 6, and $12 to Bank 7. When it defaults, $s'_i = 17$ since initial shock is greater than its interbank debt. Hence, a $3 loss is faced by creditors outside the banking network. However, our concern in the network will be $5 loss of Bank 6, and $12 loss of Bank 7. Assume that net worth of Bank 6 is $20, and net worth of Bank 7 is $2. Bank 7 then will default. Let Bank 7 initially owe $1 to Bank 6. Bank 6 now faces with $1+$5 loss. Since its net worth was $20, it survives. Hence, we do not count Bank 6 in the number of defaults. On the contrary, since it lost 6/20 of its initial net worth, we count it in the "number of banks below CAR". Hence, it is a more sensitive indicator of the risk. Since Bank 6 is more vulnerable now with less equity, it is more prone to default from lower shocks than it was in its initial position.

2.1. Methodology

In this section, we explain the simulation procedure. The exogenous parameters of the system are number of banks (N), leverage vector (γ_{Nx1}), the ratio of external deposits to total liabilities (θ) and total assets (A). Benchmark values are represented in Table 4. We construct a 25 bank system.[14] As we noted before, benchmark leverage sequence is not important for qualitative results, but there may be quantitative changes. To take care of this, we also conduct experiments using a mean preserving spread for leverage sequence. The fraction θ is taken as 0.75 as a benchmark, but we conduct sensitivity tests with different values of this parameter. Asset size (A) does not have any effect on our results since we define shock as a fraction. In baseline experiments, we take shock as 0.4, and conduct several experiments, to see the effect of shock size.

Using the exogenous values in the balance sheet, we determine components that are independent from the network. Finally, we create realizations of an unweighted network.[15] Using geometric distribution in network, we have several banks with a high degree of connectedness to many banks with lower degrees of connectedness. Having constructed the network, we determine A_i^I and A_i^E, endogenously. Links are not netted.[16]

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[14] The results do not depend on the number of banks in the system. If the same experiments are conducted with 250 banks, all findings will be scaled by 10.

[15] Following empirical studies, as discussed above, a geometric network is more appropriate for real world structures. In the model, the only randomness stems from the network structure. It maps to the randomness of assets of banks via interbank lending. In order to eliminate noise, we create a Monte Carlo framework for 1000 runs with 1000 network realizations, and we take average values across realizations. We follow the assumption used in Ref. [24], May and Arinaminpathy [36] and Montagna and Lux [37], and assume that shock propagation is too fast for banks to be able to revise their positions.

[16] As a convention, *ji* link represents *j* lends to *i*. Both *ij* and *ji* links can be 1. If bank *i* both lends to bank *j*, and borrows from *j*, shock may spread in both directions. "Average degree" is the average of in-degrees and out-degrees for each bank, i.e. the average number of banks that any bank is connected to.

3. Simulations and results

In this section, we illustrate and discuss our results. Banks are sorted in ascending order based on their leverages. That is, 1th the least-levered bank (i.e. the smallest borrower), and 25th bank is the most-levered one (i.e. the biggest borrower).[17] Following an idiosyncratic shock, we count the number of banks that violate default constraint in each realization of network. Then we take averages for this measure across realizations. We also introduce a new systemic risk measure which is the number of banks falling below 92% of the net worth.[18] We also propose "systemic net worth loss" in the system as another measure of systemic risk. It is defined as the total loss in equities of banks in percentages. Finally, using the depletion of individual equities, we calculate "Gini coefficient of shock spread process". These new measures are found to be more sensitive indicators of the risk.

The second crucial contribution of our study is the capture of relative systemic importance of the biggest and the most-connected borrowers in the system. In Ref. [38], highly interconnected lenders in the syndicated loan market are the greatest contributors to systemic risk, suggesting important negative externalities. Their findings are similar to ours. However, we find that the systemic significance of the biggest and the most-connected borrowers alters depending upon the initial shock size and connectivity. Two competing forces give rise to this finding: the impacts of total amount that has been borrowed, and the number of banks that can be affected following the default of the borrower. For different connectivity levels and shock sizes, these forces dominate each others.

As well as altering significance of the biggest and the most-connected borrowers, in case where the most-connected one faces the shock, network connectivity shows "knife-edge" characteristics as described by Haldane [20]. We show that when a shock hits the most-connected borrower, network becomes an absorber until a connectivity threshold. After this edge, it significantly amplifies the trigger shock that hits the most-connected borrower. By contrast, when the biggest borrower is hit, links act as shock amplifier up to a threshold level, and then they act simply as absorber. By comparing the cases in which the biggest and smallest borrowers receive the shock, we also observe that the amount of interbank borrowings of the bank that receives the shock affects the risk.

We investigate the effect of shock size on average connectivity of interbank market. Brunetti et al. [39] find that interbank links decreased during crisis. This decline in interbank transactions is directly related to the volume of the interbank market. Acharya and Merrouche [40], Gorton and Metrick [41] and Minoiu and Reyes [8] also report decreased volume of interbank transactions during the 2008 crisis. We find that, due to potentially higher number of defaults, there are more links to be broken for higher levels of shock. In line with Brunetti et al. [39], we observe the effect of the volume of interbank transactions. As the average volume of interbank transactions decreases, the system is more resilient to shocks. Since the biggest borrower stays within the upper limit of borrowing, the effect is clearer for the biggest borrower.

We observe that the initial balance sheet position of the target banks affects systemic risk consequences. The systemic significance of initially net lender and borrowers alters, depending upon average connectivity. Intuitively, there are two competing forces that give rise to this result. The net lenders are more open to net worth losses due to potential defaults of their borrowers. On the other side, net borrowers are more vulnerable to shocks. These dominate each other at different levels of connectivity.

Nier et al. [24] show, at identical leverage levels, systemic risk increases, when system-wide leverage increases. More interestingly, in the case of homogeneous leverages, we observe that the behavior of inherited risk differs significantly for scenarios in which a random bank and the most-connected bank receive the trigger shock. Their systemic importance alters depending upon average connectivity.

Apart from the benchmark leverage sequence, we observe the impact of leverage dispersion on systemic risk. We create different scenarios that include homogeneous leverages, increasing standard deviation of sequence (i.e. more disperse leverage levels), and a case in which we have two extremely low and high levered banks (with 23 homogeneous banks at the mean leverage value). "Gini coefficient of shock spread process" and "systemic net worth loss" consistently show how severity and asymmetric effects of shocks change. We note that increasing leverage heterogeneity makes the system less resilient, especially if the biggest borrower faces the shock.

We model the liquidity channel in a way that resembles to Nier et al.'s [24] model to reveal the importance of bank specific characteristics on the consequences of the liquidity channel. We note that the impact of liquidity channel is clearer in case of a shock to the biggest borrower.

Finally, last experiment examines the effectiveness of surcharge policy in three different scenarios: the biggest, the most-connected and the smallest borrowers as targets of idiosyncratic shocks. The novelty of this analysis is that it allows to observe relative effectiveness of different policies when different banks face the shock. We compare same amount of capital injections with a uniform increase in equities and a surcharge to the five mostly levered banks. We observe the effectiveness of surcharge policy as compared to uniform capital injection.

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[17] It can also be interpreted as different financial sectors with different levels of leverages, and interacting with each others.

[18] For the number of defaults (and the number of banks below CAR), 0 indicates no defaults, and 1 indicates that only the bank itself defaults. Hence, until up to a particular point, small shocks cannot make any bank default, but beyond that threshold, our measures jump from 0 to 1, meaning that bank itself is affected. In the case that there are further defaults, we take average number of defaults over realizations.
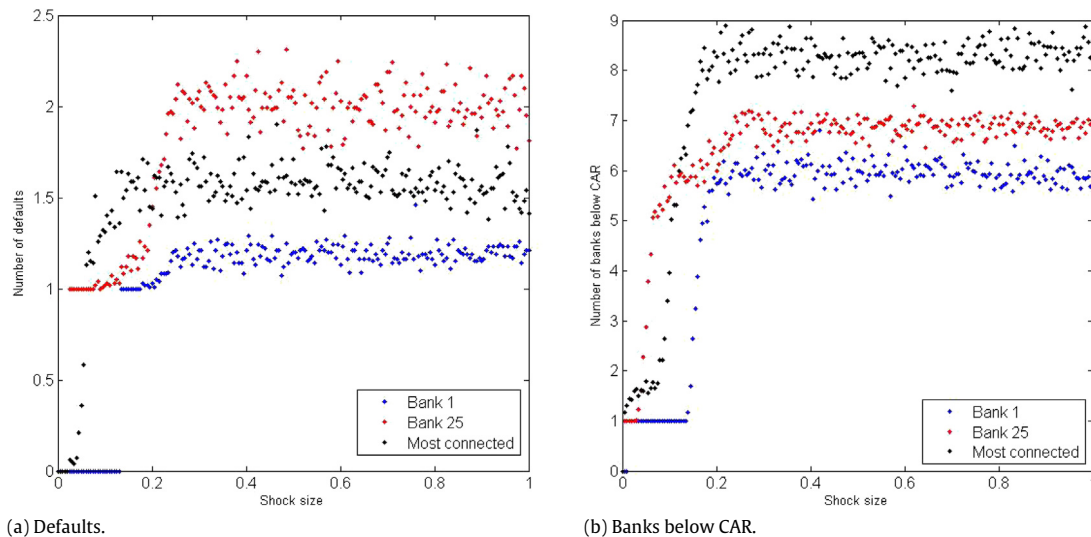
(a) Defaults.

(b) Banks below CAR.

Fig. 2. Effect of shock size.

3.1. Effect of shock size

Fig. 2(a) illustrates the effect of increasing shock size (k) for defaults. In smaller shocks, the most-levered bank (i.e. the biggest borrower) is immediately affected. It starts to spread the residual shock, contaminating to the rest of the system for even tiny shocks. On the other hand, even the most-connected lender does not necessarily default for smaller shocks, but if it does, it immediately spreads the residual shock to a large number of banks, since it has many creditors. That is why it inherits more risk to the system than the biggest borrower for shock levels around 0.1. The least-levered (i.e. the smallest borrower) bank does not lose its entire net worth from relatively larger shocks. Even after it defaults, since it has the least capacity to transmit shock, when a shock hits Bank 1, the consequences are less severe compared to those for other targets. There is another tipping point of shock around 0.2. Since the most-connected bank spreads the shock among many banks, its effect is severe up to this point. On the other hand, after this threshold, since the biggest borrower has the maximum capacity to transmit shock, the volume effect for the biggest borrower dominates the interconnectedness effect for the most-connected one. Hence, for larger shocks, the biggest borrower makes system more vulnerable. We also observe that systemic significance of the biggest and the most-connected borrowers varies according to shock size.[19]

Fig. 2(b) shows the number of banks below CAR. For this measure, since a shock contaminates many lenders via the most-connected one, after a tipping point around 0.1, it is the one which may affect the most number of banks. Unlike to the number of defaults, size effect cannot dominate the connectedness effect in this case. We observe that this is a more sensitive indicator. For instance, around a shock level of approximately 0.2, many banks already fall below the critical limit, whereas there are few banks to default. For low levels of shock, this allows us to see the banks that are more vulnerable, that is, banks that are more prone to default resulting from possible future shocks. As we mentioned earlier, levels may change as CAR limit changes, but the conclusion that this is a more sensitive measure stays same.

We also analyze the decline in the connectivity of the system after a shock. Due to defaults, interbank claims are not paid, and links may be broken. Fig. 3 illustrates the result. We first calculate average number of links in the network in normal times (i.e. without any shock). Then, after a shock hits the most-connected bank, we calculate average number of links. We observe a decrease in the average degree in the network in line with empirical research that we mentioned earlier. As shock size increases, more banks default, and more links on average are broken.

3.2. Effect of initial balance sheet positions

We analyze the effect of balance sheet position on the strength and systemic significance of individual banks. We aim to identify the banks that are weaker solely due to initial market segmentation. We determine initial positions of banks (i.e. whether they are a net lender or a borrower) endogenously via network. In our model, there are 2 competing forces depending on bank balance sheets. Net lenders are smaller borrowers, but they have higher capital. Since they have higher E_i values, they are more resilient to the trigger shock. However, since they lend in large amounts, they are more open to shocks potentially that may arise from borrowers. The opposite is true for the net borrowers. Although they are more prone

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[19] We also note that after shock levels around 0.3, since the volume of transaction in interbank market limits the potentially transmitted amount, the rest of the shock is borne by outside depositors.
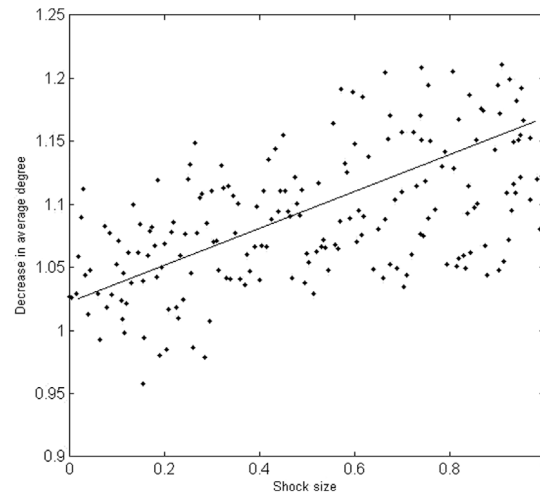
Fig. 3. Shock to the most-connected bank.

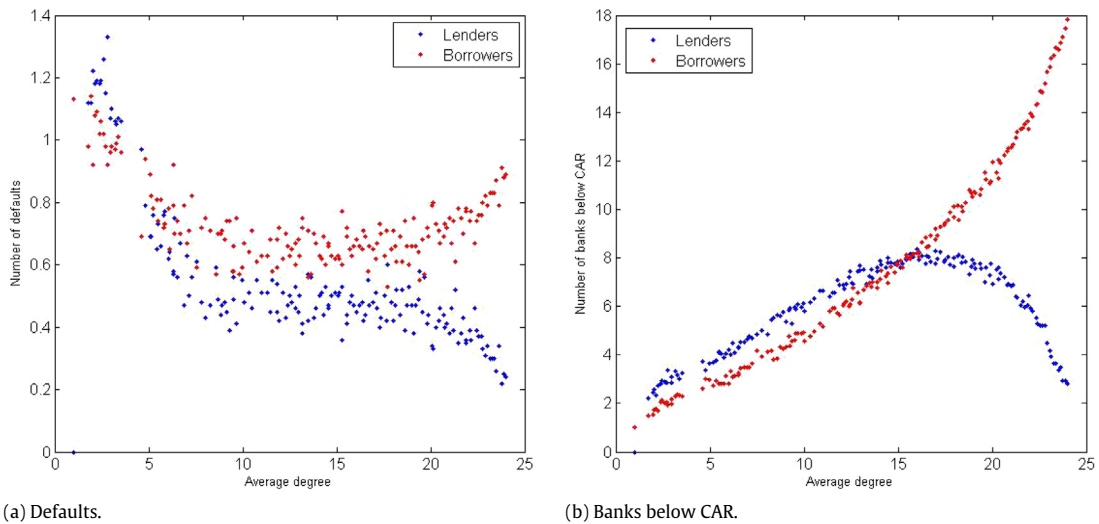(a) Defaults.	(b) Banks below CAR.

Fig. 4. Effect of initial net balance sheet positions.

to default with first hand shocks, since they do not lend large amounts, they are unlikely to lose interbank assets arising from counterparty defaults. We see the effect of connectivity on these competing forces, and the resulting effect of banks' initial positions on financial health.

In order to eliminate first shock bias from the measures, we apply idiosyncratic shocks to random banks, and take the averages. Fig. 4 illustrates the result. We observe that lenders are more vulnerable for low level of connectivity. Although they have higher capital buffers, since the shocks from borrowers are not distributed enough, the size effect for interbank claims overcomes the impact of high capital. They are affected more severely than borrowers by losses arising from counterparty defaults. As connectivity increases, since lenders distribute total the amount of lending among many borrowers, the losses from counterparty defaults do not affect them. Thus, higher capital dominates the risk depending interbank market assets. That is, even if one or more counterparties default, a lender is affected due to high connectivity, hence its equity buffer is enough to sustain solvency constraint. For highly connected networks, the gap is even greater and the impact of connectedness is observed more clearly. The intuition is valid for the number of banks below CAR, too. On the other hand, the threshold for these forces to dominate each others is higher in this case, an approximate average degree of 15. Moreover, after this turning point, the gap in the strength of the two types of banks is clearer with this measure. Depending upon the degree of connectivity, initial balance sheet positions matter for risk consequences. To the best of our knowledge, this kind of result is new in the literature. It is highly relevant to banking regulation, however. This kind of analysis requires more attention in determining relevant policies that target specific banks.

(a) Bank 1 vs. Bank 25. (b) The most-connected vs. Bank 25.
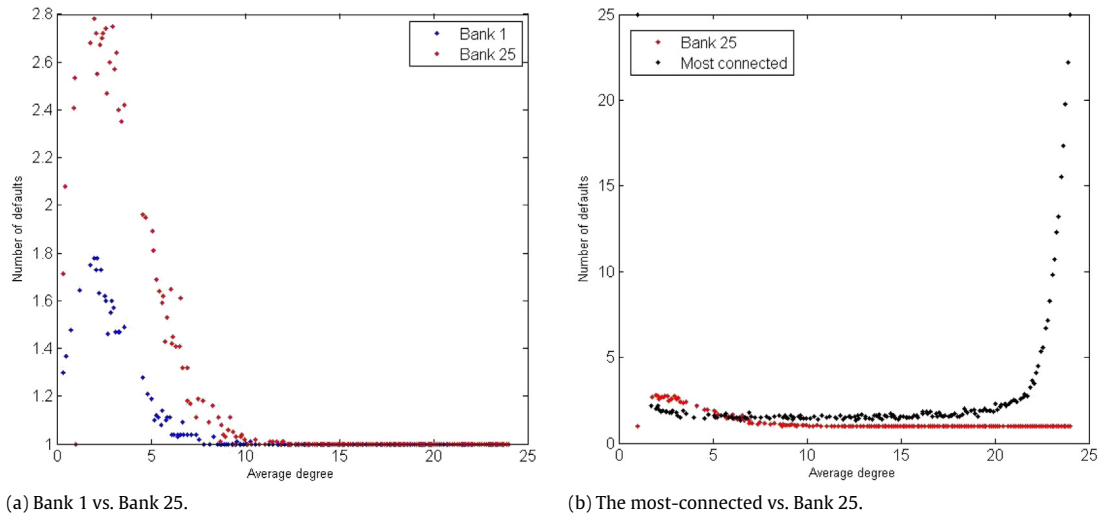
Fig. 5. Effect of average connectivity.

3.3. Effect of connectivity

In this section, we analyze the impact of connectivity in case of different target banks. Fig. 5(a) illustrates that the most-levered bank creates higher risk for the system, when compared with the least-levered bank. The sources of higher inherited risk are low capital, high L_i^I, and thus a high residual shock from Bank 25. The gap is persistent for a wide range of connectivity levels. Beyond a threshold, the network starts to absorb losses in both cases. Moreover, we observe the effect of connectivity on relative systemic significances of the most-connected and the biggest borrowers. In Fig. 5(b), if the network is less connected, the biggest borrower (i.e. the most-levered) is the systemically important one. It causes more banks to default than the most-connected borrower does. Since it transmits more shock, it makes banks default in the second round. In contrast, after a connectivity of around 6, the connectedness of the borrower overcomes the size effect. Thus, the most-connected borrower spreads the shock more, and affects system severely. This reveals the "knife-edge" property as discussed by Haldane [20].

3.4. Effect of interbank market size

We observe the effect of interbank market size on systemic risk in the case of the biggest, the smallest and the most-connected banks receiving the shock. Due to Eq. (3), keeping net worths at the original level, as θ increases, the total amount of interbank borrowing decreases. Fig. 6 illustrates the results. In Fig. 6(a), as θ increases (i.e. size of interbank claims decreases), the system becomes more resilient since transmittable shock reduces. Since Bank 25 is the bank which can potentially transmit the highest amount, decreasing interbank claims has the largest positive impact on the rest of the system. The decline in the number of defaults is sharper when it receives the shock.

3.5. Effect of system-wide leverage

We first take leverage values equal to the mean of the distribution, which corresponds to the homogeneous system. Since we want to eliminate noise from differences of network positions of banks that are hit, we shock a random bank in each case, and then take averages. We also shock the most-connected borrower. Fig. 7 represents the results. We note that this experiment is similar to the one conducted by Nier et al. [24], with all homogeneous banks. However, banks differ in the network positions. Since we have some borrowers with high degrees of connectivity, we still have bank-specific characteristics. We exploit this aspect in our experiment. We use 2 targets (i.e. shock to a random bank and shock to the most-connected borrowers) in order to observe the role of network positions of banks in the homogeneous case. The most-connected bank spreads shock even for lower leverage levels, whereas defaults do not increase until a level of 28 in case of random target. We also note that number of defaults is high, when a random bank receives the shock for high leverage values. The intuition behind this is that transmitted shock is higher for high leverages (since capital is low), but risk distributing role of most-connected lender dominates this size effect. There are turning points in the significance of these two banks in terms of the number of the banks below CAR.
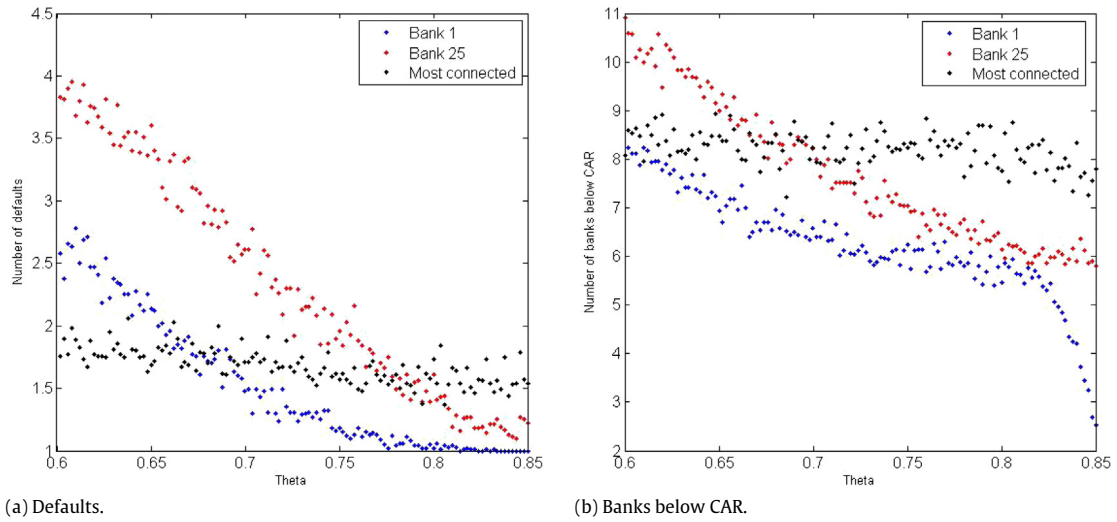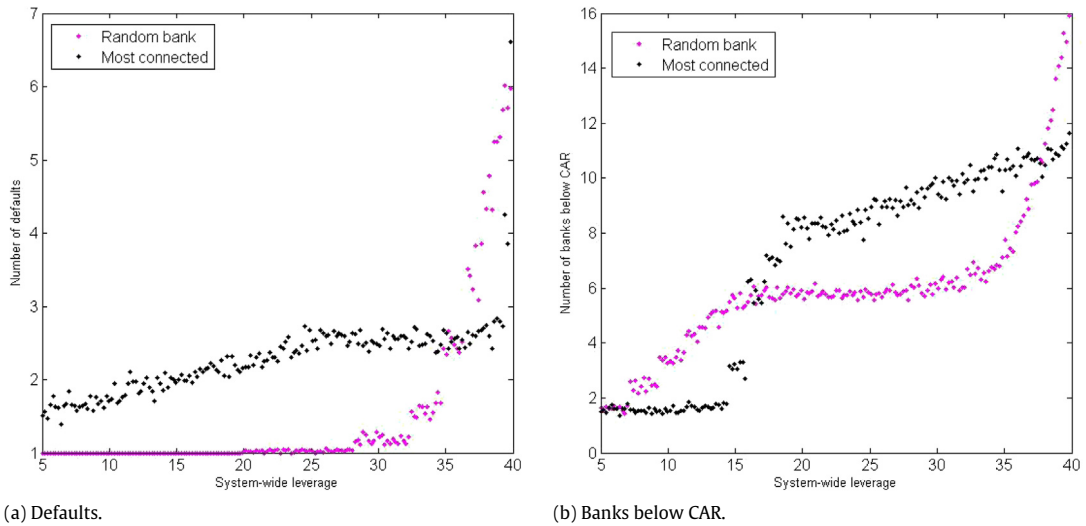
(a) Defaults.   (b) Banks below CAR.

Fig. 6. Effect of L_i^I.

(a) Defaults.   (b) Banks below CAR.

Fig. 7. Effect of system-wide leverage (homogeneous case).

3.6. Sensitivity of systemic risk to leverage dispersion

Using the mean and standard deviation from the data to illustrate the effect of a mean-preserving spread with normal distribution.[20] While the standard deviation of the leverage sequence is increasing, since stronger banks become even stronger with a relatively lower leverage, hence a shock hitting the strongest bank has a less effect. On the other hand, if a shock hits the most-levered bank, its systemic impact is more significant, since the peak of the leverage sequence increases. We observe no significant difference in the impacts of the most-connected banks as leverages become more asymmetric. In addition, we do not observe a remarkable change in the number of banks below CAR (see Fig. 8).

We also calculate the Gini coefficient of the shock spread process. This allows us to measure how unequally the shock propagates through the system. It is calculated in terms of melted percentages of net worth. The asymmetry of spread of the shock is crucial, because a higher level of asymmetry implies that more banks are affected significantly, i.e. a higher Gini coefficient means that more banks lose remarkable percentages of their net worth. In Fig. 9(a), as dispersion of leverage sequence increases, more banks are affected asymmetrically. Hence, both the total level of capital in the system and leverage dispersion are crucial. We note that although the shock spread more asymmetrically for all cases, the risk inherited by the biggest borrower is the greatest.

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[20] We fit a distribution to the empirical leverage sequence. Normal distribution provides a reasonable fit, comparing log likelihood values for different distributions such as Beta, Binomial, Extreme Value, Gamma, Pareto, Lognormal, Poisson.
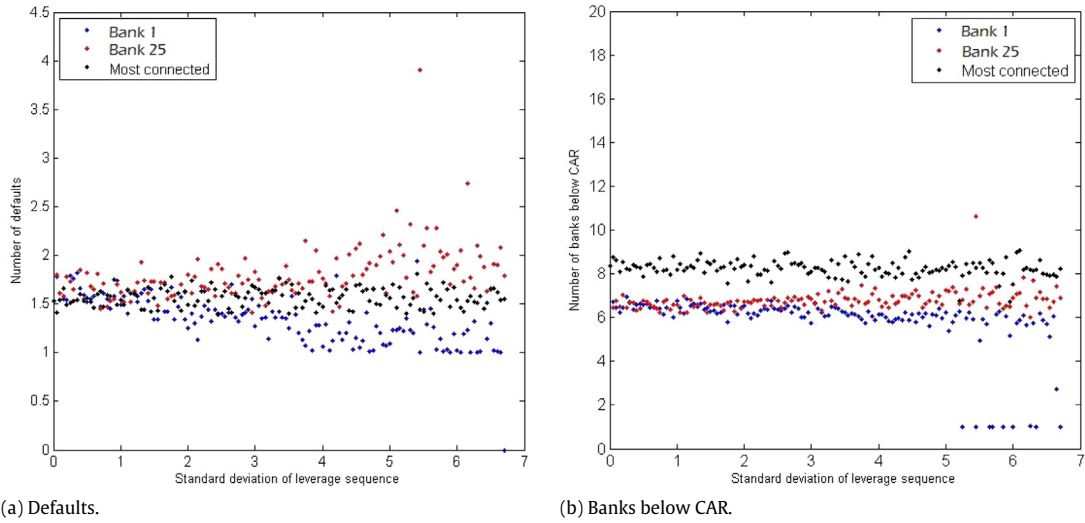
(a) Defaults.

(b) Banks below CAR.

Fig. 8. Effect of leverage dispersion.

(a) Gini coefficient of shock spread process.
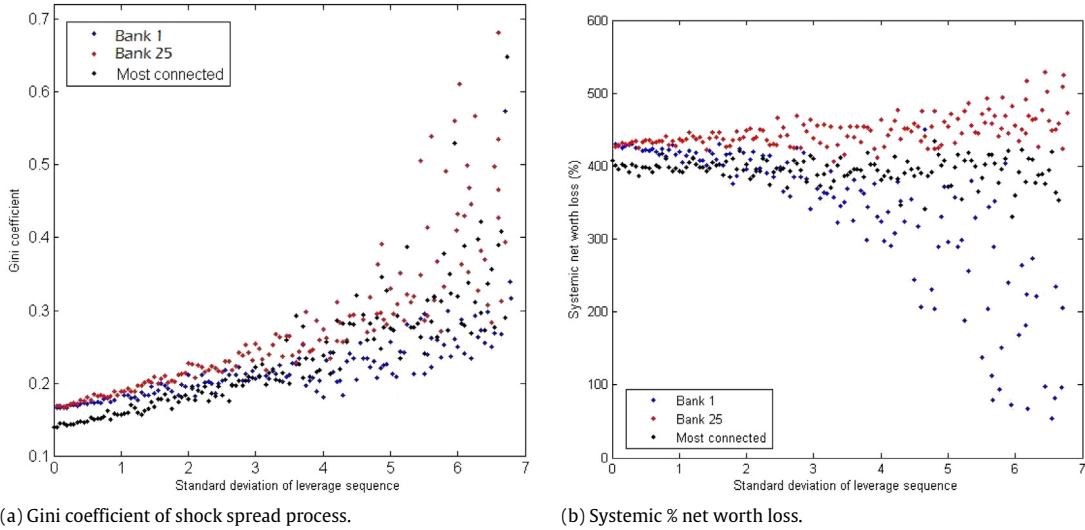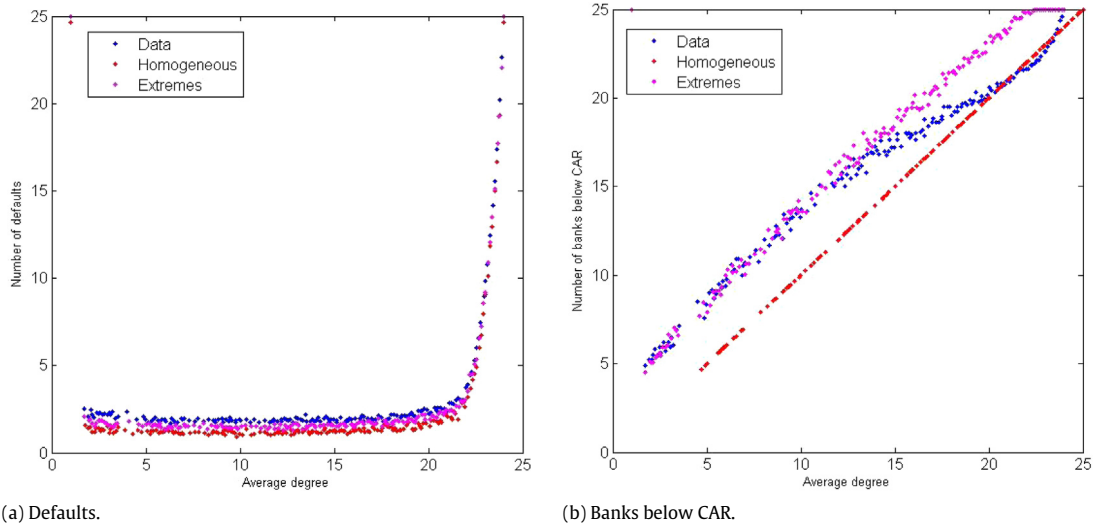
(b) Systemic % net worth loss.

Fig. 9. Systemic risk measures.

Moreover, we calculate a new systemic risk measure: systemic net worth loss which is defined as the sum of % losses in net worths of individual banks.[21] Fig. 9(b) illustrates the results. The greater this measure, the more banks affected severely. Since it reflects percentage losses, it can capture the stress when we have several banks severely affected. When the most-levered bank receives a shock, we observe that the sum of percentage net worth losses of banks increase, as leverage dispersion increases. Although the trend is not strongly upward, the same sort of effect is present when the most-connected borrower is hit. On the other hand, since the smallest lender becomes even smaller when standard deviation increases (as its leverage decreases and net worth increases), its systemic impact is less. The result is consistent with Fig. 9(a). We also note that, despite the fact that total systemic net worth loss decreases in the case of a shock to the smallest borrower, the asymmetry of loss among banks increases following from Fig. 9(a).

In addition to the data and homogeneous leverage sequence at the mean of the data, we introduce two extremely high and low levered banks into the homogeneous system. We refer this sequence as "extremes" in our experiments. We use 23 homogeneously levered banks at the mean value of benchmark leverage sequence. We symmetrically add two banks with

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[21] An example: Suppose that Bank 1, 2 and 3 have $5, $10, $15 net worths respectively. After the shock hits one of these banks, assume their net worths become $4, $5, $7.5, respectively. Our measure, systemic % net worth loss, is calculated as $\left(\frac{1}{5} + \frac{5}{10} + \frac{7.5}{15}\right)100$. When some banks in the system lose large % of their net worths, this measure is higher.

(a) Defaults.

(b) Banks below CAR.

Fig. 10. Shock to the most-connected borrower.

(a) Defaults.

(b) Banks below CAR.
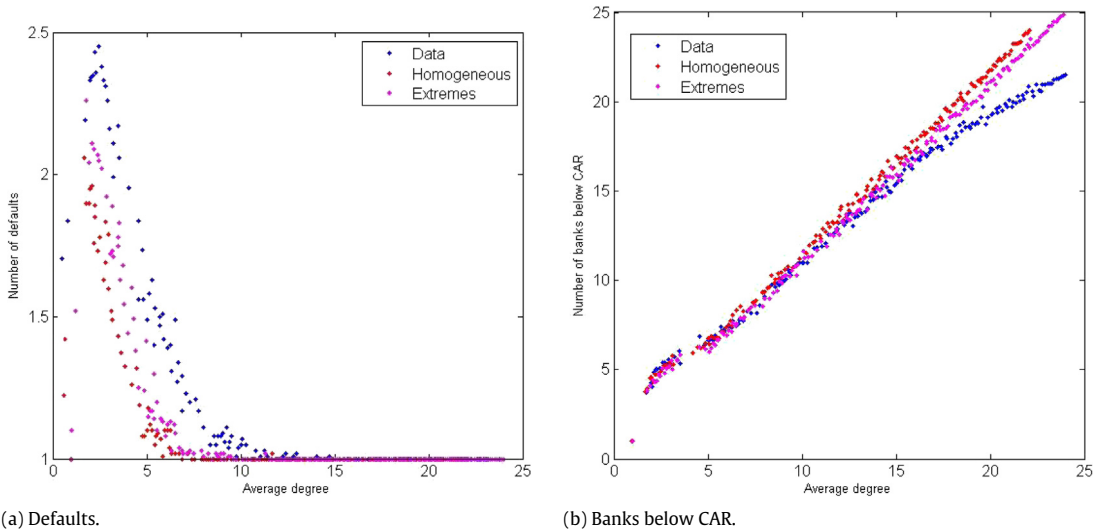
Fig. 11. Shock to a random bank.

extreme leverage, one is highly and one is less levered. That is, their leverage values are the mean value $+/-1$ the standard deviations from the mean. Hence, we keep overall level of capital same for the system. For these three distributions, we aim to support our previous result that the asymmetry decreases the resilience of the system. We introduce shocks to the most-connected, the biggest borrowers and random banks.[22]

Fig. 10 represents the result when the most-connected borrower receives a shock in the case of these three leverage distributions. For both measures, homogeneous distribution yields the best results in terms of the strength of the network. Adding two extremes makes the system less resilient, and the more dispersed the leverages (i.e. data), the more vulnerable the system.

Fig. 11 illustrates the results with three sequences when a random bank receives the shock. The result of the most-connected borrower case is still valid. The worst systemic consequences are observed with the data, and the least number of defaults is received in the homogeneous case. The sequence with extreme banks gives the middle consequences for both measures. This result is crucial showing the relevance of the degree of leverage heterogeneity in the system and is highly related to our motivation.

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[22] In this experiment, the shock to the least-levered bank yields expected results, since it has the lowest leverage in the "extremes" sequence; when it receives a shock, the "extremes" sequence will be the one with the minimum number of defaults, since we create and shock the strongest bank.
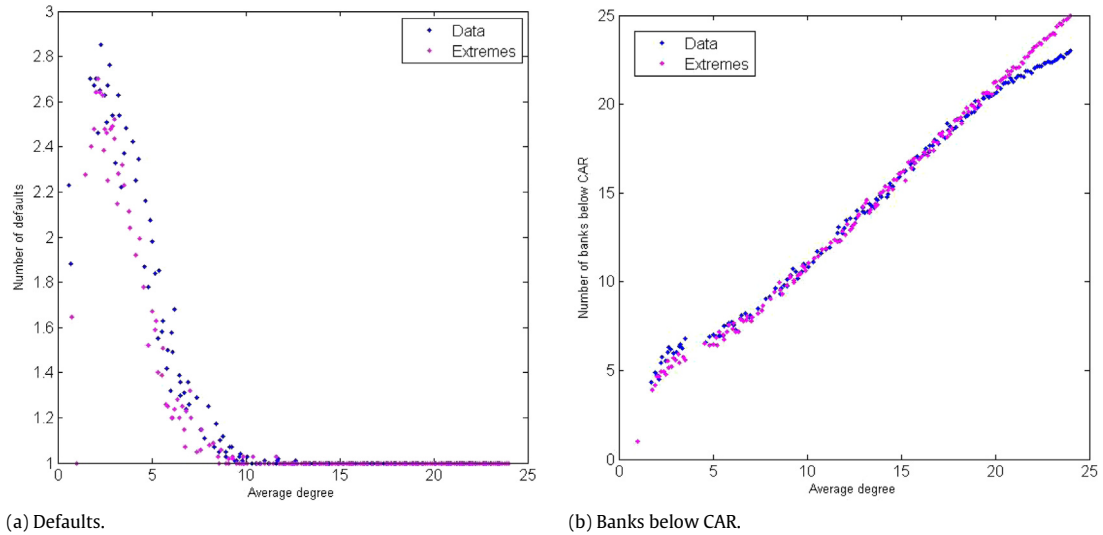
(a) Defaults.   (b) Banks below CAR.

Fig. 12. Shock to the biggest borrower.

We introduce a shock to the biggest borrower in the case of only data and "extremes" sequences, since we do not have a "the biggest" borrower in the homogeneous case. In this case, data again makes system more vulnerable than a relatively more equal distribution (i.e. "extremes"). The previous results are consistent with those of this set of experiments (see Fig. 12).

3.7. Effect of liquidity channel

We investigate the effect of liquidity on systemic risk for different target banks. We assume that when a bank defaults, its remaining assets are liquidated. However, market fails to provide enough liquidity to absorb these assets. We follow Nier et al. [24], and assume that the price of assets is a decreasing function of the amount of assets that needs to be liquidated with inverse demand function $P_r(x) = e^{\alpha x}$, where P_r represents the price of assets in the system at any round r after a shock hits, and α is a measure of limited liquidity of the asset market.[23] Following May and Arinaminpathy [36], x is defined as percentage of the assets to be sold to all assets in the system. When there is no default, the price of assets is equal to 1. If there is a default, $x > 0$, and thus $P_r < 1$. As a result, a shock has an additional effect in the amount of $(1 - P_r)$ on the bank it hits. It also has an additional effect on all other banks, since value of their assets and their net worths decrease. Therefore, we expect to observe that results shift upward for all cases studied, since pricing effect makes all banks more vulnerable.[24] We examine the gap in the impacts of a shock when the biggest and the smallest borrowers receive it. Results are provided in Figs. 13 and 14.

Since the liquidity channel introduces further endogenous and sequential shocks to all banks, when the systemic impact of shock is higher due to higher first level contagion, the effect of liquidity is clearer. That is, when the target bank is more vulnerable in the first round, it triggers higher endogenous shocks. It is also valid for the number of banks below CAR. We infer that when the first level transmitted amount is higher, endogenous shocks arising from the liquidity channel during the stress period have more devastating consequences. This is the intuition why we observe a higher gap in Fig. 14 for both measures.

3.8. Policy implications and recent banking regulations

In November 2011, Financial Stability Board made a critical framework change to reduce the risks by GSIBs. The following regulation[25] has altered the definition and requirements for the GSIBs.

The BIS stated, "The negative externalities associated with institutions that are perceived as not being allowed to fail due to their size, interconnectedness, complexity, lack of substitutability or global scope are well recognized". In order to mitigate the negative externalities that might arise from these banks, an additional capital surcharge will be implemented on these. A bank is chosen as a GSIB using various criteria, including its asset size and interconnectedness. Consequently,

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[23] When $\alpha = 0$, there is no liquidity channel.

[24] We choose $\alpha = -1$ to introduce a liquidity channel, following Nier et al. [24]. Note that, it is a dynamic pricing scheme. In each round, when further defaults occur, and the amount of assets to be sold increases, and the value of all assets that remain in the system decreases.
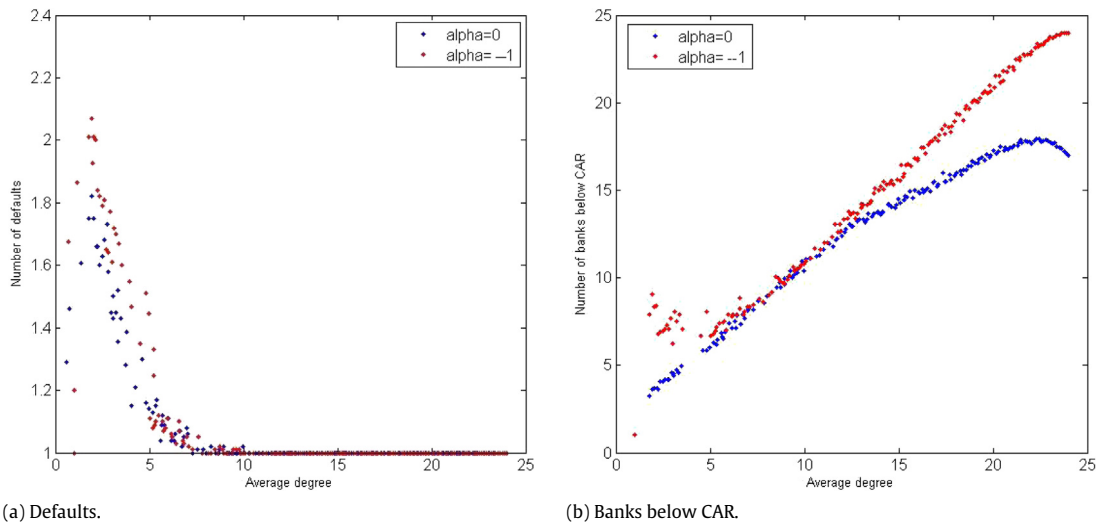
[25] See http://www.bis.org/publ/bcbs201.pdf.

(a) Defaults.

(b) Banks below CAR.

Fig. 13. Shock to the smallest borrower.
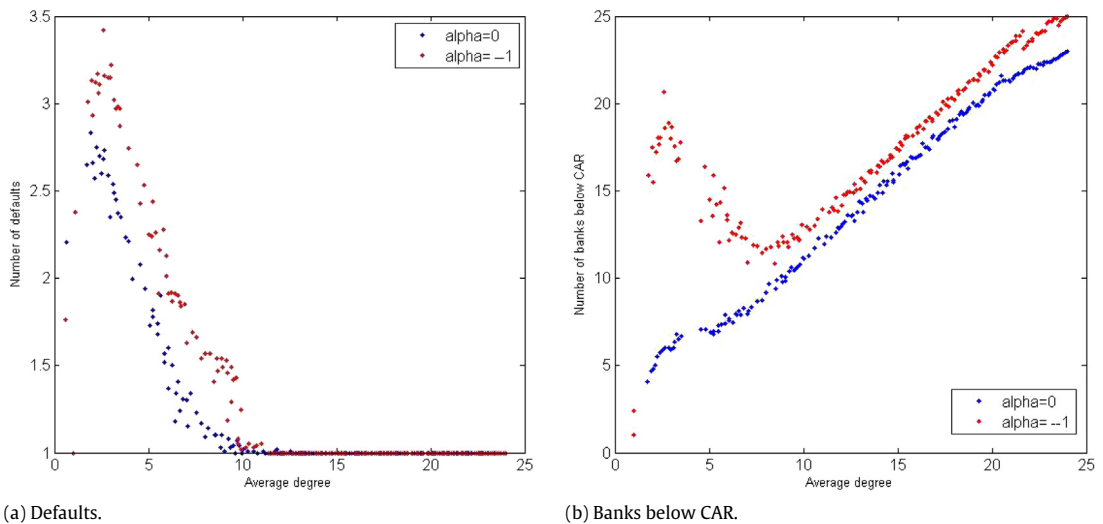

(a) Defaults.

(b) Banks below CAR.

Fig. 14. Shock to the biggest borrower.

Table 5
Additional capital requirement.

Bucket	Score range	Minimum additional capital
5	D–	3.5%
4	C–D	2.5%
3	B–C	2.0%
2	A–B	1.5%
1	Cut-off point–A	1.0%

a bank that is chosen to be a GSIB will be required to hold an additional capital between 3.5% to 1%. As of November 2015, 30 banks have been qualified as GSIBs. From a regulatory perspective, a high capital surcharge for a systemically important bank is expected to reduce the system-wide risk (see Table 5).

In our analysis, we want to see how much risk can be reduced by a surcharge to highly levered banks. We therefore investigate the effectiveness of GSIB surcharge policy in the system, depending only on leverages. We have designed the banking network simulation analysis so as to include the application of the recent surcharge policy on 5 mostly levered banks in the system. We have increased the capital adequacy by an additional 3.5% for the most-levered bank, a 2.5% for the 2nd most-levered bank, 2% for the 3rd most-levered bank, 1.5% for the 4th most-levered, and 1% for the 5th most-levered
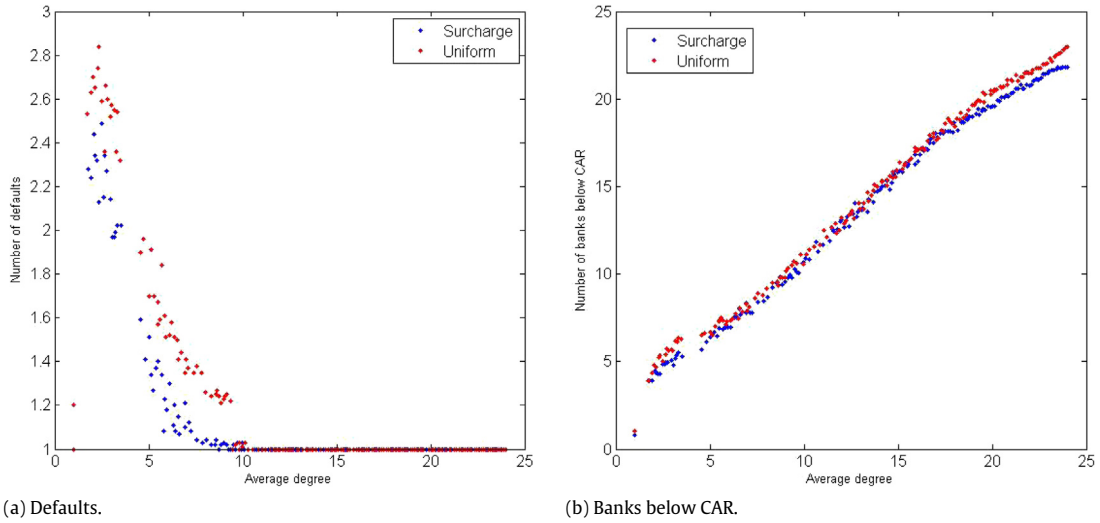
(a) Defaults.

(b) Banks below CAR.

Fig. 15. Shock to the biggest borrower.
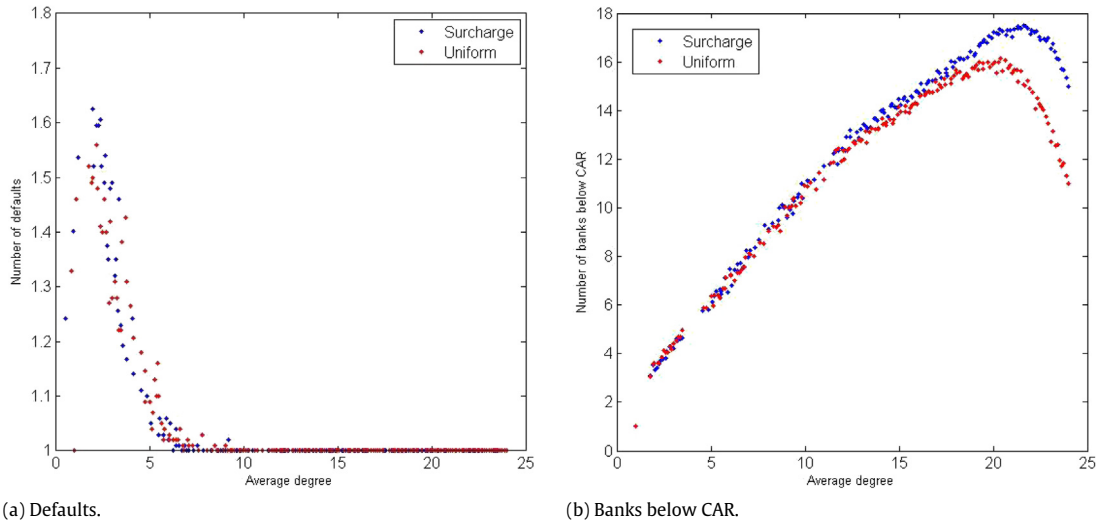

(a) Defaults.

(b) Banks below CAR.

Fig. 16. Shock to the smallest borrower.

bank.[26] Another policy alternative is to distribute same amount of capital equally among banks. We observe effectivenesses of the two policies in the case of shocks to the smallest, the biggest and the most-connected borrowers. Figs. 15–17 represent the results.

The surcharge applied for the most-levered banks improves the health of the system relative to the alternative policy. We observe that same amount of capital injection with surcharge policy is more effective than a uniform capital increment for all banks. Especially, when the most-connected and the biggest borrowers receive shock, the result is clearer. Surcharge is even more effective when highly levered banks are more likely to receive an adverse shock. That is because of the direct effect of its increased leverage when Bank 25 receives the shock. If Bank 1 faces with a shock, in the first step, surcharge is not effective because its leverage remains same, but after the first round, while the shock is spreading from borrowers to lenders, whenever one of most-levered 5 banks (the surcharged banks) is linked to banks that default, the effect of surcharge becomes apparent. On the other hand, the effectiveness of surcharge is observable when the most-connected borrowers receive the shock, since it is likely to be linked to one of the 5 most-levered banks. We conclude that surcharge policy is more effective than a uniform injection in all cases.

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26 The system-wide increase in equity (*E*) is ≈525.
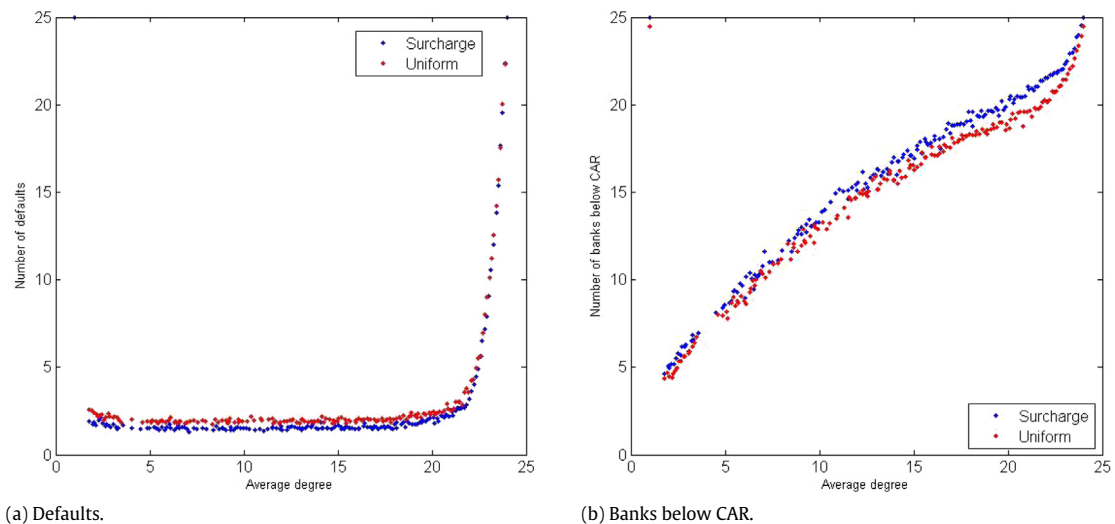
(a) Defaults.

(b) Banks below CAR.

Fig. 17. Shock to the most-connected borrower.

4. Conclusion

Financial leverage is one of the main culprit of the recent financial crisis. Studying the effect of the leverage in a banking system is therefore a crucial step to understand systemic risk. Our financial network simulations indicate that differences in leverage sharply deteriorated the systemic risk measures. Introducing financial leverage into the banking system has caused many of the banks to fail to attain the minimum capital requirements. On the other hand, the default rate in the banking system has increased drastically with the existence of more asymmetrically levered institutions. Our results are particularly important given that central banks typically conduct their stress testing analysis without considering the connectedness and the effect of leverage differentials across banks. We also applied our methodology to test the impact of recent Basel III regulations on GSIBs that aim to charge higher capital requirement for banks with higher leverage. Our analysis revealed that surcharge for highly levered banks makes the system more resilient. In other words, an idiosyncratic shock will be better handled, if banks with higher leverage are asked to hold higher capital, compared to an alternative policy increasing capitalization slightly for all banks. Our results suggest that stress testing without bank interaction and leverage differentials may understate the level of systemic risk hidden in the system. Network simulations should be used as complementary tools in conducting stress testing. Comparing market based systemic risk measures with network based measures is left for future research.

References

[1] Z. He, A. Krishnamurthy, A macroeconomic framework for quantifying systemic risk. No. w19885. National Bureau of Economic Research, 2014.
[2] P. Erdös, A. Rényi, On random graphs, Publ. Math. 6 (1959) 290–297.
[3] P. Bonancich, Power and centrality: a family of measures, Am. J. Sociol. 92 (1987) (1987) 1170–1182.
[4] S.P. Borgatti, Centrality and network flow, Social Networks 27 (2005) 55–71.
[5] K. Soramäki, S. Cook, SinkRank: An algorithm for identifying systemically important banks in payment systems, Econ.: Open-Access, Open-Assessment E-J. 7 (2013) 2013–2028.
[6] N. Paltalidis, D. Gounopoulos, R. Kizys, Y. Koutelidakis, Transmission channels of systemic risk and contagion in the European financial network, J. Bank. Finance (2015).
[7] T.U. Kuzubaş, I. Omercikoğlu, B. Saltoğlu, Network centrality measures and systemic risk: An application to the turkish financial crisis, Physica A 405 (2014) 203–215.
[8] C. Minoiu, J.A. Reyes, A network analysis of global banking: 1978-2010, J. Financ. Stab. 9 (2) (2013) 168–184.
[9] G. Hale, C. Minoiu, T. Kapan, Crisis transmission in the global banking network, in: Workshop on the Economics of Cross-Border Banking, Paris (December 13-14), 2013.
[10] B. Saltoglu, T. Yenilmez, When does low interconnectivity cause systemic risk?, Quant. Finance 15 (12) (2015) 1933–1942.
[11] K. Soramäki, M.L. Bech, J. Arnold, R.J. Glass, W. Beyeler, The topology of interbank payment flows, Staff Reports 243, Federal Reserve Bank of New York, 2006.
[12] C. Puhr, R. Seliger, M. Sigmund, Contagiousness and vulnerability in the austrian interbank market, Financial Stability Report, Austrian Central Bank, 2011.
[13] G. Iori, G.D. Masi, O.V. Precup, G. Gabbid, G. Caldarelli, A network analysis of the italian overnight money market, J. Econom. Dynam. Control 32 (2007) 259–278.
[14] R. Cont, A. Moussa, E.B. Santos, Network structure and systemic risk in banking systems, 2010. Available at http://dx.doi.org/10.2139/ssrn.1733528.
[15] R. Iyer, J.L. Pedro, Interbank contagion at work evidence from a natural experiment, Rev. Financ. Stud. 24 (4) (2011) 1337–1377. Society for Financial Studies.
[16] P. Gai, A. Haldane, S. Kapadia, Complexity, concentration and contagion, J. Monetary Econ. 58 (5) (2011) 453–470. July.
[17] G. Iori, S. Jafarey, F.G. Padilla, Systemic risk on the interbank market, J. Econ. Behav. Organ. 61 (2006) 525–542.
[18] H.J. Jo, Managing systemic risk from the perspective of the financial network under macroeconomic distress, Financial Stability Institute, 2012.
[19] J.A. Chan-Lau, Regulatory capital charges for too-connected-to-fail institutions: A practical proposal, IMF Working Paper, 10/98, 2010.
[20] A.G. Haldane, Rethinking the financial network, Bank of England, 2009.

[21] L. Eisenberg, T.H. Noe, Systemic risk in financial systems, Manage. Sci. 47 (2) (2001) 236–249.
[22] D. Diamond, P. Dybvig, Bank runs, deposit insurance and liquidity, J. Polit. Econ. 91 (3) (1983) 401–419.
[23] J.P. Gleeson, T.R. Hurd, S. Melnik, A. Hackett, Systemic risk in banking networks without Monte Carlo simulation, in: E. Kranakis (Ed.), Advances in Network Analysis and its Applications, Springer, 2012, pp. 27–56.
[24] E. Nier, J. Yang, T. Yorulmazer, A. Alentorn, Network Models and Financial stability, J. Econom. Dynam. Control 31 (2007) 2033–2060.
[25] P. Gai, S. Kapadia, Contagion in financial networks, Proc. R. Soc. Lond. Ser. A Math. Phys. Eng. Sci. 466 (2120) (2010) 2401–2423.
[26] M. Bluhm, E. Faia, J.P. Krahnen, Endogenous banks' networks, cascades and systemic risk, SAFE Working Paper No. 12, 2013.
[27] T. Adrian, H.S. Shin, Liquidity and financial cycles, Bank for International Settlements, BIS Working Papers 256, 2008.
[28] T. Adrian, H.S. Shin, Liquidity and leverage, J. Financ. Intermed. 19 (3) (2010) 418–437.
[29] J. Danielsson, K.R. James, M. Valenzuela, I. Zer, Dealing with systematic risk when we measure it badly, in: European Center for Advanced Research in Economics and Statistics, 2012.
[30] J. Danielsson, H.S. Shin, J.-P. Zigrand, Endogenous and systemic risk, in: Quantifying Systemic Risk, National Bureau of Economic Research, Inc., 2012, pp. 73–94. NBER Chapters.
[31] S. Thurner, Systemic financial risk: agent based models to understand the leverage cycle on national scales and its consequences, in: Multi-Disciplinary Issues International Futures Programme, OECD/IFP Project on Future Global Shocks, 2011.
[32] M.K. Brunnermeier, Y. Sannikov, A macroeconomic model with a financial sector, National Bank of Belgium Working Paper No. 236, 2012.
[33] Z.S. Ramadan, Does leverage always mean risk? Evidence from ASE, Int. J. Econ. Finance 4 (12) (2012).
[34] T. Kapan, C. Minoiu, Balance sheet strength and bank lending during the global financial crisis, 2014. Available at SSRN 2247185.
[35] L. Laeven, L. Ratnovski, H. Tong, Bank Size and Systemic Risk' IMF Staff Discussion Note, SDN/14/04, 2014.
[36] R.M. May, N. Arinaminpathy, Systemic risk: the dynamics of model banking systems, J. R. Soc. Interface 7 (2010) 1742–5689. Pages:823–838.
[37] M. Montagna, T. Lux, Hubs and resilience: towards more realistic models of the interbank markets, Kiel Institute for the World Economy, Working Paper, No:1826, 2013.
[38] J. Cai, A. Saunders, S. Steffen, Syndication, interconnectedness, and systemic risk, 2011.
[39] Celso Brunetti, Jeffrey H. Harris, Shawn Mankad, George Michailidis, Interconnectedness in the interbank market, in: Finance and Economics Discussion Series 2015-090. Washington: Board of Governors of the Federal Reserve System, 2015.
[40] V.V. Acharya, O. Merrouche, Precautionary hoarding of liquidity and inter-bank markets: Evidence from the sub-prime crisis. NYU Working Paper No. FIN-09-018, 2010.
[41] G. Gorton, A. Metrick, Haircuts, Fed. Reserve Bank St. 92 (6) (2010) 507–519. November/December.