Interbank Lending and the Spread of Bank Failures: A Network Model of Systemic Risk☆

Andreas Krause[a,*], Simone Giansante[a]

[a] *School of Management, University of Bath, Bath BA2 7AY, Great Britain*

Abstract

We model a stylized banking system where banks are characterized by the amount of capital, cash reserves and their exposure to the interbank loan market as borrowers as well as lenders. A network of interbank lending is established that is used as a transmission mechanism for the failure of banks through the system. We trigger a potential banking crisis by exogenously failing a bank and investigate the spread of this failure within the banking system. We find the obvious result that the size of the bank initially failing is the dominant factor whether contagion occurs, but for the extent of its spread the characteristics of the network of interbank loans are most important. These results have implications for the regulation of banking systems that are briefly discussed, most notably that a reliance on balance sheet regulations is not sufficient but must be supplemented by considerations for the structure of financial linkages between banks.

Keywords: interbank loans, banking crises, systemic risk, network topology, tiering, ”too big to fail”

> *”We [believed] the problem would come from the failure of an individual institution. That was the big mistake. We didn’t understand just how entangled things were.”*
>
> Gordon Brown, former British Prime Minister at the Institute for New Economic Thinking’s Bretton Woods Conference on 9 April 2011.

1. Introduction

The current financial crisis has raised questions about the adequacy of financial regulation to ensure the stability of the banking system. A particular feature was the threat of systemic risk, where the failure of one bank spreads to other banks, arising from financial links between them. These financial links, either through interbank loans, payment systems or OTC derivatives positions, have received significant attention in the literature in recent years, although a thorough analysis of their impact on systemic risk is still outstanding. In this paper we seek to develop a model of such financial linkages and investigate how they contribute to the spread of bank failures. This study is the first of its kind that seeks to explicitly evaluate the role of the network structure of interbank loans as well as the balance sheet structure of individual banks in the spread of bank failures. In contrast to previous contributions we do not assume all

☆This research has been supported by a research grant from the British Academy.

*Corresponding author

Email addresses: mnsak@bath.ac.uk (Andreas Krause), sg473@bath.ac.uk (Simone Giansante)

banks to be identical, have random links with each other or to have interbank loans of equal sizes, but rather allow the characteristics of banks and their interactions to vary in a much more realistic setting that captures more aspects of real banking systems.

Systemic risk is defined by the Bank for International Settlements as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties", Bank for International Settlements (1994). A common approach to modeling systemic risk is that of bank runs, where customers loose confidence in a bank and withdraw their deposits. Observing a run on one bank then undermines confidence in other banks which in turn may suffer a bank run, thus spreading the problems beyond the initially affected bank, although no fundamental reason for this development is present. An alternative approach is to assume a common exogenous shock that affects all banks, e. g. a currency crisis, which as a consequence of this common shock experience a large number of failures, see e. g. Kaufman and Scott (2003) and Kaufmann (2005) for a non-technical overview. While such origins of crises are certainly relevant, the focus of this paper will be the spread of failures due to direct and indirect financial linkages between banks as arising from interbank loans or similar financial connections such as OTC derivatives markets.

The following section provides a brief overview of the current research on the relation of systemic risk and interbank loans, together with an outline of the empirical properties of the interbank loan market before we introduce the model investigated developed in section 3. The variables considered in our subsequent analysis are described in section 4 and section 5 shows how we derive the main factors that can be identified from those variables in a principal components analysis. The main results of our model are discussed in section 6 with policy implications of these results being outlined in section 7. Finally section 8 concludes our findings and makes numerous suggestions for further research.

2. Literature on the interbank loan market

This section will provide a brief overview of the current state of the literature on systemic risk arising from interbank loans and in the second part outline the main empirical characteristics of banking systems and interbank loans.

2.1. Relevance of interbank loans for systemic risk assessment

Systemic risks are one of the main concerns of central banks and bank regulators, consequently the amount of work conducted in this area is significant; it also serves as the main justification for the tight regulation of bank activities. This section seeks to provide a brief overview of some of the works conducted in this area and from there point out the differences to the model we develop in this paper. A number of contributions seek to provide an overview of different origins and forms of systemic risks and the associated modeling approaches as well as empirical evidence, e. g. Bandt and Hartmann (2000), Kaufman and Scott (2003), or Chan-Lau et al. (2009).

A significant part of the theoretical models developed over the years investigate the impact reduced liquidity has on the spread of bank failures. The idea in such models is that banks suffer losses in the value of their assets due to "fire sales" arising from the liquidations by failing banks. This also reduces the value of the assets of non-failing banks, which can lead to losses exceeding their capital base and they might fail subsequently, see Allen and Gale (2001) and Diamond and Rajan (2005). Another strand of literature models the interbank lending and how it can reduce systemic risk. They do so either by providing incentives to banks to monitor each other's behavior as the exposure to interbank loans makes them susceptible to any other bank failing as in Rochet and Tirole (1996), or as a means to cushion the impact of any withdrawals from depositors as shown by Freixas et al. (2000). An empirical investigation supporting such models has been conducted by Cocco et al. (2009). It has also been shown by Eichberger and Summer (2005) that an increase in capital adequacy can actually increase systemic risks in equilibrium. A common feature of these models is that they are equilibrium models and while interactions with other banks are acknowledged, they are not explicitly modeled and a direct investigation into the impact of interbank loans are not possible, in particular the structure and properties of the network cannot be considered in those models.

More recently models have become popular that explicitly model the financial connections between banks as networks and employ simulation techniques to assess the spread of any bank failures. A general overview of the issues surrounding such modeling techniques is given by Haldane (2009). The range of network models applied is wide; for example in Vivier-Lirimont (2004) we find a contribution that investigates the determination of the optimal network structure of interbank loans from a bank's perspective. While this approach might allow us to explain the existence of specific network structures we observe, it does not directly contribute to our understanding of systemic risk. On the other hand, there exist a range of models that concentrate on the implications of liquidity effects, similar to the equilibrium models discussed in the previous paragraph, see e. g. Cifuentes et al. (2005) and Iori et al. (2006). The difference of these models compared to those mentioned in the previous paragraph is that these models explicitly use the network structure of financial connections to assess the spread of bank failures arising from to liquidity effects.

While the models considered thus far only model the banks themselves in a rudimentary way, other models such as those in Eboli (2007), Gai and Kapadia (2007), Nier et al. (2007), and Battiston et al. (2009), and May and Arinaminpathy (2010) explicitly include the balance sheets of banks and how the failure of a bank spreads through interbank loans in the banking system via losses they incur in their balance sheets. These models make a variety of assumptions on the network structure, properties of the banks and how failures spread. Some common assumptions are an Erdös-Renyi random network of interactions between banks, all banks having the same size, all banks having the same capital base, or all interbank loans to be for an identical amount, thus not taking into account empirical facts about real banking systems as well as the heterogeneity of banks. Furthermore, given the restrictive nature of their assumptions, these contributions do not provide a comprehensive analysis of the determinants of banking crises and their extent, often relying on mean-field approximations to derive results based on a small number of parameters. A common finding in such models is that a higher interconnection between banks can increase the spread of failure, although for very high interconnections this can reduce again. A somewhat more obvious result is that a higher capital base reduces the extent of a banking crisis.

An attempt to provide more insights on the relevance of the network structure for the spread of banking failures is provided in Sui (2009); this contribution also investigates the relevance of the originator of the crisis in a very stylized model. Finally, Canedo and Jaramillo (2009a) focus on the distribution of losses arising from such a model.

In addition to the mostly theoretical papers above, a significant number of empirical contributions exist that seek to investigate the vulnerability of a specific banking system to systemic risks. Most of such papers focus on the banking systems of individual countries and either use the actual structure of interbank loans, usually obtained from central bank sources, or estimate this structure before conducting their empirical analysis. The contributions in this field include Sheldon and Maurer (1999), Blavarg and Nimander (2002), Wells (2002), Boss et al. (2004b), Graf et al. (2004), Upper and Worms (2004), Iyer and Peydro-Alcalde (2005), Mistrulli (2005), Elsinger et al. (2001), Elsinger et al. (2006), Gropp et al. (2006), Iori et al. (2006), Lelyveld and Liedorp (2006), Müller (2006), Degryse and Nguyen (2007), Estrada and Morales (2008), Canedo and Jaramillo (2009b), and Toivanen (2009). A general overview of the empirical methodology and the results obtained in many of the papers mentioned before can be found in Upper (2007). We observe generally a wide range of vulnerability of banking systems to systemic risks arising from interbank loans, which is not surprising given the very different properties of the banking systems in each country. This disparity in results confirms the need for a comprehensive tool for analyzing the systemic risks in a banking system.

Apart from works that directly evaluate systemic risks arising from interbank loans in banking systems, a number of investigations have been conducted in related areas that can inform the modeling and interpretation of results: payment networks in Eisenberg and Noe (2001), Furfine (2000) and May et al. (2008), counter party exposures in credit default swaps in Markose et al. (2010) or trade credits between companies as in Kiyotaki and Moore (1997), and Battiston et al. (2007). After briefly looking at the empirical structure of the interbank loan market, the coming section will present the model used during our analysis and explicitly point out those aspects that are missing from other contributions and may allow us to further enhance our understanding of contagion in banking systems using a wide range of characteristics. We will allow our model to exhibit a banking system with heterogenous banks of different sizes, different balance sheet structures, different interbank loan sizes, and also different network topologies as can be commonly found in real markets.

2.2. The structure of the interbank market

Empirical studies on interbank loan networks show that connections between banks exhibit a powerlaw tail[1] as established in Boss et al. (2004a), amongst others. Soramäki et al. (2007) and Becher et al. (2008) analyze the US FedWire system that consists of more than 9000 banks and find a power law exponent of 1.76 for the outdegree. Similarly, **?** and Cajueiro and Tabak (2008) analyze the Austrian interbank market, showing a degree distribution that follows a power law with a power law exponent 1.85 among the 900 banks observed from 2000 to 2003; the

[1]A random variable x follows a power law distribution if $Prob(x < v) \propto v^{-\lambda}$, where λ denotes the power law exponent and $\frac{1}{\lambda}$ is denoted the tail index. A distribution has a power law tail if for sufficiently large v the distribution is a power law distribution. A smaller power law exponent corresponds to a fatter tail, i.e. more extremely large observations.

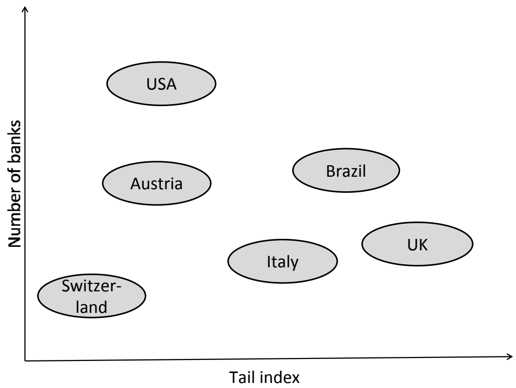


Figure 1: Empirical properties of interbank loan networks of selected countries

investigation by Edson and Cont (2010) finds interconnections in the Brazilian banking system to exhibit a power law exponent in the range of 2.23-3.37 for the about 600 banks from June 2007 to November 2008. Smaller banking systems like the UK and Italian market, as studied by Becher et al. (2008) and Iori et al. (2008), are characterized by a high level of tiering, i. e. a few banks dominate the majority of connections with a long tail in the distribution of links among banks. The Swiss interbank network as analyzed in Müller (2006) showed a relatively small system of approximately 100 Swiss banks with a much more skewed distribution of links than the other systems. It is characterized by only two big banks holding a dominant position in the interbank loan market, which would imply a small power law exponent. Figure 1 illustrates the size of power law exponent and the size of the banking system of selected countries. We observe that banking systems are characterized by a wide range of power law exponents in the distribution of the size of banks as well as their interconnections. These findings make the assumption of random networks as well as assuming banks of equal size very questionable if we want to gain an understanding of the properties of banking crises.

Tiering properties of interbank markets are analyzed in detail in the much larger banking system of Germany by Craig and von Peter (2010). They develop a core-periphery model in order to identify the tiering structure of a system and showed the highly tiered structure of the German network in which the core comprises only 2% of the banks in the system. This structure appears to be very consistent over time when using data on bilateral exposures from 1999 to 2007.

The results from these empirical investigations, which can be assumed to be valid in principle for most banking systems, provides us with some guidance on the properties of the network structure as well as the size of banks that we should be able to use in our model. The lack of publicly available data on actual bilateral exposures, makes it more difficult to obtain a model that captures all empirical aspects of interbank loans fully, and every modeler has to rely on additional assumptions in this important aspect of the model.

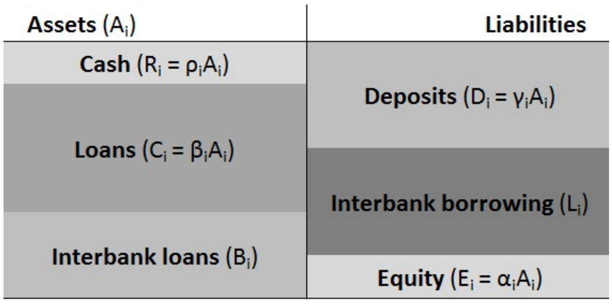


Figure 2: Stylized balance sheet of individual banks

3. The model

We develop a framework that represents a stylized model of a real banking system. We model each bank individually through their balance sheets as well as their interactions with other banks arising from interbank loans that act as a transmission mechanism for any bank failures. While our focus is on interbank loans, this idea is easily extended to other financial linkages such as OTC derivatives positions or payment systems without changing the key aspects of our analysis.

3.1. The banking system

Each bank $i = 1, 2, \ldots, N$ is assumed to have a balance sheet with total assets (and liabilities, as these have to equal total assets by definition) of A_i; we assume that all entries into this balance sheet represent current market values for simplicity. The assets are divided up between cash reserves (R_i) that include cash holdings and other highly liquid and risk-free assets such as treasury bonds, loans to customers (C_i) and loans to other banks (B_i). The liabilities of each bank consist of deposits by customers (D_i), loans received from other banks (L_i) and the equity (E_i). For simplicity we can identify the balance sheet of each bank by certain ratios; we define the capital ratio $\alpha_i = \frac{E_i}{A_i}$, the reserve ratio $\rho_i = \frac{R_i}{A_i}$, the fraction of deposits $\gamma_i = \frac{D_i}{A_i}$ and the fraction of loans to customers $\beta_i = \frac{C_i}{A_i}$. Thus a bank's balance sheet is characterized by the quintuplet $(A_i, \alpha_i, \rho_i, \gamma_i, \beta_i)$.[2] Figure 2 depicts schematically the balance sheet of such a bank. We will assume that the total assets A_i of a bank follow a power law distribution as has been found to be empirically valid.

While this balance sheet does not capture all aspects of the real balance sheet of banks, e. g. there is no provision of fixed assets such as buildings, the proposed structure includes all those balance sheet positions that make the vast majority of the total assets and liabilities and all those that are relevant for our analysis. A few additional assumptions are required in order to make our model of banks feasible for analysis. Firstly we assume that all interbank loans are overnight loans, i. e. they can be withdrawn at no cost at short notice. Furthermore, loans given to customers can be recalled only if the bank is liquidated; then banks are only able to recover a fraction $0 \leq \kappa \leq 1$, common for all

[2] In the remainder we will refer to the capital ratio as "capital" for simplicity. Likewise the reserve ratio is referred to as "reserves", the fraction of depotits as "deposits", the fraction of loans to customers as "loans", and the fraction of of interbank loans given and received as "interbank loans".

banks, taking into account the costs of recalling these types of loans. This recovery rate might also be interpreted as the liquidity impact from selling assets in a banking crisis. We finally assume that no deposits are withdrawn or added, no new loans to customers are granted or repaid and the bank is not exposed to any other risks that could cause them losses. While these assumptions may seem very restrictive, they allow us to focus exclusively on the impact of interbank loans on systemic risk without being impeded by other factors.

3.2. The interbank network

In order to establish a complete banking system we need to model explicitly the network of interbank loans. A bank does not give a loan to every other bank and does not receive loans from every other bank, hence we need to determine those banks that have a loan arrangement. We therefore generate a random directed network of such loans using a Albert-Barabasi scale-free network, see Barabasi and Albert (1999), in which the number of outgoing and incoming links are correlated with the total asset value of the bank; this network gives us an adjacency matrix $\left[\Theta_{ij}\right]_{\{i,j=1,2,\ldots,N\}}$. In this network structure an incoming link from another bank corresponds this bank taking an interbank loan from the other bank; an outgoing link therefore corresponds to a loan given to another bank. Using this network structure provides us with a power law distribution of the in and out degrees which was observed empirically as described in section 2.2, because we assume that the asset values A_i are following a power law distribution as outlined above. Therefore using this network structure provides us with a banking system that exhibits properties that were previously established empirically and that other network types, e. g. random networks, cannot provide.

Once we have established which banks are linked by interbank loans we need to determine their size. We set the amount of the interbank loan bank i gives to bank j as $L_{ij} = \Theta_{ij}\frac{L_j B_i}{\sum_i L_i}$, i. e. the amount lent will be larger the larger either bank becomes. Given that not all banks are interconnected this procedure results in balance sheets of banks that are no longer showing equal assets and liabilities; we thus have to make adjustments to the balance sheets which we describe in more detail in section 4.1. While these adjustments do not perfectly preserve the power law distribution of the assets and the correlation of total assets and number of interbank loans, the distortion is sufficiently small to show no significant differences to the properties of actual banking systems.

3.3. The contagion mechanism

The failure of a bank can affect other banks through their financial linkages. Below we describe two mechanisms through which financial linkages can transmit such failures. The term contagion here refers to a situation in which the initial failure of a bank leads to the failure of at least one additional bank through one of these mechanisms. The extent of contagion is measured by the fraction of banks that are failing through these mechanisms.

If a bank incurs a loss that exceeds its equity, the bank is wound up. In this wind-up process the bank calls in all interbank loans given to other banks as well as loans given to customers; from the latter the bank is assumed only to recover a fraction $0 \leq \kappa \leq 1$. These monies thus raised are then distributed together with the cash reserves to creditors, where first depositors are paid, any remaining monies are then used to pay interbank loans granted. If not all interbank loans can be repaid in full, all interbank loans get repaid the same fraction of the outstanding amount, thus assuming

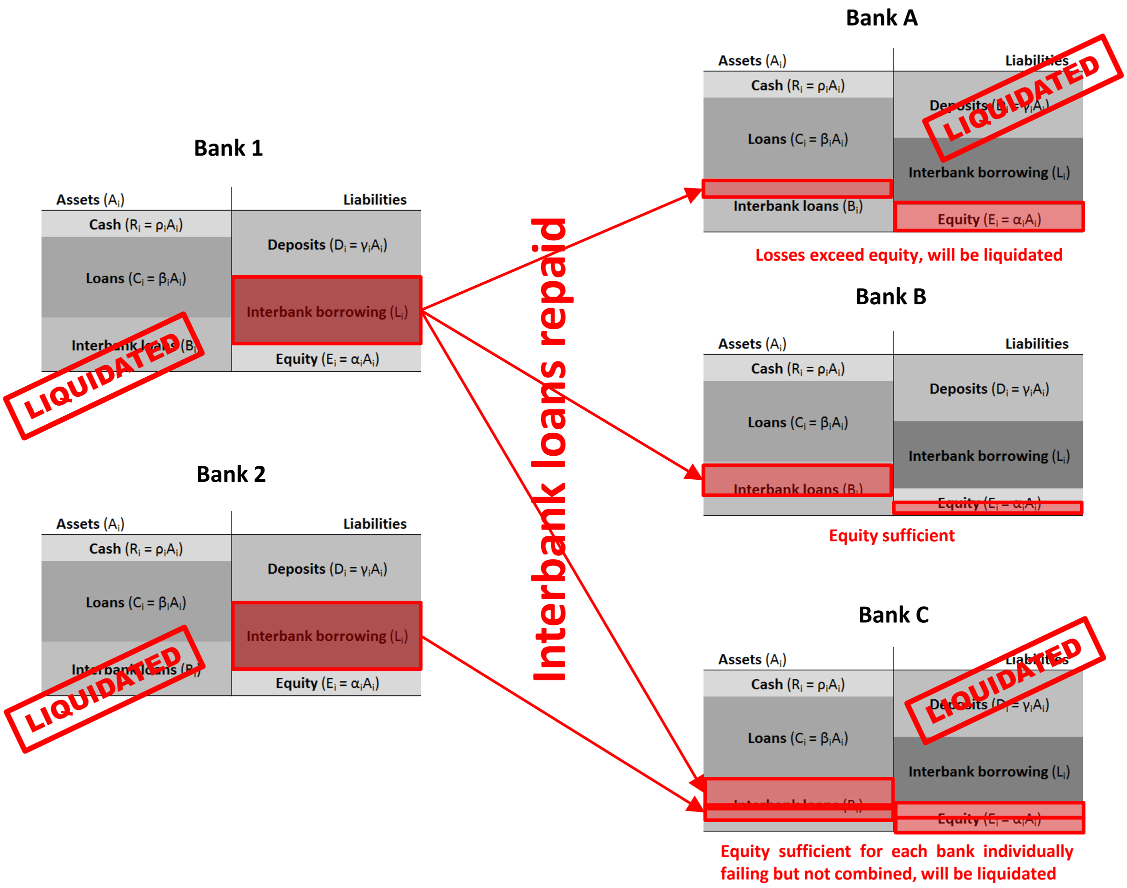


Figure 3: Illustration of the default mechanism. Detailed explanations are found in the main text.

equal seniority of all interbank loans. If an interbank loan cannot be repaid in full, the bank granting this loan will face a loss of the difference between the outstanding amount and the amount actually received. This loss will then reduce the equity of this bank, which in turn might have to be wound up due to this loss if it exceeds the equity available. Any losses incurred from several banks to which a bank has granted interbank loans are cumulative, thus it may not be that the failure of a single bank alone would cause another bank to fail but only its aggregate losses from the exposure to several banks that failed. We call this mechanism the *default mechanism*.

Figure 3 illustrates this mechanism. We assume that banks 1 and 2 are to be liquidated and thereby repaying their interbank loans to banks A, B and C for bank 1 and bank C for bank 2. The losses of banks 1 and 2 from liquidating customer loans does not allow them to repay their interbank loans in full. This leads to bank A incurring losses exceeding its equity and it will therefore be wound up in a subsequent step. Bank B has sufficient equity to cover these losses and will therefore not be directly affected and continue to exist, albeit with a lower equity than before. Bank C would be able to survive the losses incurred from either bank 1 or bank 2, but the cumulative losses from

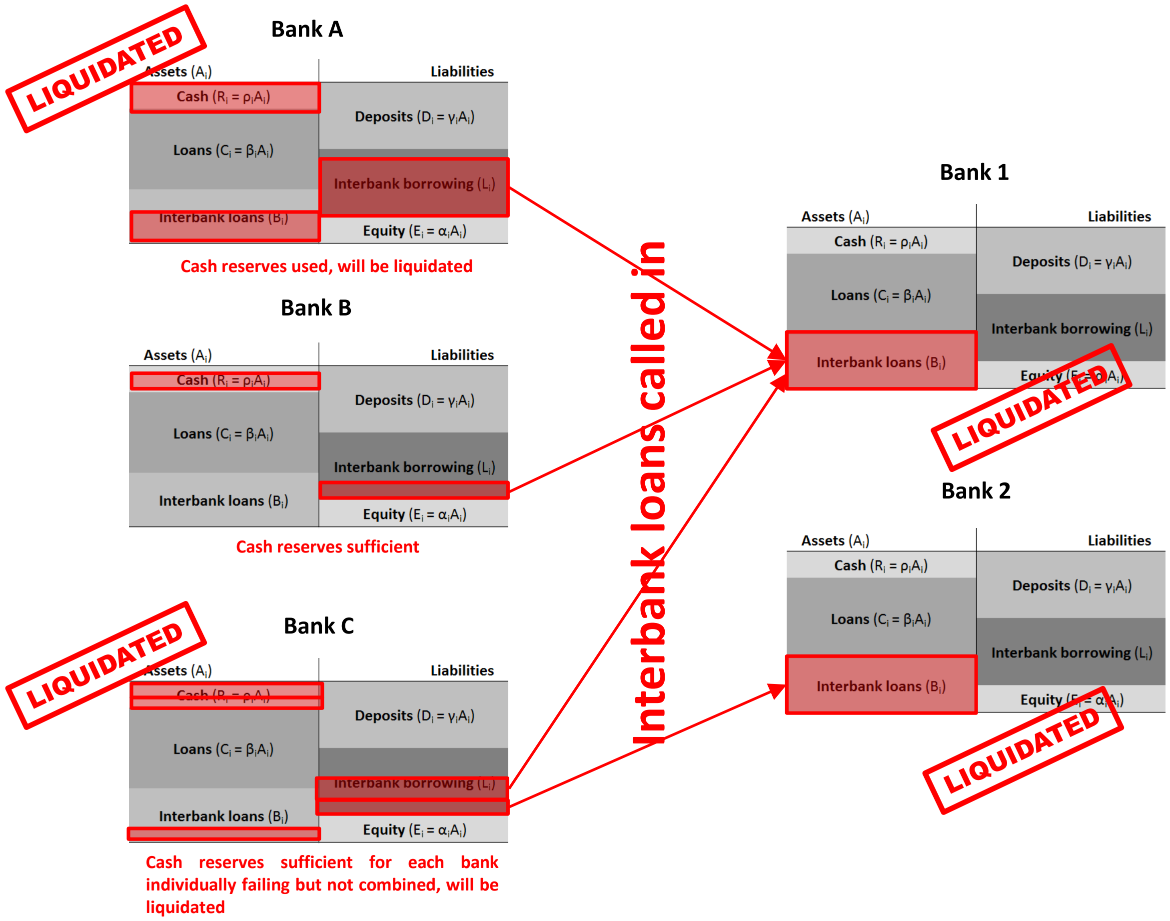


Figure 4: Illustration of the failure mechanism. Detailed explanations are found in the main text.

both of these banks repaying their interbank loans causes cumulative losses exceeding its equity and it will therefore be liquidated in a subsequent step. It must be stressed that it is not necessary for banks 1 and 2 to be liquidated in the same step, but it could be that bank 2 was liquidated prior to bank 1 and the losses arising for bank C on this occasion had reduced its equity and once bank 1 was liquidated, these losses would have eliminated its remaining equity, causing it to default. The liquidation of banks A and C may then in subsequent steps causer other banks to fail.

Another problem arises when calling in any interbank loans as the bank from which the loan has been called in will be required to fulfill this request using its cash reserves. If it is not able to do so, the bank will be wound up in order to obtain the cash required, employing the default mechanism described above, and thereby in turn call in interbank loans. We thus have a second mechanism which can lead to the failure of banks, the *failure mechanism* that arises from a cash shortage. This failure mechanism can lead to default as the recovery of loans to customers will depend on the recovery rate κ and a low recovery rate may not allow all interbank loans to be repaid, causing losses to other banks.

Figure 4 illustrates the failure mechanism. We assume again that banks 1 and 2 are to be liquidated and thereby calling in their interbank loans to banks A, B and C for bank 1 and bank C for bank 2. Bank A has insufficient cash reserves to repay the entire interbank loan called in and therefore will be wound up in a subsequent step. Bank B has sufficient cash reserves to cover the interbank loan called in and will therefore not be directly affected and continue to exist, albeit with lower cash reserves than before. Bank C would be able to survive if either bank 1 or bank 2 called in their interbank loans, but the cumulative cash requirements from both banks calling in their interbank loans exceeds them and it will therefore be liquidated in a subsequent step. It must again be stressed that it is not necessary for banks 1 and 2 to be liquidated in the same step, but it could be that bank 2 was liquidated prior to bank 1 and the cash reserves of bank C on this occasion had reduced and once bank 1 was liquidated, these cash reserves would have been insufficient to repay this second interbank loan. The liquidation of banks A and C may then in subsequent steps causer other banks to fail.

Thus the failure of a single bank can spread through the system and cause more banks to fail through either of the above mechanism and cause the contagion of the failure of more banks, a banking crisis.

3.4. The trigger of a banking crisis

The banking crisis is started exogenously by assuming that a single bank fails. This bank is assumed to suffer losses equal to its equity and is then wound up, starting the contagion mechanism described above. We are interested in the conditions that lead to the spread of this initial failure and how far it spreads, i. e. how many banks will be affected. Hence, in contrast to much of the literature we do not seek to evaluate the performance of a generally weakened banking system, but that of a strong banking system with a single bank collapsing for exogenous reasons, e. g. fraud or losses arising from operational risks. This approach allows us to focus solely on the impact of interbank loans on the spread of any failures rather than investigating the influence of a generally weakening banking system.

4. The computer experiments

Given the complexity of the model outlined above, it is not possible to derive analytical solutions. We therefore employ computer simulations of a large number of banking systems with a wide range of characteristics in order to obtain data that can be analyzed in a subsequent step.

4.1. Parameters used

We investigate banking systems with $N \in [13; 1,000]$ banks, randomly drawn from a uniform distribution. For each bank we determine the total value of the assets $A_i \in [100; 10,000,000,000]$ drawn from a powerlaw distribution with power law exponent $\lambda \in [1.5; 5]$, which in turn is drawn from a uniform distribution for each system. The recovery rate from loans to customers in cases where they have to be called in is drawn from a uniform distribution with $\kappa \in [0; 1]$, identical for all banks in a system. The initial balance sheet of each bank is determined randomly with the parameters drawn from uniform distributions in the following ranges: the amount of equity is $\alpha_i \in [0; 0.25]$, the deposits are $\gamma_i \in [0; 1 - \alpha_i]$, the cash reserves are $\rho_i \in [0; 0.25]$, and the amount of loans given to the public are $\beta_i \in [0; 1]$ such that $C_i = \max\{\beta_i A_i - R_i; 0\}$.

After having set up all banks in the banking system, we determine the allocation of interbank loans as described in the model above. Using $L'_i = \sum_{j=1}^{N} L_{ij}$ and $B'_j = \sum_{i=1}^{N} L_{ij}$ we determine the new total assets as $A'_i = \max\left\{R_i + C_i + B'_i; D_i + L'_i + E_i\right\}$ and then adjust the other balance sheet items according to $R'_i = R_i \frac{A'_i - B'_i}{A_i - B_i}$, $C'_i = C_i \frac{A'_i - B'_i}{A_i - B_i}$, $D'_i = R_i \frac{A'_i - L'_i}{A_i - L_i}$ and $E'_i = E_i \frac{A'_i - L'_i}{A_i - L_i}$. We use this adjustment to ensure that the balance sheets of individual banks are showing equal assets and liabilities as well as retaining as much of the initial balance sheet structure as possible. The so adjusted balance sheets of banks are then used in the following analysis and it is this actual balance sheet structure that is used in the further analysis. Distortions in terms of deviations from the power law distribution of the size of assets are minimal as are any deviations in the correlation between assets and the number of interbank loans.

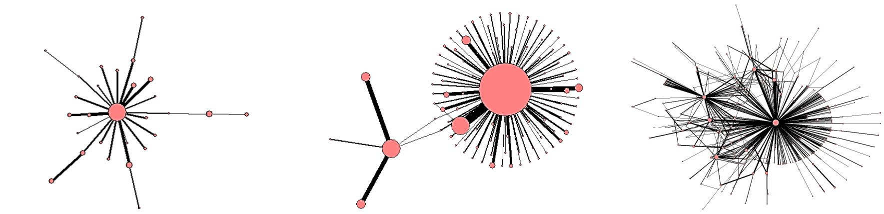
We choose a single bank in the system to fail exogenously. The bank chosen can be the largest bank, the second largest bank in terms of their assets, or a random bank from each of the ten size deciles following these two banks. We let the contagion spread until no more failures are observed and record any failures of banks. In total we use 10,000 banking systems as set out before, each triggered by 12 different banks individually, giving a total of 120,000 potential banking crises to investigate with approximately 5,000,000 individual banks.

Before investigating the results of the model and considering the variables we investigate, we briefly illustrate the resulting networks and some of their key properties. Figure 5 shows representative examples of such networks for a range of power law exponents in the distribution of the size of banks (and thereby the number of interbank loans given and taken as per our model) and the number of banks in a banking system. We clearly observe that for low power law exponents there exists one bank that dominates the network in terms of size and also interbank loans given and taken. As the power law exponent increases we see that individual banks tend to dominate less and less with banks becoming more equal in size and the same is observed for interbank loans, reflecting the steeper drop off of the distribution of bank sizes. Banking systems with large power law exponents appear similar to random networks and the banks are of approximately equal size. We also see that for small power law exponents the network is tiered with a core consisting of a small number of banks being highly connected and a periphery that is mainly connected with this core but not exhibiting many links between them; as the power law exponent increases this tiering becomes less pronounced. Thus we capture a wide range of network types that cover the entire range of networks typically found in reality, as summarized in section 2.2. Key properties of the networks exhibiting different ranges of the power law exponents are shown in table 2 and more extensive statistics can be obtained from appendix Appendix A.1

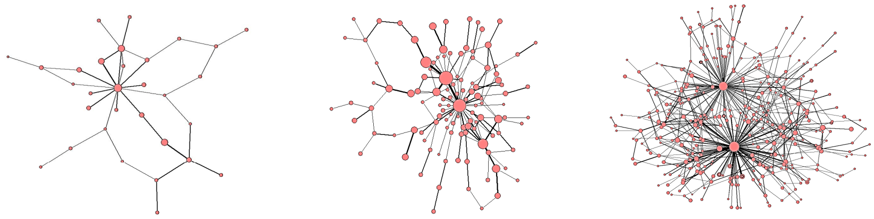
4.2. Variables investigated

In order to determine the main factors that affect the extent of contagion, we will investigate the fraction of banks failing in a banking system, i. e. the number of banks failing divided by the total number of banks in the banking system, denoted FRACTION FAILING.

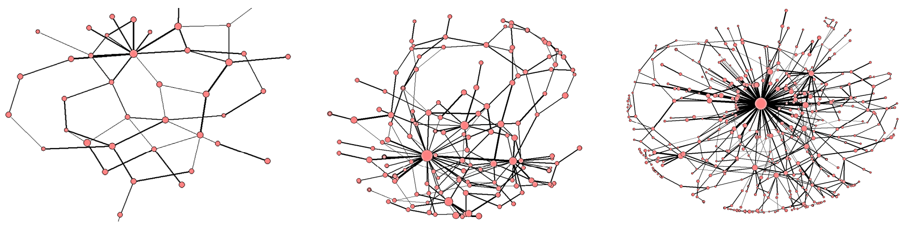
As explanatory variables we use the balance sheet structure of the banks: EQUITY denotes the amount of equity



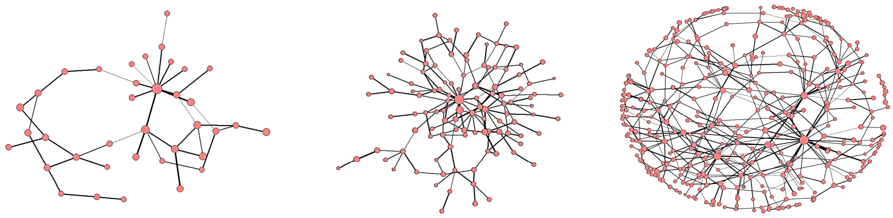
(a) $1.5 \leq \alpha < 2.0$



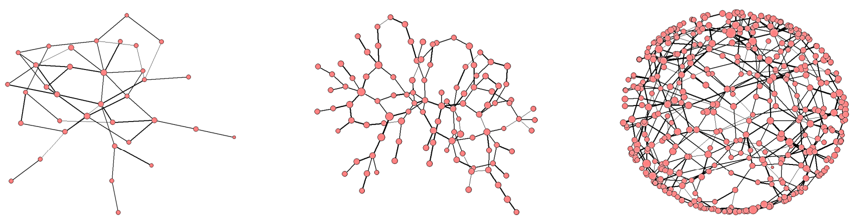
(b) $2.0 \leq \alpha < 2.5$



(c) $2.5 \leq \alpha < 3.0$



(d) $3.0 \leq \alpha < 3.5$



(e) $3.5 \leq \alpha \leq 5$

For each range of power law exponents we show one representative network with a small number of banks ($13 \leq N \leq 50$), a mid-sized banking system ($50 < N \leq 200$) and a large banking system ($200 < N \leq 1000$). The individual banks are represented by nodes whose size is proportional to their relative size in the banking system they belong to and the interbank loans are the vertices whose thickness is proportional to the relative size of the loan. We only show the largest component of the network, eliminating any isolated nodes.

Figure 5: Sample networks with different power law exponents and sizes.

(capital) relative to the total assets of a bank (α_i), RESERVES denotes the amount of cash reserves relative to the total assets (ρ_i), LOANS GIVEN denotes the amount of interbank loans given relative to the total assets ($1-\rho_i-\beta_i$), LOANS TAKEN are the amount of interbank loans taken relative to the total assets ($1-\alpha_i-\gamma_i$), and SIZE denotes the absolute amount of total assets of a bank (A_i).

The number of interbank loans given to other banks is denoted by NUMBER GIVEN while the number of interbank loans taken from other banks is NUMBER TAKEN, i. e. they represent the outdegree and indegree, respectively. In addition to the number of interbank loans, we also investigate the concentration of interbank loans from and to individual banks, HERF GIVEN denotes the normalized Herfindahl index of the interbank loans given to other banks, defined via the Herfindahl index as $H_i = \sum_{k=1}^{N}\left(\frac{B'_{ik}}{B_k}\right)^2$, where N represents the number of banks, and normalized according to $H_i^* = \frac{H_i-\frac{1}{N}}{1-\frac{1}{N}}$, see Hirschman (1964). Similarly, HERF TAKEN denotes the Herfindahl index of interbank loans taken from other banks with $H_i = \sum_{k=1}^{N}\left(\frac{L'_{ik}}{L_k}\right)^2$ and subsequently normalized as before.

We furthermore investigate a number of variables that describe the network structure of interbank loans in more detail: CLUSTERING is determined as the local clustering coefficient of a bank, see e. g. Watts and Strogatz (1998), and measures how close to being in a complete subgraph (clique) a node is, thus how closely integrated the bank is into its immediate neighborhood. More formally the clustering coefficient is defined as the fraction of possible links that exist between the nodes to which the node in question is connected. Another measure we employ is the SHORTEST PATH, that determines the maximum of the distance between any two banks in the banking system, restricted to the largest component of the network. We also consider the betweenness centrality, denoted BETWEENNESS, which measures how many shortest paths between any two banks pass through the node, see e. g. Freeman (1977). Thus this variable measures how much the network relies on the existence of this node to transmit any failures quickly. We furthermore consider the average neighbor degree, DEGREE NEIGHBOR, which measures how well connected a bank is via interbank loans with its immediate neighborhood. We use the eigenvector centrality, denoted EV CENTRALITY, as a measure of the importance of the nodes. This measure indicates whether a bank is connected to other important banks and is formally obtained as the eigenvector associated with the largest eigenvalue of the adjacency matrix. The node correlation, CORRELATION, explains whether highly connected nodes are connected to other highly connected nodes and is measured by the Pearson correlation coefficient of the degrees between connected nodes, see Newman (2003). A good overview of these network properties and how to measure them is given in (Newman, 2010, Ch. 7). As we investigate the aggregate failure within a banking system and how the overall network structure affects systemic risk, the unweighed average across all banks is taken for all variables.

Apart from the properties of individual banks and their location in the network, we also consider some variables that describe the banking system as a whole: The total number of bank in the banking system is denoted as NUMBER BANKS, the fraction of assets recovered in case of failure is RECOVERY, the power law exponent λ of the distribution of asset sizes is given by DISTRIBUTION, the normalized Herfindahl index of the banking system as measured by the total assets is given by HERF BANKS. Finally we also record which bank has triggered the failures, denoted by

TRIGGER. We set this variable to 1 for the largest bank, 2 for the second largest bank, 3 for a bank from the top decile beyond these two banks, 4 for the second decile, and so on until 12 for the last decile.

Table 1 provides an overview of the descriptive statistics of the explanatory variables we investigate, while table 2 shows some key network variables across smaller ranges of the power law exponent of the size distribution of banks; the full descriptive statistics can be found in Appendix A.1 for information.

Using these variables as dependent and explanatory variables we now can investigate what determines whether contagion occurs and if it does, the extent of the bank failures. In order to prepare for this step the next section describes how we obtain the main factors that we will consider in this analysis.

5. Principal components analysis of the variables

As discussed above, we consider a large number of explanatory variables, many of which will be correlated with each other, e. g. a network that is highly clustered will normally have a small shortest path. Despite these correlations between variables, they nevertheless provide information on different aspects of the network structure and thus information from both variables would be of interest in our investigation. Using a large number of potentially correlated variables will inevitably give rise not only to issues of multi-collinearity, but will also impede the appropriate interpretation of the results obtained. In order to overcome this problem, we decided to employ a principal components analysis that allows us to reduce the number of variables significantly and ensures that the variables considered are then uncorrelated as well as capturing the essence of these dependencies.

5.1. The idea of a principal components analysis

The idea behind a principal component analysis is to transform all variables such that they are uncorrelated with each other. This is achieved by a rotation of the data such that they become orthogonal. In mathematical terms we can state that our aim is to change the data such that the covariance matrix of the transformed data becomes diagonal, i. e. only has entries along the main diagonal indicating that the covariances between the transformed variables are zero. A more detailed description of this methodology can be found in Joliffe (2002). Below we provide a brief outline of the main steps in such an analysis.

Assume our explanatory variables, assembled into a matrix $\mathbf{X}$, have been normalized with mean zero and variance one, then the covariance matrix of these variables is given by $\Sigma = \frac{1}{N-1}\mathbf{X}\mathbf{X}'$. If we transform the variables into a new set $\widehat{\mathbf{X}} = \mathbf{P}\mathbf{X}$, we obtain a covariance matrix $\widehat{\Sigma} = \frac{1}{N-1}\widehat{\mathbf{X}}\widehat{\mathbf{X}}' = \frac{1}{N-1}\mathbf{P}(\mathbf{X}\mathbf{X}')\mathbf{P}'$. $\mathbf{X}\mathbf{X}'$ is a symmetric matrix and as such it can be decomposed using the matrix of eigenvectors $\mathbf{E}$ of $\mathbf{X}$: $\mathbf{X}\mathbf{X}' = \mathbf{E}\mathbf{D}\mathbf{E}'$, where $\mathbf{D}$ is a diagonal matrix of eigenvalues. If we set $\mathbf{P} = \mathbf{E}'$ and noting that $\mathbf{P}' = \mathbf{P}^{-1}$, we find that $\widehat{\Sigma} = \frac{1}{N-1}\mathbf{D}$, i. e. the covariance matrix of the transformed variables is a diagonal matrix. This implies that the transformed variables are uncorrelated and thereby should be easier to interpret than the correlated original variables. The transformation of variables is achieved by using the eigenvectors of the covariance matrix of our explanatory variables.

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	5.9809	1.6277	2.8627	12.7639	4.7955	5.0839	5.3186	6.0720	18.6746
CORRELATION	-0.1070	0.1871	-2.0700	8.0743	-0.9967	-0.1392	-0.0499	-0.0017	0.7168
DISTRIBUTION	3.2502	1.0088	0.0000	1.7851	1.5010	2.3640	3.2471	4.1402	4.9987
NUMBER BANKS	506.2368	284.2481	0.0025	1.8133	13.0000	262.0000	506.0000	749.0000	1000.0000
RECOVERY	0.5000	0.2870	-0.0110	1.7919	0.0003	0.2500	0.5008	0.7502	0.9996
log(HERF BANKS)	-5.8809	1.8041	0.7773	2.8104	-8.7270	-7.3231	-6.3076	-4.7594	-0.0167
EQUITY	0.1774	0.0136	1.2167	12.8053	0.0834	0.1704	0.1761	0.1831	0.3430
RESERVES	0.2394	0.0287	-1.6866	12.7090	0.0156	0.2318	0.2431	0.2532	0.4934
LOANS GIVEN	0.2885	0.0570	3.8715	26.4697	0.0138	0.2670	0.2762	0.2891	0.9218
LOANS TAKEN	0.2886	0.0290	-1.3099	12.2314	0.0118	0.2788	0.2928	0.3034	0.5242
NUMBER GIVEN	1.2484	0.1693	1.9787	7.6280	0.6923	1.1569	1.1991	1.2734	2.1197
NUMBER TAKEN	1.2487	0.1697	1.9692	7.6017	0.6923	1.1566	1.2000	1.2734	2.1154
CLUSTERING	0.0140	0.0318	4.4643	30.4541	0.0000	0.0009	0.0028	0.0099	0.4733
HERF TAKEN	0.6181	0.0523	3.2696	20.5625	0.3583	0.5948	0.6102	0.6270	0.9984
HERF GIVEN	0.6121	0.0548	2.9592	18.2442	0.2661	0.5868	0.6030	0.6227	0.9967
DEGREE NEIGHBOR	22.3818	93.4224	8.7247	99.5451	0.9000	2.3048	2.6040	4.8306	1705.2030
log(BETWEENNESS)	4.8666	1.3537	-0.8136	3.7630	-2.5649	4.0261	5.0488	5.9254	7.5395
log(SHORTEST PATH)	1.5345	0.4061	-0.4472	3.5753	-0.6190	1.2844	1.5529	1.8193	2.6731
log(EV CENTRALITY)	-0.6723	2.3675	4.5203	27.8094	-2.6368	-1.6319	-1.3415	-0.8189	22.9414
TRIGGER	6.5000	3.4521	0.0000	1.7830	1.0000	3.5000	6.5000	9.5000	12.0000

Table 1: Descriptive statistics of the independent variables investigated

This table shows the mean values of selected network variables for networks with different power law exponents in the distribution of size of the assets of banks. The detailed statistics can be found in Appendix A.1.

	$1.5 \leq \alpha < 2.0$	$2.0 \leq \alpha < 2.5$	$2.5 \leq \alpha < 3.0$	$3.0 \leq \alpha < 3.5$	$3.5 \leq \alpha \leq 5.0$
CORRELATION	-0.4485	-0.1665	-0.0721	-0.0282	-0.0106
log(HERF BANKS)	-2.7378	-4.5757	-5.7222	-6.4787	-7.2231
NUMBER GIVEN	1.5236	1.2928	1.2174	1.1890	1.1717
NUMBER TAKEN	1.5241	1.2931	1.2190	1.1890	1.1715
CLUSTERING	0.0555	0.0193	0.0076	0.0051	0.0033
HERF TAKEN	0.6729	0.6159	0.6085	0.6072	0.6074
HERF GIVEN	0.6738	0.6203	0.6046	0.5988	0.5956
DEGREE NEIGHBOR	123.0041	18.3660	4.8925	2.8672	2.4319
log(BETWEENESS)	5.2774	5.4256	5.2061	4.8729	4.4276
log(SHORTEST PATH)	1.3364	1.6067	1.6641	1.6220	1.5046
log(EV CENTRALITY)	2.3139	-0.6766	-1.0870	-1.2980	-1.3216

Table 2: Comparison of key network characteristics for networks with different power law exponents

The analysis thus far has not reduced the dimensionality of the problem. In order to select those transformed variables that are most relevant, we would therefore concentrate on those that contribute most to the total variance of the data. As the eigenvalues represent the variance of the transformed variables, it seems natural to focus on those that have the largest eigenvalues. A criteria to determine how many variables to choose is to consider all those whose variance exceeds the average variance. The average variance is 1, thus we would select those components whose variance, and thereby eigenvalue, is larger than 1. This criteria should ideally be complemented by a significant drop in the next largest eigenvalue beyond those selected.

Once we have selected the appropriate number of transformed variables, also called factors, we seek to optimize their values in the reduced matrix **P** to aid their interpretation. This is achieved by rotating the factors such that high absolute values are increased and low absolute values reduced closer to zero. There are various methods to conduct this rotation of which we choose the varimax methodology. Using an orthogonal matrix **T** we define $\mathbf{R} = \mathbf{PT}$ and the criterion used is to maximize the expression $V = \sum_{k=1}^{N} \left(\sum_{j=1}^{p} r_{jk}^4 - \frac{1}{p} \left(\sum_{j=1}^{N} r_{jk} \right)^2 \right)$ over **T**, where r_{ij} denotes the elements of the matrix **R**. The resulting matrix **R** contains the rotated factors as its vectors and these are used as the basis for further analysis and are presented below.

5.2. *Identifying the main factors*

Conducting a principal components analysis on our set of independent variables as outlined above, the eigenvalue criterion suggests we consider 6 factors as their eigenvalues are above the threshold of 1 and the seventh eigenvalue is significantly lower. The resulting rotated factor loadings are displayed in table 3. In order to interpret the factors obtained, we identify for each variable the factor for which it has the highest factor loading and then seek to identify common features in those variables that allow us to interpret these factors in the appropriate way for the remainder of this paper; the names of these factors are shown in the top row of table 3.

The variables associated with the first factor are SIZE, CORRELATION, DISTRIBUTION, HERF BANKS, NUMBER GIVEN, NUMBER TAKEN, and CLUSTERING. All these variables are directly or indirectly associ-

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	TOPOLOGY	TIERING	BALANCE SHEET	LOAN STRUCTURE	RECOVERY	TRIGGER
log(SIZE)	**0.2718**	-0.0021	0.1736	0.0904	0.0113	0.0000
CORRELATION	**-0.2987**	0.0140	-0.0658	-0.1302	0.0026	0.0000
DISTRIBUTION	**-0.4755**	-0.0731	-0.0284	0.2246	0.0028	0.0000
NUMBER BANKS	-0.1122	**0.4952**	0.0979	0.0679	0.0363	0.0000
RECOVERY	0.0018	-0.0051	0.0018	-0.0091	**-0.9975**	0.0000
log(HERF BANKS)	**0.4467**	-0.1519	0.0376	-0.1162	-0.0074	0.0000
EQUITY	0.0543	-0.0144	**0.4966**	-0.2010	0.0340	0.0000
RESERVES	0.0930	-0.0263	**-0.4377**	-0.2425	0.0301	0.0000
LOANS TAKEN	-0.0604	0.0196	**0.4851**	0.2107	-0.0139	0.0000
LOANS GIVEN	-0.1363	0.0338	**-0.4757**	0.2503	-0.0031	0.0000
NUMBER TAKEN	**0.3090**	0.1123	-0.0464	0.1651	-0.0061	0.0000
NUMBER GIVEN	**0.3104**	0.1114	-0.0493	0.1645	-0.0070	0.0000
CLUSTERING	**0.3757**	-0.1007	-0.1877	0.0332	0.0167	0.0000
HERF TAKEN	0.0049	0.0057	0.0795	**0.3936**	-0.0055	0.0000
HERF GIVEN	0.0907	0.0149	-0.0607	**0.3802**	0.0065	0.0000
DEGREE NEIGHBOR	0.0121	0.0120	-0.0110	**0.4427**	0.0033	0.0000
log(BETWEENNESS)	0.1273	**0.6005**	-0.0260	-0.0407	-0.0072	0.0000
log(SHORTEST PATH)	0.0001	**0.5662**	-0.0575	-0.0812	-0.0257	0.0000
log(EV CENTRALITY)	0.0853	-0.0828	0.0089	**0.3753**	0.0042	0.0000
TRIGGER	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**
Eigenvalue	8.5511	2.5423	2.1001	1.3265	1.0008	1.0000
Factor mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Factor standard deviation	2.2925	1.5836	1.6363	1.9504	1.0009	1.0000
Factor skewness	1.6430	-0.7036	3.3043	4.9452	0.0080	-0.0009
Factor kurtosis	5.5509	3.5858	23.1426	34.9859	1.8001	1.7832
Minimal factor value	-2.8963	-7.9874	-7.7025	-5.6100	-1.9239	-1.5932
25% quantile of factor	-1.5825	-0.9279	-0.7269	-0.7328	-0.8747	-0.8690
Factor median	-0.7433	0.1948	-0.3547	-0.4071	-0.0003	0.0000
75% quantile of factor	0.7533	1.1404	0.2056	-0.0155	0.8660	0.8690
Maximal factor value	12.4992	3.5801	18.2751	22.3342	1.8884	1.5932

Table 3: Rotated factor loadings from a principal components analysis

ated with the network topology. The size of the banks, the Herfindahl index as well as the power law exponent of the distribution of bank sizes all determine important aspects of the degree distribution and how the banks are interconnected. The number of loans given and taken represent the average in and out degree, and clustering relates to the local network structure. Therefore we conclude that this factor represents aspects of the network topology and will in the remainder refer to it as TOPOLOGY. Looking at the relevant variables and their signs we observe that the value of the factor increases with a network that is more interconnected: NUMBER GIVEN representing the outdegree, NUMBER TAKEN the indegree, CLUSTERING the local connectedness, SIZE being proportional to the number of links of the banks, HERF BANK and DISTRIBUTION indicate more large banks with many connections, and CORRELATION allowing for a more homogeneous spread of those links over the entire network by connecting highly and less highly connected banks.

The second factor provides a good measure of the TIERING of the network. In a tiered network a small number of banks (the core) will be highly connected with each other and have connections to the remaining banks (the periphery), while the banks in the periphery are not much connected with each other but only to the core. This structure would imply a small shortest path as most banks will be connected via the core in only a few steps, but also a low betweenness as those in the periphery will have low values. Additionally, a core can easier be established if the banking system is large enough. It is exactly these parameters that load highly with the second factor and thus a higher value corresponds to a more tiered network.

Those variables that represent the balance sheet structure of banks, EQUITY, RESERVES, LOANS GIVEN, and LOANS TAKEN are concentrated in the third factor and we therefore call this factor BALANCE SHEET. As a result of the signs of the individual variables, we observe that overall a higher value of this factor is associated with more loans being given and/or less deposits received, i. e. banks relying more on interbank loans rather than deposits and equity to finance any loans to non-bank clients.

The fourth factor is associated with the Herfindahl index of the interbank loans given and taken, average neighbor degree and the eigenvector centrality, thus representing aspects of the structure of the interbank loans and how they are spread between banks. We therefore call this factor LOAN STRUCTURE. A larger value of this factor will be associated with the concentration of interbank loans given and taken to only a few other banks of a similar size (HERF TAKEN, HERF GIVEN, DEGREE NEIGHBOR), that have a high importance in the network (EV CENTRALITY).

The final two factors are straightforward as they are only associated with a single variable each, the recovery rate and trigger bank, respectively, and for that reason we retain those names for these factors.

In the remainder of this paper we will only refer to these factors identified rather than individual variables. We therefore briefly summarize the identified factors and their interpretation for convenience:

TOPOLOGY measures the interconnectedness of the interbank loan network

TIERING provides a measure for the degree of tiering in the network of interbank loans

BALANCE SHEET provides a measure for the reliance of the bank on interbank loans

LOAN STRUCTURE measures whether banks provide loans to banks of a similar size to their own

RECOVERY is representing the recovery rate in case of bank failures

TRIGGER measures the size of the initially failing bank

6. Results of the model

In this section we analyze the main results from our model. We firstly consider some general distributional properties on the extent of the contagion before conducting a more detailed analysis of the influence the different factors have on the likelihood of observing a banking crisis and the extent of contagion. The remaining parts then compare the effects of banking systems with different power law exponents in their distribution of bank sizes and conduct a comparison with random networks.

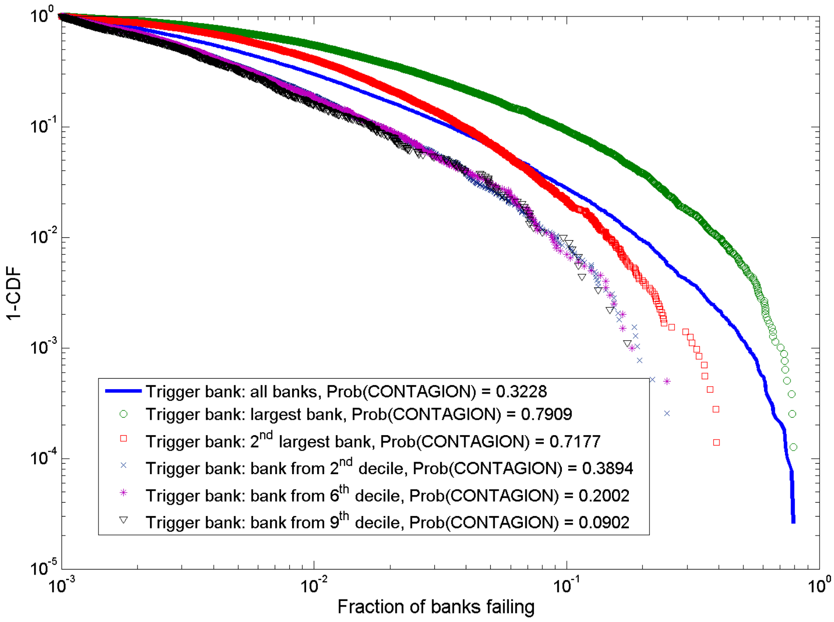
6.1. Distributional properties of the contagion

Using the 10,000 banking systems we generated randomly as detailed above, we investigate in a first step how many banks are affected by any contagion. To this effect we determined the fraction of banks that fail in each banking system in which we observe contagion and then aggregated these data to show the decumulative distribution, i.e. one minus the cumulative distribution function (CDF), as shown in figure 6. In doing so we also distinguished between the impact of different trigger banks and power law exponents on the extent of contagion.

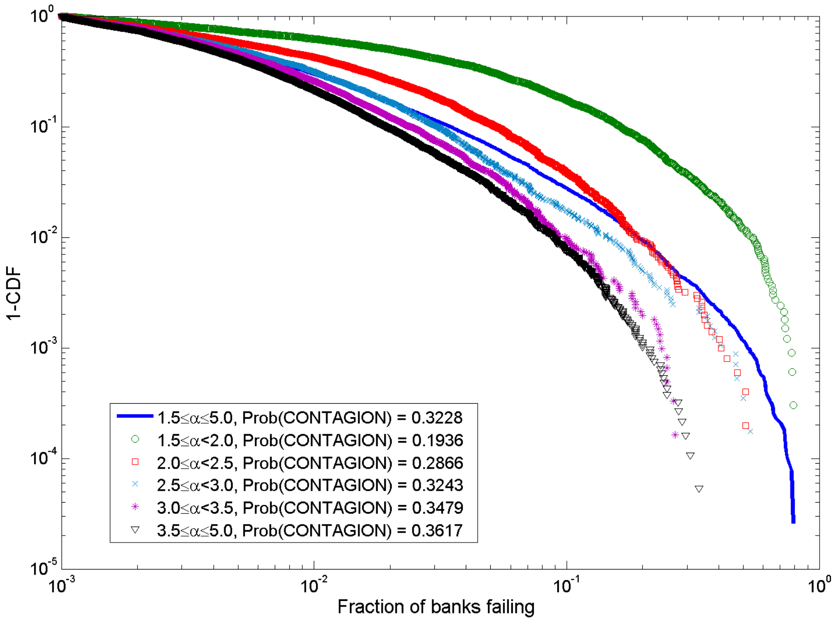
Our results clearly show that while large banking crises are rare occurrences, they would nevertheless happen regularly. There is approximately a 1 in 1,000 probability that more than half of all banks are failing and approximately a 1 in 80 probability of more than 10% of banks failing. It has to be noted that this result does not include any effects arising from the loss of confidence in the banking system and the subsequent withdrawal of funding in such a case, although this would be highly likely in a real banking crisis and exacerbate the crisis. As would be expected, the larger the bank triggering a crisis, the more likely and widespread a banking crisis will be on average. Nevertheless, we found that on occasions the failure of a relatively small bank can cause a significant spread of failures in the banking system. For a failing bank in the 9^{th} decile in terms of its size, i. e. a relatively small bank, there is still a 1 in 100 probability that more than 10% of all banks fail and in nearly 10% of cases at least one other bank fails as a consequence of such a small bank failing. Apart from the largest banks, the distribution of the fraction of banks failing does not vary significantly with the size of the bank triggering the crisis. Another observation is that a larger bank failing initially increases the likelihood of contagion occurring, as we would commonly expect to be the case.

These findings show clearly that it is not only important to focus on preventing the biggest bank(s) from failing (”too big to fail”), but also that small banks can have a significant impact on the systemic risk. It is therefore important to investigate further in more detail what determines the extent of such crises, in addition to an investigation into the emergence of contagion itself.

We also observe from figure 6(b) that the power law exponent of the size distribution of banks has a significant impact on the emergence of contagion as well as the extent of any banking crisis. We clearly see that a higher power



(a) Cumulative distribution function of the fraction of banks failing in the banking system, divided by the size of the trigger bank (all banks refers to all 12 types of trigger banks being used in generating the distribution)



(b) Cumulative distribution function of the fraction of banks failing in the banking system

Figure 6: Cumulative distribution functions of the extent of banking crises, split by trigger banks and the power law exponent of the distribution of the size of the banks

This table shows the estimates of a logit regression on the probability of a banking system exhibiting contagion (Prob(CONTAGION)) and an OLS regression on the fraction of banks failing in those cases we observe contagion (FRACTION FAILING). We show the estimates of these regressions, with numbers in parentheses denoting the t-values, as well as a sensitivity measure. This measure uses the difference between the 25% and 75% quantile of the factor value (the number associated with CONSTANT and exhibiting a ♯ is the value of the median for each factor for comparison).

	Prob(CONTAGION)		FRACTION FAILING	
	Estimates	Sensitivity	Estimates	Sensitivity
CONSTANT	-1.0055***	0.7035♯	0.0173***	0.0076♯
	(-129.11)		(81.49)	
TOPOLOGY	-0.1392***	0.0665	0.0047***	0.0110
	(-28.79)		(40.44)	
TIERING	0.0393***	0.0169	-0.0056***	0.0116
	(8.77)		(-54.94)	
BALANCE SHEET	-0.0810***	0.0157	-0.0006***	0.0006
	(-13.49)		(-4.07)	
LOAN STRUCTURE	-0.0036	0.0005	0.0133***	0.0096
	(-0.65)		(90.67)	
RECOVERY	-0.0121*	0.0044	-0.0001	0.0002
	(-1.71)		(-0.62)	
TRIGGER	-1.2180***	0.4209	-0.0052***	0.0091
	(-146.23)		(-27.36)	
Sample size	119,988		38,280	
R^2			0.16	

Table 4: Logit and OLS regressions for the existence and extent of systemic risk

law exponent is associated with a more likely contagion, i. e. banking systems in which banks are more equal in their size are more vulnerable to systemic risk. On the other hand, however, the extent - measured by the fraction of banks in a banking system failing - of any crisis is smaller the higher the power law exponent is. Here the equal size of banks prevents the spread as most losses that spread will be relatively small, hence they will be more quickly absorbed within the banking system and less banks will fail. We also investigated the size of the banking system, as measured by the number of banks, and did not find any meaningful relationship with the likelihood and extent of contagion.

6.2. *Determinants of the extent of banking crises*

In order to assess the likelihood of observing contagion we conduct a logit regression of the probability of observing a spread of the initial failure. As explanatory variables we use the factors from the principal components analysis as outlined above and show the results in table 4. We used the data from all 10,000 banking systems, each of which is triggered by 12 different banks; we lost one banking system in our sample as it was totally disconnected and as such no contagion could be observed.

Given the sample size of nearly 120,000 banking systems, a detailed analysis of statistical significance is not very meaningful, although we observe that the LOAN STRUCTURE is statistically not significant and RECOVERY is only so at a level of 10%. A more appropriate analysis would investigate the sensitivity of the likelihood of observing contagion to changes in the factor. To this effect we looked at the 25% and 75% quantile of the distribution of the factors and assessed how much a change of only this variable between those two values would affect the dependent variable, assuming all other factors to be fixed at their median. Looking at this sensitivity we see that the largest impact arises from the size of the trigger bank; the larger the bank the more likely contagion becomes, as we would expect to observe. A larger bank has more connections and thereby the possibility to spread any losses wider. In addition the loans taken from other banks also tend to be relatively large, thus inflicting larger losses on them, that can more easily result in their subsequent failure. Furthermore, the interbank loans given will also be relatively large and calling them in is likely to exceed the cash reserves of the smaller banks, causing them to fail via our failure mechanism.

The second most important factor is the network topology of the interbank loans; here we find that a more interconnected network reduces the likelihood of observing contagion. A more highly interconnected network results in any losses being spread more equally amongst banks rather than only a few other banks as would be the case in a less connected network. Thus each bank will only have to take a relatively small loss and is therefore more likely to survive, thus the initial losses do not spread. The same argument also can be applied for interbank loans being called in and causing banks to fail through the failure mechanism.

Furthermore, we observe that a less tiered network structure reduces the likelihood of observing contagion. In a less tiered network the initial losses are spread wider amongst banks rather than being focused on the small core, thus reducing the risk of losses quickly accumulating in the core and from there spreading out to the periphery. The final noteworthy factor affecting the contagion is the balance sheet structure. Here a larger reliance on interbank loans reduces the likelihood of contagion, which arises as with more interbank loans the relative losses from each individual loan defaulting reduces and thus the probability of another bank failing is reduced. For both factors the effects arising from interbank loans being called in are comparable.

Although those four factors are showing a statistically significant influence on the probability of contagion, it has to be noted that only the trigger bank has any economically significant impact. The other variables, even if changed considerably within its reasonable range, only have a limited impact on this probability, hence any policy measures to address the contagion using those variables will have a very limited impact. We can therefore conclude that the ”too big to fail” paradigm is supported for the emergence of contagion as it is mainly the size of the initially failing bank that determines whether contagion occurs.

In order to assess the impact of the initial failure on the banking system in more detail we also investigated the fraction of banks that failed if contagion occurs. Table 4 provides the OLS estimates of a regression of this variable on the factors identified before. Focussing again on the sensitivity rather than the size of the coefficients of the estimation and their statistical significance, we clearly see that the most important factor is the tiering of the network of interbank loans. A more tiered network reduces the fraction of banks failing as most larger banks in the core will be linked with each other and their larger size allows them to absorb any losses more easily amongst them and the spread of failures will be limited. In particular, losses from the periphery are unlikely to spread as the core will in most cases be able to absorb these losses. It is worth noting at this point that while a more tiered network reduces the fraction of banks failing, it actually increases the likelihood of observing contagion as outlined above, although the impact there is relatively small. Hence it is not only the number of links between banks that are important, but the structure of any interconnections.

The second most important factor for the spread of bank failures is the network topology. The more interconnected banks are by interbank loans, the more banks will fail. The reason for this finding is obvious: the more links a bank has the more its losses will be spread and close-knit banks may well accumulate losses from multiple banks and only because of this accumulation fail themselves. This influence is opposite to that it has on the probability of contagion in the first place as once the capacity to absorb losses is breached, they will spread more easily in a closely interconnected banking system. Once again the impact of interbank loans being called in on cash reserves has an equivalent impact in all cases.

The next important factor is the structure of interbank loans. A banking system in which loans are given amongst banks of more similar sizes actually increases the risk of more widespread bank failures as any losses will be quite substantial. The similar size of banks giving interbank loans to each other will result in relatively large loans being given, thus in the case of one bank failing, it will impose relatively large losses to those banks that provided these loans, causing them to fail.

The final important factor for the spread of bank failures is the size of the bank initially triggering the default. As would be expected, the larger the initial bank is the more widespread failures becomes; this arises from the fact that with a bigger bank the amount of losses that need to be covered are larger and thus other banks are more likely to be failing in turn. The other two factors, the balance sheet structure and the statistically insignificant recovery rate of losses, have a negligible influence on the failure rate.

The influence of the four main factors on the failure rate is substantial and roughly of equal sensitivity. It is thus particularly noteworthy that the balance sheet structure has no meaningful influence on the spread of failures, but that network properties are clearly dominating. In contrast to the emergence of contagion, the paradigm of ”too big to fail” has only limited validity for the extent of a banking crisis but rather network aspects are more relevant. However, it is more than a simple ”too interconnected to fail” as the structure of these interconnections, especially the tiering, are of relevance.

6.3. The impact in banking systems with different power law exponents

One important aspect in modeling banking systems is to have the correct basic network structure of interbank loans. What most importantly determines the network structure in our model is the power law exponent of the distribution of the size of banks. We have chosen this value to be between 1.5 and 5, in line with empirical results for interbank loan networks, and it was part of the factors identified to influence the probability of contagion as well as the spread of any failure. Given the importance of this variable, we investigate the stability of our results if we restrict our analysis to banking systems that differ only within a very narrow range of the power law exponent. As discussed above, figure 6(b) shows that a larger power law exponent reduces the spread of any failure, but at the same time the likelihood of contagion emerging increases. This provides us with a clear indication of a trade-off between those two aspects that any regulator seeking to affect the structure of the banking system has to be aware of, e. g. if through allowing for mergers the power law exponent is increased or decreased through the break-up of large banks.

Table 2 provides an overview of the key network characteristics and how they change with the power law exponent. As the network increases its power law exponent, it becomes ever closer to a random network and this is reflected in the variables. For the subsequent analysis we followed the same steps as above, including the determination of factors that now will exclude the power law exponent and then conducted the same regressions. The factors identified are similar to those observed before when we did not distinguish banking systems with different power law exponents, but we observe that the network topology as well as the balance sheet structure easily splits into two separate factors. The details of the factor loadings as well as the regressions with the parameter estimates are shown in appendix Appendix A.2. Tables 5 and 6 show the sensitivities of the regressions as used before and we focus our discussion on this aspect.

From inspecting table 5 we clearly observe that as the power law exponent increases, the importance of the size of the triggering bank as the dominant factor in determining the probability of contagion, remains largely unaffected. As we observed before, the other factors are of much less importance. Nevertheless we do observe an increasing importance of the reliance of the bank on interbank loans (LOAN STRUCTURE) as the power law exponent increases. The same can be observed for the structure of the balance sheet while the opposite is true for the interconnectedness of the network (TOPOLOGY). Thus overall we do not observe a significant difference to the results we obtained without splitting our sample up by power law exponents; this gives us an indication of the stability and validity of our results.

Investigating the extent of the spread of bank failures from table 6, we observe that for higher power law exponents, i. e. banking systems not dominated by a few large banks, the importance of the bank triggering the contagion is diminishing as is the importance of the interconnectedness of the banks via interbank loans. On the other hand, the importance of tiering is remaining largely unaffected. This result re-enforces our previous assessment that the structure of the network, in particular tiering, is an important determinant of the spread of any failure. We confirm here that the balance sheet structure does not play an important role in this assessment and the size of the triggering bank is of less importance for larger power law exponents.

Overall we conclude that the results derived before when considering banking system covering the full range of power law exponents are robust to splitting the analysis up into banking systems with power law exponents in a small range. In particular the ”too big too fail” paradigm is again shown to be of limited validity and the network structure to play an at least equally important role in the assessment of systemic risk.

6.4. Comparison with random networks

As a further assessment of the stability of our results we conducted an analysis using a random network of interbank loans rather than a scale-free network, thus decoupling the connection between the distribution of bank sizes and network structure. We maintained that the bank size has a power-law tail, but do not any longer assume that the number of interbank loans given and received is correlated with the size of the bank, but rather that the network structure is entirely random using the same overall connectivity as would have been emerged from a scale-free network. Descriptive statistics of all variables considered are provided in appendix Appendix B. Firstly, inspecting the distribution of the fraction of banks failing as well as the probability of observing contagion in figure 7, we clearly

This table shows sensitivity measure of a logit estimation of the probability of observing contagion, in analogy to table 4. This measure uses the difference between the 25% and 75% quantile of the factor value. We show these measures for banking systems in a small range of the power law exponent of the distribution of the size of banks. The full details of the principal components analysis and full estimation results are presented in appendix Appendix A.2.

	$1.5 \leq \alpha < 2$	$2 \leq \alpha < 2.5$	$2.5 \leq \alpha < 3$	$3 \leq \alpha < 3.5$	$3.5 \leq \alpha \leq 5$
TOPOLOGY	0.0214	0.0230	0.0044	0.0047	0.0009
TOPOLOGY II			0.0284	0.0164	0.0065
BALANCE SHEET I	0.0072	0.0064	0.0102	0.0026	0.0144
BALANCE SHEET II		0.0351	0.0095	0.0019	0.0044
TIERING	0.0076	0.0152	0.0095	0.0077	0.0084
LOAN STRUCTURE	0.0041		0.0104	0.0130	0.0136
RECOVERY	0.0019				
TRIGGER	0.3636	0.4759	0.4367	0.4057	0.3582

Table 5: Sensitivity of the probability of contagion on the factors identified from a principal components analysis

This table shows sensitivity measure of an OLS estimation of the fraction of banks failing if contagion occurs, in analogy to table 4. This measure uses the difference between the 25% and 75% quantile of the factor value. We show these measures for banking systems in a small range of the power law exponent of the distribution of the size of banks. The full details of the principal components analysis and full estimation results are presented in appendix Appendix A.2.

	$1.5 \leq \alpha < 2$	$2 \leq \alpha < 2.5$	$2.5 \leq \alpha < 3$	$3 \leq \alpha < 3.5$	$3.5 \leq \alpha \leq 5$
TOPOLOGY I	0.0633	0.0125	0.0015	0.0003	0.0004
TOPOLOGY II			0.0010	0.0006	0.0001
BALANCE SHEET I	0.0090	0.0016	0.0010	0.0002	0.0015
BALANCE SHEET II		0.0039	0.0026	0.0006	0.0001
TIERING	0.0104	0.0154	0.0180	0.0150	0.0130
LOAN STRUCTURE	0.0028		0.0087	0.0055	0.0026
RECOVERY	0.0016				
TRIGGER	0.0669	0.0227	0.0101	0.0057	0.0027

Table 6: Sensitivity of the fraction of banks failing on the factors identified from a principal components analysis

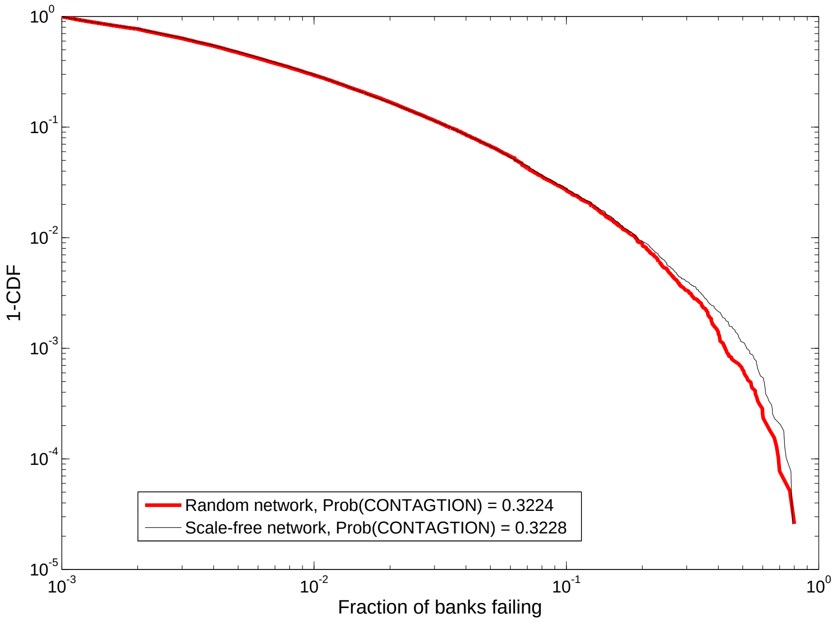


Figure 7: Comparison of the cumulative distribution function of the extent of the banking crises for random and scale-free networks

see that there are no noteworthy differences between the two network types.

As we conduct a principal components analysis we identify eight factors that are more difficult to interpret than in the case of scale-free networks, appendix Appendix B provides details of the rotated factor loads. We find three factors related to the topology of the interbank loan network, two related to the balance sheet, one describing the concentration of interbank loans, one for the recovery rate and one for the trigger bank. No tiering emerges as a factor, which is not surprising given that in a random network no such structure should emerge consistently.

Conducting a regression using these factors, we observe that the size of the trigger bank is the most important determinant of whether contagion occurs or not, see table 7. The only other factor that has a meaningful influence is BALANCE SHEET II, looking mainly at the liabilities and size of the banks. This result is in slight contrast to that of a scale free network in that no network topology factors have a meaningful impact on the likelihood of contagion, although there the impact was also very limited.

With respect to the determinants of the extent of the crisis, we find that the most important factor is again BALANCE SHEET II, followed by the size of the trigger bank, TOPOLOGY II, mainly representing the eigenvector centrality, and TOPOLOGY I. While the interpretation of these results are not as easily conducted as in the case of scale-free networks, it nevertheless confirms our assertion that the network structure is relevant for the spread of any initial failure and should be taken into account in any assessment of the systemic risk of banking systems.

Although the choice of network structure is important for our results, we find some similar outcomes for a random

This table shows the estimates of a logit regression on the probability of a banking system exhibiting contagion (Prob(CONTAGION)) and an OLS regression on the fraction of banks failing in those cases we observe contagion (FRACTION FAILING). We show the estimates of these regressions, with numbers in parentheses denoting the t-values, as well as a sensitivity measure. This measure uses the difference between the 25% and 75% quantile of the factor value (the number associated with CONSTANT and associated with $^\sharp$ is the value of the median for each factor for comparison).

	Prob(CONTAGION)		FRACTION FAILING	
	Estimates	Sensitivity	Estimates	Sensitivity
CONSTANT	-1.0010***	0.2921$^\sharp$	0.0142***	0.0072$^\sharp$
	(-129.12)		(65.20)	
TOPOLOGY I	0.0145***	0.0059	-0.0034***	0.0066
	(3.77)		(-34.62)	
TOPOLOGY II	0.0157***	0.0069	-0.0048***	0.0102
	(2.70)		(-35.48)	
TOPOLOGY III	-0.0045	0.0009	-0.0004**	0.0004
	(-0.63)		(-2.51)	
LOAN STRUCTURE	-0.0090*	0.0010	-0.0033***	0.0017
	(-1.70)		(-27.29)	
BALANCE SHEET I	-0.0054	0.0009	-0.0030***	0.0025
	(-0.88)		(-19.44)	
BALANCE SHEET II	-0.2006***	0.0890	0.0079***	0.0175
	(-48.27)		(73.42)	
RECOVERY	-0.0088	0.0031	0.0003	0.0004
	(-1.24)		(1.57)	
TRIGGER	1.2110***	0.4158	0.0060***	0.0104
	(145.82)		(30.62)	
Sample size	119952		38683	
R^2			0.26	

Table 7: Logit and OLS regressions for the existence and extent of systemic risk in the case of random networks

network as for scale-free networks, providing further evidence for the robustness of our results. The properties of the interbank loan networks are shown to be an important determinant and should be included when assessing systemic risk.

7. Policy implications

Current banking regulation attempts to limit systemic risk by preventing banks from failing in the first place, putting particular emphasis on large banks ("too big to fail"). The focus of most regulations, including the latest Basel III guidelines, is on the amount of equity and aspects of liquidity, i. e. balance sheet structures. Our above analysis suggests that the scope of regulation should be extended by taking into account the structure and extent of interbank loans and other financial relationships between banks. It has become clear that the size of the bank initially failing is the main determinant whether the failure spreads, and hence any policy should pay more attention to larger banks and potentially have tighter regulations for those banks in order to prevent them failing and cause their failure to spread. This result is very much in line with the current thinking in banking regulation and is shown in our model to be a valid concern. It has, however, to be remembered that once the failure spreads, the influence of this variable on the extent of the crisis will be very limited and other factors, primarily associated with the network structure of interbank loans, will be become more important.

Interestingly, the balance sheet structure, the main focus of current regulation with minimum capital requirements, maximal leverage and liquidity constraints, has no meaningful impact on whether contagion occurs. Thus, it might be a well placed approach to prevent the failure of a bank in the first place (our initial trigger for the banking crisis that we assumed to be exogenously given), but it has very limited impact on systemic risk itself, be it to limit the occurrence of contagion or the extent of any banking crisis that develops.

The implications of our findings are that regulators seeking to address systemic risk should pay particular attention to the network structure of financial relationships between banks that determine the extent of any banking crisis. It is beyond the scope of this contribution to develop specific policy propositions that allow regulators to affect systemic risk. Our results nevertheless suggest that in order to reduce the extent of any banking crisis, regulators should seek measures that reduce the interconnectedness of banks in the interbank loan market, and reduce the interbank loans given to banks of similar size. While direct interference in the interbank market might be unfeasible, any regulator could provide incentives to banks to take these aspects in consideration in their decision-making on providing and seeking interbank loans. How these incentives are best achieved remains unanswered at this stage.

It should finally be noted that a more tiered banking system, i. e. a banking system which is dominated by a small number of highly connected large banks, is less vulnerable to large banking crises. Thus a higher concentration in the banking system is reducing systemic risk, provided a failure of those banks in the core can be prevented effectively.

8. Conclusions

We have developed a model of interbank loans given and received by banks of different sizes and with heterogeneous balance sheets. Establishing a network of such interbank loans amongst banks with the number of loans being correlated with the asset size of the banks, which follows a power-law distribution, we then continue to investigate how the exogenous failure of a single bank spreads through the banking system and causes other banks to fail. We find that the determinants of whether a spread occurs includes aspects of the network structure, namely the interconnectedness of nodes in the network and the tiering; the same variables also affect the extent of a crises. The size of the bank initially failing determines to a large degree whether contagion happens, with the network structure having only a very limited influence. The size of the failing bank, however, has a very limited impact on the number of banks affected from contagion, it is the network structure that has a much more significant impact on this measure of systemic risk.

Our findings clearly suggest that aspects of the network structure are a determinant for the likelihood of a banking crisis and in particular its extent. In contrast, current regulation exclusively focuses on the balance sheet structure of banks, notably the amount of equity required and more recently liquidity aspects, neglecting any effects arising from the network structure of interbank loans or other financial contracts between banks. Our analysis suggests that this aspect has only a very limited impact on the systemic risk, although it might be more important to determine whether a bank fails initially and causes a banking crisis. This deficit in current regulation has been shown to have a potentially significant effect on the systemic risk that currently is not addressed.

Future research arising from this paper is manifold. Firstly, it would be worth looking at the determinants of the failure of individual banks and establish how the local network structure affects the likelihood of an individual bank failing. It would furthermore be worth to investigate real banking systems by using actual balance sheets, even if the interactions themselves are not known, with the aim to understand firstly how vulnerable banking systems are, but also to understand how this vulnerability evolves over time. It would also be of interest to consider the importance of the two mechanisms employed, the default and the failure mechanism, for the emergence and extent of contagion. Finally we could extend our framework to determine an optimal regulation, e. g. by adjusting capital and liquidity requirements to the network characteristics or even the individual position of a bank in the network with the aim to reduce systemic risk. The banking system as developed here is free of any actual dynamics in the network itself. Future work might want to include how interbank loans are granted, extended, and withdrawn in response to a banking crises developing. This would allow to investigate how the actual behavior of banks contributes to or mitigates the onset of a banking crisis.

Appendix A. Detailed results of banking systems with different power law exponents

Appendix A.1. Descriptive statistics for sample split by power law exponent

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	9.2268	2.0683	1.2637	4.7461	5.4717	7.6664	8.7313	10.2863	18.6746
CORRELATION	-0.4485	0.2201	-0.5422	2.8178	-0.9967	-0.5874	-0.4118	-0.2817	0.3482
DISTRIBUTION	1.7575	0.1425	-0.0425	1.7958	1.5010	1.6282	1.7612	1.8793	2.0000
NUMBER BANKS	511.8151	280.0232	-0.0267	1.8144	13.0000	266.0000	523.5000	751.0000	1000.0000
RECOVERY	0.5012	0.2879	-0.0251	1.7742	0.0006	0.2479	0.5058	0.7512	0.9970
log(HERF BANKS)	-2.7378	0.9827	0.1467	2.5334	-5.3908	-3.4633	-2.7692	-2.0321	-0.0167
EQUITY	0.1878	0.0211	0.7174	8.0497	0.1204	0.1769	0.1869	0.1983	0.3430
RESERVES	0.2087	0.0490	-0.5728	4.3575	0.0156	0.1848	0.2154	0.2373	0.4032
LOANS GIVEN	0.3611	0.1161	1.0543	5.4106	0.0138	0.2937	0.3402	0.4093	0.9218
LOANS TAKEN	0.2592	0.0501	0.1172	6.0263	0.0118	0.2352	0.2587	0.2794	0.4543
NUMBER GIVEN	1.5236	0.2407	-0.0952	2.6458	0.8000	1.3591	1.5148	1.7025	2.1197
NUMBER TAKEN	1.5241	0.2409	-0.1002	2.6589	0.7500	1.3653	1.5162	1.7037	2.1154
CLUSTERING	0.0555	0.0578	1.9941	8.7305	0.0000	0.0150	0.0357	0.0771	0.4733
HERF TAKEN	0.6729	0.0983	1.5193	5.0628	0.3586	0.6127	0.6405	0.6986	0.9984
HERF GIVEN	0.6738	0.0974	1.4831	4.9185	0.4439	0.6125	0.6429	0.7012	0.9967
DEGREE NEIGHBOR	123.0041	214.6224	3.3973	16.8774	0.9167	14.4275	38.0022	122.3817	1705.2030
log(BETWEENESS)	5.2774	1.1746	-1.6458	6.3676	-0.6592	4.8167	5.5965	6.1054	7.0641
log(SHORTEST PATH)	1.3364	0.3148	-1.0161	5.1559	-0.1335	1.1894	1.3704	1.5476	2.3068
log(EV CENTRALITY)	2.3139	4.3469	1.8738	6.5298	-1.9300	-0.6402	0.5531	3.6981	22.9414
TRIGGER	6.5000	3.4522	0.0000	1.7828	1.0000	3.5000	6.5000	9.5000	12.0000

Table A.8: Descriptive statistics of the independent variables investigated for $1.5 \leq \alpha < 2.0$

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	6.3933	0.6265	4.2123	46.2258	5.2849	6.0120	6.2601	6.6644	15.7353
CORRELATION	-0.1665	0.1264	-1.7458	10.8641	-0.9820	-0.2069	-0.1438	-0.1011	0.3154
DISTRIBUTION	2.2506	0.1433	-0.0281	1.8284	2.0001	2.1337	2.2501	2.3705	2.5000
NUMBER BANKS	501.4390	281.0430	0.0239	1.8594	13.0000	267.5000	494.0000	740.5000	1000.0000
RECOVERY	0.5012	0.2842	-0.0248	1.8108	0.0025	0.2573	0.5018	0.7477	0.9985
log(HERF BANKS)	-4.5757	0.8771	0.6005	3.3466	-6.4636	-5.2191	-4.6241	-4.0594	-1.1391
EQUITY	0.1806	0.0129	0.1474	9.0904	0.1040	0.1742	0.1802	0.1866	0.2569
RESERVES	0.2388	0.0247	-0.4966	10.5851	0.0479	0.2277	0.2396	0.2508	0.3819
LOANS GIVEN	0.2884	0.0400	1.5906	14.2178	0.0997	0.2702	0.2839	0.3029	0.5988
LOANS TAKEN	0.2793	0.0227	-0.1672	9.6079	0.0982	0.2682	0.2802	0.2910	0.3961
NUMBER GIVEN	1.2928	0.1388	0.7886	5.4541	0.7674	1.2120	1.2780	1.3591	1.9600
NUMBER TAKEN	1.2931	0.1391	0.8307	5.4556	0.7674	1.2117	1.2770	1.3584	1.9600
CLUSTERING	0.0193	0.0293	3.0454	13.6976	0.0000	0.0039	0.0086	0.0198	0.2114
HERF TAKEN	0.6159	0.0418	2.5034	20.6443	0.3583	0.5957	0.6118	0.6286	0.9912
HERF GIVEN	0.6203	0.0456	1.8620	14.8568	0.3206	0.5980	0.6143	0.6371	0.9646
DEGREE NEIGHBOR	18.3660	53.3598	8.7480	107.3476	1.2188	3.7189	5.7865	11.3677	940.0629
log(BETWEENESS)	5.4256	1.2912	-1.5488	5.9695	-1.7047	4.8792	5.7976	6.3366	7.5395
log(SHORTEST PATH)	1.6067	0.3692	-1.0821	5.1773	-0.6061	1.4271	1.6657	1.8568	2.4924
log(EV CENTRALITY)	-0.6766	1.8057	4.7067	30.2246	-2.1186	-1.4455	-1.1649	-0.6674	16.3085
TRIGGER	6.5000	3.4522	0.0000	1.7828	1.0000	3.5000	6.5000	9.5000	12.0000

Table A.9: Descriptive statistics of the independent variables investigated for $2.0 \leq \alpha < 2.5$

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	5.6370	0.3091	10.7025	208.5738	5.0415	5.4911	5.5988	5.7325	12.5759
CORRELATION	-0.0721	0.0826	-2.5474	21.9283	-0.8616	-0.1003	-0.0671	-0.0349	0.2721
DISTRIBUTION	2.7524	0.1419	-0.0375	1.8599	2.5001	2.6317	2.7549	2.8744	3.0000
NUMBER BANKS	497.0591	283.1765	0.0220	1.8025	13.0000	249.0000	492.0000	747.0000	1000.0000
RECOVERY	0.4982	0.2909	-0.0073	1.7359	0.0032	0.2402	0.5032	0.7563	0.9985
log(HERF BANKS)	-5.7222	0.8081	0.9604	4.3719	-7.3535	-6.3055	-5.8511	-5.2822	-1.8875
EQUITY	0.1769	0.0114	0.2998	14.7137	0.0834	0.1717	0.1767	0.1824	0.2797
RESERVES	0.2439	0.0204	1.2221	25.4342	0.0808	0.2342	0.2439	0.2533	0.4934
LOANS GIVEN	0.2765	0.0215	2.6085	27.8385	0.1712	0.2664	0.2753	0.2848	0.5331
LOANS TAKEN	0.2912	0.0199	0.7452	21.8682	0.1368	0.2818	0.2910	0.3013	0.5242
NUMBER GIVEN	1.2174	0.0882	0.4347	9.2995	0.6923	1.1722	1.2142	1.2573	1.7826
NUMBER TAKEN	1.2190	0.0881	0.6339	9.1849	0.7143	1.1734	1.2144	1.2599	1.8000
CLUSTERING	0.0076	0.0166	5.4901	40.3914	0.0000	0.0014	0.0030	0.0066	0.1758
HERF TAKEN	0.6085	0.0313	1.4029	15.5176	0.4267	0.5933	0.6076	0.6223	0.8737
HERF GIVEN	0.6046	0.0341	0.7573	14.8758	0.3728	0.5882	0.6031	0.6191	0.8801
DEGREE NEIGHBOR	4.8925	10.8507	13.0530	222.7334	0.9048	2.6356	3.0863	4.0200	238.6532
log(BETWEENESS)	5.2061	1.3833	-1.0499	3.9938	-1.4351	4.4144	5.5414	6.2983	7.3333
log(SHORTEST PATH)	1.6641	0.4126	-0.8821	3.8067	-0.0846	1.4406	1.7442	1.9583	2.5616
log(EV CENTRALITY)	-1.0870	1.3833	6.2252	52.2918	-2.3212	-1.6249	-1.3930	-1.0357	15.8169
TRIGGER	6.5000	3.4522	0.0000	1.7828	1.0000	3.5000	6.5000	9.5000	12.0000

Table A.10: Descriptive statistics of the independent variables investigated for $2.5 \leq \alpha < 3.0$

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	5.3337	0.2115	13.0368	261.6744	4.8782	5.2542	5.3138	5.3784	10.3406
CORRELATION	-0.0282	0.0736	0.4640	23.2648	-0.6706	-0.0621	-0.0309	0.0030	0.7168
DISTRIBUTION	3.2460	0.1433	0.0318	1.8134	3.0001	3.1221	3.2454	3.3691	3.4997
NUMBER BANKS	512.1735	291.3586	-0.0030	1.7795	13.0000	258.0000	506.0000	767.0000	1000.0000
RECOVERY	0.5002	0.2873	-0.0192	1.8006	0.0012	0.2471	0.5001	0.7517	0.9979
log(HERF BANKS)	-6.4787	0.8087	1.2149	4.6192	-7.9674	-7.0645	-6.6542	-6.1133	-2.9262
EQUITY	0.1749	0.0102	0.1437	10.3324	0.1025	0.1698	0.1749	0.1801	0.2564
RESERVES	0.2461	0.0173	0.1160	8.4529	0.1499	0.2371	0.2458	0.2547	0.3533
LOANS GIVEN	0.2731	0.0159	0.3222	13.7035	0.1620	0.2656	0.2731	0.2811	0.4230
LOANS TAKEN	0.2948	0.0174	-1.5217	16.4336	0.1254	0.2870	0.2958	0.3041	0.3851
NUMBER GIVEN	1.1890	0.0682	0.8350	11.8693	0.8667	1.1559	1.1876	1.2202	1.8056
NUMBER TAKEN	1.1890	0.0693	0.7139	10.7915	0.8000	1.1548	1.1882	1.2215	1.7778
CLUSTERING	0.0051	0.0142	9.1401	121.5796	0.0000	0.0007	0.0019	0.0040	0.2675
HERF TAKEN	0.6072	0.0277	0.5785	11.2061	0.4304	0.5935	0.6065	0.6201	0.8120
HERF GIVEN	0.5988	0.0299	-0.0349	10.5107	0.4273	0.5846	0.5987	0.6140	0.8061
DEGREE NEIGHBOR	2.8672	2.4376	17.1617	374.7643	1.2727	2.3551	2.5375	2.7843	64.9701
log(BETWEENESS)	4.8729	1.4031	-0.7797	3.5866	-1.2993	3.9780	5.0886	5.9305	7.4756
log(SHORTEST PATH)	1.6220	0.4329	-0.5057	3.1670	0.0572	1.3639	1.6551	1.9428	2.6731
log(EV CENTRALITY)	-1.2980	0.9936	8.9638	112.1055	-2.4129	-1.6878	-1.4625	-1.1780	14.1130
TRIGGER	6.5000	3.4522	0.0000	1.7828	1.0000	3.5000	6.5000	9.5000	12.0000

Table A.11: Descriptive statistics of the independent variables investigated for $3.0 \leq \alpha < 3.5$

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	5.0875	0.1755	14.5623	334.5967	4.7955	5.0110	5.0652	5.1352	10.0077
CORRELATION	-0.0106	0.0647	-0.6198	10.4032	-0.7098	-0.0418	-0.0086	0.0232	0.4002
DISTRIBUTION	4.2498	0.4289	-0.0288	1.8207	3.5000	3.8834	4.2557	4.6200	4.9987
NUMBER BANKS	506.9940	284.5787	-0.0007	1.8118	13.0000	262.0000	509.0000	748.0000	1000.0000
RECOVERY	0.4997	0.2864	0.0001	1.8075	0.0003	0.2546	0.4971	0.7477	0.9996
log(HERF BANKS)	-7.2231	0.8810	1.2117	4.7162	-8.7270	-7.8630	-7.4277	-6.7801	-2.9319
EQUITY	0.1740	0.0097	0.4224	8.8989	0.1063	0.1689	0.1737	0.1786	0.2433
RESERVES	0.2462	0.0173	0.3220	10.6632	0.1129	0.2379	0.2461	0.2545	0.3852
LOANS GIVEN	0.2733	0.0144	0.2960	11.6321	0.1776	0.2660	0.2733	0.2806	0.4227
LOANS TAKEN	0.2987	0.0169	-0.6519	10.8125	0.1612	0.2908	0.2988	0.3073	0.3950
NUMBER GIVEN	1.1717	0.0604	0.2462	10.8271	0.6923	1.1414	1.1710	1.2015	1.6286
NUMBER TAKEN	1.1715	0.0613	0.1138	12.6076	0.6923	1.1414	1.1709	1.2014	1.6818
CLUSTERING	0.0033	0.0079	7.5201	83.6861	0.0000	0.0004	0.0014	0.0031	0.1500
HERF TAKEN	0.6074	0.0285	-0.0882	11.6180	0.3746	0.5933	0.6073	0.6210	0.8198
HERF GIVEN	0.5956	0.0286	-0.2875	15.7338	0.2661	0.5815	0.5955	0.6090	0.8826
DEGREE NEIGHBOR	2.4319	1.2301	24.5365	755.0894	0.9000	2.1994	2.3115	2.4581	43.9359
log(BETWEENESS)	4.4276	1.2552	-0.5865	3.9224	-2.5649	3.6604	4.5032	5.2980	7.4520
log(SHORTEST PATH)	1.5046	0.4045	-0.2885	3.5477	-0.6190	1.2460	1.5107	1.7763	2.6513
log(EV CENTRALITY)	-1.3216	1.0678	7.9513	88.2955	-2.6368	-1.7278	-1.5092	-1.1887	15.7842
TRIGGER	6.5000	3.4521	0.0000	1.7828	1.0000	3.5000	6.5000	9.5000	12.0000

Table A.12: Descriptive statistics of the independent variables investigated for $3.5 \leq \alpha \leq 5.0$

Appendix A.2. Principal component analysis for sample split by power law exponent

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	TOPOLOGY I	BALANCE SHEET I	TIERING	LOAN STRUCTURE	RECOVERY	TRIGGER
log(SIZE)	**-0.3265**	0.1790	-0.0655	0.0606	0.0044	0.0000
CORRELATION	**0.2806**	-0.0706	0.0937	0.1802	-0.0146	0.0000
NUMBER BANKS	-0.1851	0.0465	**0.5227**	0.1854	0.0230	0.0000
RECOVERY	0.0175	-0.0038	-0.0040	0.0043	**0.9923**	0.0000
log(HERF BANKS)	-0.1457	0.1028	**-0.2769**	-0.1821	0.0736	0.0000
EQUITY	0.1400	**0.4931**	-0.0220	0.0288	-0.0055	0.0000
RESERVES	0.1170	**-0.4274**	-0.0218	0.0741	0.0008	0.0000
LOANS TAKEN	-0.1139	**0.4780**	0.0092	-0.0130	-0.0152	0.0000
LOANS GIVEN	-0.1570	**-0.5153**	0.0093	-0.0372	-0.0241	0.0000
NUMBER TAKEN	-0.0882	0.0345	0.0813	**-0.4837**	-0.0149	0.0000
NUMBER GIVEN	-0.0881	0.0347	0.0792	**-0.4835**	-0.0154	0.0000
CLUSTERING	0.1444	-0.1131	-0.1609	**-0.5775**	0.0271	0.0000
HERF TAKEN	**-0.3302**	0.0208	-0.0524	-0.0863	-0.0292	0.0000
HERF GIVEN	**-0.3634**	-0.0430	-0.0334	-0.0464	-0.0486	0.0000
DEGREE NEIGHBOR	**-0.4305**	-0.0960	0.1316	0.0874	0.0436	0.0000
log(BETWEENNESS)	-0.0190	0.0038	**0.5891**	-0.1458	0.0261	0.0000
log(SHORTEST PATH)	0.2466	0.0292	**0.4746**	-0.2205	-0.0111	0.0000
log(EV CENTRALITY)	**-0.4049**	-0.0533	0.0599	0.0027	0.0335	0.0000
TRIGGER	0.0000	0.0000	0.0000	0.0000	0.0000	**-1.0000**
Eigenvalue	7.2467	3.1037	2.4167	1.1981	1.0023	1.0000
Factor Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Factor standard deviation	2.3566	1.7698	1.5744	1.6716	1.0042	0.9999
Factor skewness	-1.7195	1.1395	-0.8084	-0.0658	-0.0312	0.0000
Factor kurtosis	6.1330	6.6757	3.7050	3.2825	1.7941	1.7837
Minimal factor value	-11.5128	-5.7939	-6.0635	-7.3465	-1.8821	-1.5932
25% quantile of factor	-0.7687	-0.9998	-0.8967	-1.1951	-0.8707	-0.8690
Factor Mmedian	0.7686	-0.2273	0.2503	0.1252	0.0276	0.0000
75% quantile of factor	1.6187	0.7278	1.1553	1.1009	0.9027	0.8690
Maximal factor value	3.4615	9.5970	3.8438	5.2028	1.8450	1.5932

Table A.13: Rotated factor loadings from a principal components analysis for $1.5 \leq \alpha < 2$

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	TOPOLOGY	TIERING	BALANCE SHEET II	BALANCE SHEET I	TRIGGER
log(SIZE)	0.2197	-0.0293	**0.3611**	0.0327	0.0000
CORRELATION	**-0.3438**	0.0388	-0.1584	-0.0042	0.0000
NUMBER BANKS	0.0513	**0.4983**	0.1887	-0.1061	0.0000
RECOVERY	-0.0694	-0.0708	-0.2941	**0.4308**	0.0000
log(HERF BANKS)	0.1534	**-0.3291**	0.2304	-0.0494	0.0000
EQUITY	-0.0983	0.0264	**0.5079**	0.0260	0.0000
RESERVES	-0.0074	-0.0211	-0.0355	**-0.6431**	0.0000
LOANS TAKEN	0.0146	0.0320	0.1994	**0.5710**	0.0000
LOANS GIVEN	0.1069	0.0083	**-0.5541**	-0.0411	0.0000
NUMBER TAKEN	**0.3733**	0.1294	-0.0762	0.0076	0.0000
NUMBER GIVEN	**0.3735**	0.1246	-0.0690	0.0097	0.0000
CLUSTERING	**0.3192**	-0.1601	0.0047	-0.0905	0.0000
HERF TAKEN	**0.2477**	-0.0019	-0.0144	0.1909	0.0000
HERF GIVEN	**0.3291**	-0.0199	-0.2035	0.0719	0.0000
DEGREE NEIGHBOR	**0.3511**	0.0304	0.0238	-0.0414	0.0000
log(BETWEENNESS)	0.0832	**0.5592**	0.0394	-0.0255	0.0000
log(SHORTEST PATH)	-0.0379	**0.5001**	-0.0813	0.0727	0.0000
log(EV CENTRALITY)	**0.3147**	-0.1085	0.0484	-0.0028	0.0000
TRIGGER	0.0000	0.0000	0.0000	0.0000	**-1.0000**
Eigenvalue	5.9249	3.0895	2.2190	1.1252	1.0000
Factor Mean	0.0000	0.0000	0.0000	0.0000	0.0000
Factor standard deviation	2.3565	1.7502	1.4374	1.2946	0.9999
Factor skewness	3.2652	-0.9045	1.1372	1.4889	0.0000
Factor kurtosis	18.9415	3.9246	9.2516	12.7625	1.7837
Minimal factor value	-4.0710	-8.8835	-7.1525	-5.7455	-1.5932
25% quantile of factor	-1.2256	-0.9961	-0.8607	-0.6980	-0.8690
Factor Mmedian	-0.5938	0.3408	-0.1762	-0.0790	0.0000
75% quantile of factor	0.4453	1.2806	0.6685	0.5530	0.8690
Maximal factor value	19.4214	3.7858	12.9034	10.5285	1.5932

Table A.14: Rotated factor loadings from a principal components analysis for $2 \leq \alpha < 2.5$

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	LOAN STRUCTURE	TIERING	BALANCE SHEET II	BALANCE SHEET I	TOPOLOGY II	TOPOLOGY	TRIGGER
log(SIZE)	-0.0761	-0.0125	-0.0739	0.0915	**-0.6908**	0.1083	0.0000
CORRELATION	-0.1211	-0.0386	-0.0217	0.0689	**0.4513**	0.1077	0.0000
NUMBER BANKS	-0.1105	**-0.5158**	-0.0212	-0.0212	-0.0775	-0.0576	0.0000
RECOVERY	0.2474	0.2001	-0.0312	0.0792	0.1289	**0.3033**	0.0000
log(HERF BANKS)	0.1258	**0.4303**	-0.0732	0.0263	-0.2665	0.1014	0.0000
EQUITY	-0.2053	-0.0985	**-0.4264**	0.0640	-0.1612	-0.1039	0.0000
RESERVES	0.0431	0.0041	-0.0111	**-0.6842**	-0.0674	0.0319	0.0000
LOANS TAKEN	0.0250	0.0039	0.0151	**0.6708**	-0.0757	0.0184	0.0000
LOANS GIVEN	0.0126	0.0044	**0.6347**	0.1270	0.1121	-0.0027	0.0000
NUMBER TAKEN	**0.5282**	-0.0752	0.0544	-0.0119	-0.0582	-0.0071	0.0000
NUMBER GIVEEN	**0.5467**	-0.0515	0.0596	-0.0413	-0.0440	-0.0079	0.0000
CLUSTERING	0.2845	0.1691	-0.0357	-0.0800	-0.0412	**-0.3493**	0.0000
HERF TAKEN	**0.3359**	0.0149	-0.3200	0.1624	0.0592	-0.0599	0.0000
HERF GIVEN	-0.0399	-0.0541	**0.5382**	-0.0068	-0.3152	-0.1029	0.0000
DEGREE NEIGHBOR	0.0386	-0.0887	-0.0035	0.0360	-0.1201	**-0.5909**	0.0000
log(BETWEENNESS)	0.1416	**-0.5003**	-0.0268	0.0052	-0.0520	0.0506	0.0000
log(SHORTEST PATH)	0.2234	**-0.4335**	-0.0359	0.0476	0.0795	0.1133	0.0000
log(EV CENTRALITY)	-0.0298	0.1061	-0.0192	0.0542	0.2083	**-0.5984**	0.0000
TRIGGER	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**-1.0000**
Eigenvalue	3.9582	3.4758	1.6264	1.4972	1.1869	1.0261	1.0000
Factor Mean	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
Factor standard deviation	1.5896	1.7609	1.2790	1.2294	1.3227	1.2680	0.9746
Factor skewness	1.1265	0.8657	-0.2510	1.1552	-4.2961	-6.8662	0.0000
Factor kurtosis	11.3000	3.5677	16.8686	23.9936	43.0958	75.7929	1.8775
Minimal factor value	-8.9439	-3.2877	-10.2058	-10.7584	-16.9473	-20.1896	-1.5932
25% quantile of factor	-0.8113	-1.3656	-0.5515	-0.5526	-0.4242	-0.0799	-0.7242
Factor Mmedian	0.0000	-0.2215	0.0000	0.0000	0.1196	0.1936	0.0000
75% quantile of factor	0.6128	0.9502	0.6069	0.5130	0.7035	0.5376	0.7242
Maximal factor value	11.5553	6.8901	11.6048	13.9469	3.3651	1.9315	1.5932

Table A.15: Rotated factor loadings from a principal components analysis for $2.5 \leq \alpha < 3$

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	TIERING	LOAN STRUCTURE	BALANCE SHEET II	BALANCE SHEET I	TOPOLOGY II	TOPOLOGY	TRIGGER
log(SIZE)	-0.0468	-0.0383	-0.0344	-0.2625	**-0.6239**	0.1907	0.0000
CORRELATION	-0.0723	0.0029	0.0213	-0.1704	**0.5113**	0.1575	0.0000
NUMBER BANKS	**0.4744**	-0.0732	0.0052	0.0596	-0.0545	0.0244	0.0000
RECOVERY	0.0240	-0.0432	0.0429	-0.0347	0.2883	**-0.4883**	0.0000
log(HERF BANKS)	**-0.4697**	0.1204	0.0102	-0.0786	-0.1590	0.0052	0.0000
EQUITY	0.1086	-0.2692	**0.3649**	-0.2268	-0.2002	-0.2751	0.0000
RESERVES	0.0424	-0.0018	-0.1014	**0.4968**	0.1071	-0.1057	0.0000
LOANS TAKEN	0.0035	0.0194	-0.0687	**-0.6724**	0.1176	-0.0624	0.0000
LOANS GIVEN	0.0754	0.0149	**-0.5039**	-0.3282	0.1582	-0.1725	0.0000
NUMBER TAKEN	0.0482	**0.5695**	0.0189	-0.0197	0.0055	-0.0070	0.0000
NUMBER GIVEN	0.0527	**0.5692**	-0.0012	-0.0044	0.0220	-0.0099	0.0000
CLUSTERING	-0.3030	**0.3193**	0.0258	0.0478	-0.1051	-0.0085	0.0000
HERF TAKEN	-0.0124	0.2677	**0.4415**	-0.1266	0.1158	-0.0638	0.0000
HERF GIVEN	-0.0205	0.0396	**-0.6250**	0.0289	-0.0887	-0.0117	0.0000
DEGREE NEIGHBOR	0.0458	0.1338	-0.0765	0.0823	-0.3178	**-0.4947**	0.0000
log(BETWEENNESS)	**0.4786**	0.1391	-0.0206	-0.0262	-0.0988	0.0160	0.0000
log(SHORTEST PATH)	**0.4276**	0.2072	0.0374	-0.0743	-0.0470	0.0264	0.0000
log(EV CENTRALITY)	-0.1246	-0.0084	-0.0089	0.0243	-0.0412	**-0.5738**	0.0000
TRIGGER	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**
Eigenvalue	3.6950	2.8232	1.8072	1.4445	1.2237	1.0209	1.0000
Factor Mean	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000	0.0000
Factor standard deviation	1.8388	1.6131	1.3020	1.2287	1.1738	1.1149	0.9913
Factor skewness	-1.1331	1.9713	0.9563	0.0760	-3.7619	-6.3838	0.0000
Factor kurtosis	4.9368	21.3444	15.2272	10.1650	39.4074	86.9343	1.8148
Minimal factor value	-9.5297	-5.9339	-10.3002	-9.3105	-14.6188	-19.1338	-1.5932
25% quantile of factor	-1.0106	-0.8328	-0.6730	-0.6213	-0.4256	-0.3931	-0.7242
Factor Mmedian	0.3183	-0.0430	-0.0238	0.0032	0.0926	0.0976	0.0000
75% quantile of factor	1.3368	0.6778	0.5825	0.6201	0.5907	0.5801	0.7242
Maximal factor value	3.3709	19.0240	10.5466	7.8208	6.7409	4.1375	1.5932

Table A.16: Rotated factor loadings from a principal components analysis for $3 \leq \alpha < 3.5$

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	TIERING	LOAN STRUCTURE	BALANCE SHEET II	BALANCE SHEET I	TOPOLOGY	TOPOLOGY I	TRIGGER
log(SIZE)	-0.0076	-0.0186	-0.0744	-0.1339	0.1126	**0.6090**	0.0000
CORRELATION	-0.0367	-0.0698	-0.1106	-0.1815	-0.0122	**-0.5415**	0.0000
NUMBER BANKS	**-0.5005**	-0.0716	0.0023	0.0441	-0.0100	0.0085	0.0000
RECOVERY	-0.0079	-0.0143	0.0057	-0.0146	-0.1453	**0.4868**	0.0000
log(HERF BANKS)	**0.4826**	0.0962	-0.0428	-0.0318	0.1100	0.1262	0.0000
EQUITY	-0.0490	-0.2068	**-0.4594**	-0.1522	0.0808	0.1467	0.0000
RESERVES	-0.0227	0.0242	0.2012	**0.5237**	0.0672	-0.1213	0.0000
LOANS TAKEN	0.0114	0.0202	0.0184	**-0.6160**	0.0341	-0.0960	0.0000
LOANS GIVEN	-0.0097	0.0316	0.3892	**-0.4704**	-0.0223	-0.0268	0.0000
NUMBER TAKEN	0.0381	**0.5854**	-0.0020	-0.0176	-0.0196	0.0160	0.0000
NUMBER GIVEEN	0.0311	**0.5854**	0.0248	-0.0019	-0.0174	0.0130	0.0000
CLUSTERING	**0.3894**	0.2413	-0.0337	0.0742	-0.0125	-0.0456	0.0000
HERF TAKEN	-0.0017	0.1928	**-0.4691**	-0.1461	0.0379	-0.1204	0.0000
HERF GIVEN	-0.0356	-0.0025	**0.5843**	-0.1391	0.1000	0.0485	0.0000
DEGREE NEIGHBOR	-0.0731	0.0053	0.0603	0.0279	**0.7084**	0.0604	0.0000
log(BETWEENNESS)	**-0.4437**	0.2459	-0.0281	0.0080	0.0567	0.0493	0.0000
log(SHORTEST PATH)	**-0.3820**	0.3055	-0.0832	-0.0216	0.0702	0.0228	0.0000
log(EV CENTRALITY)	0.0921	-0.0287	-0.0490	0.0055	**0.6472**	-0.1033	0.0000
TRIGGER	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**
Eigenvalue	3.8177	2.8091	1.5594	1.3737	1.2145	1.0273	1.0000
Factor Mean	0.0000	0.0000	0.0001	-0.0002	0.0001	0.0003	0.0000
Factor standard deviation	1.7744	1.6121	1.2597	1.3498	1.2379	1.0550	1.0001
Factor skewness	1.1758	0.0273	-0.4584	0.2658	12.5913	3.3450	0.0000
Factor kurtosis	5.3549	10.1514	12.0425	11.4068	248.6823	47.5849	1.7821
Minimal factor value	-3.5548	-14.2038	-12.1658	-10.2897	-1.2834	-6.1273	-1.5932
25% quantile of factor	-1.2480	-0.8602	-0.5963	-0.6657	-0.4329	-0.6019	-0.8690
Factor Mmedian	-0.3262	-0.0177	0.0153	0.0319	-0.1788	-0.0442	0.0000
75% quantile of factor	0.9610	0.8706	0.6325	0.6659	0.1323	0.5292	0.8690
Maximal factor value	11.7271	11.2030	9.1199	12.2774	29.8408	16.8773	1.5932

Table A.17: Rotated factor loadings from a principal components analysis for $3.5 \leq \alpha \leq 5$

This table shows the estimates of a logit regression on the probability of a banking system exhibiting contagion (Prob(CONTAGION)). We show the estimates of these regressions, with numbers in parentheses denoting the t-values, as well as a sensitivity measure. This measure uses the difference between the 25% and 75% quantile of the factor value (the number associated with CONSTANT and associated with $^\sharp$ is the value of the median for each factor for comparison).

	$1.5 \leq \alpha < 2$		$2 \leq \alpha < 2.5$		$2.5 \leq \alpha < 3$		$3 \leq \alpha < 3.5$		$3.5 \leq \alpha \leq 5$	
	Estimates	Sensitivity	Estimates	Sensitivity	Estimates	Sensitivity	Estimates	Sensitivity	Estimates	Sensitivity
CONSTANT	-3.1848	0.9521$^\sharp$	-1.4699	0.7992$^\sharp$	-0.8965	0.7038$^\sharp$	-0.7779	0.6825$^\sharp$	-0.6914	0.6625$^\sharp$
	(-57.26)		(-56.83)		(-43.93)		(-41.03)		(-66.30)	
TOPOLOGY I	0.2083	0.0214	-0.0868	0.0230	0.0317	0.0044	0.0221	0.0047	-0.0072	0.0009
	(12.33)		(-8.70)		(1.79)		(1.25)		(-0.81)	
TOPOLOGY II					0.1116	0.0284	0.0719	0.0164	-0.0257	0.0065
					(6.42)		(4.42)		(-2.63)	
BALANCE SHEET I	-0.0925	0.0072	0.0318	0.0064	0.0432	0.0102	-0.0094	0.0026	-0.0485	0.0144
	(-5.61)		(1.73)		(2.76)		(-0.62)		(-5.95)	
BALANCE SHEET II			-0.1438	0.0351	0.0370	0.0095	-0.0067	0.0019	0.0162	0.0044
			(-9.01)		(2.48)		(-0.47)		(1.96)	
TIERING	0.0814	0.0076	0.0418	0.0152	-0.0186	0.0095	0.0149	0.0077	-0.0172	0.0084
	(4.83)		(3.47)		(-1.67)		(1.47)		(-2.82)	
LOAN STRUCTURE	-0.0393	0.0041			0.0324	0.0104	0.0393	0.0130	0.0352	0.0136
	(-1.85)				(2.34)		(3.35)		(5.10)	
RECOVERY	-0.0230	0.0019								
	(-0.88)									
TRIGGER	2.8169	0.3636	1.7237	0.4759	1.2698	0.4367	-1.1305	0.4057	-0.9617	0.3582
	(54.23)		(61.58)		(56.89)		(-55.04)		(-86.63)	
Sample size	17136		17520		16644		17220		51468	

Table A.18: Logit regressions for the probability of contagion split for different ranges of the power law exponent

This table shows the estimates of an OLS regression on the fraction of banks failing in those cases we observe contagion (FRACTION FAILING) with the sample split up by different ranges of the power law exponent. We show the estimates of these regressions, with numbers in parentheses denoting the t-values, as well as a sensitivity measure. This measure uses the difference between the 25% and 75% quantile of the factor value (the number associated with CONSTANT and associated with $^\sharp$ is the value of the median for each factor for comparison).

	$1.5 \leq \alpha < 2$		$2 \leq \alpha < 2.5$		$2.5 \leq \alpha < 3$		$3 \leq \alpha < 3.5$		$3.5 \leq \alpha \leq 5$	
	Estimates	Sensitivity	Estimates	Sensitivity	Estimates	Sensitivity	Estimates	Sensitivity	Estimates	Sensitivity
CONSTANT	0.0272	$0.0066^\sharp$	0.0115	$0.0051^\sharp$	0.0103	$0.0066^\sharp$	0.0088	$0.0063^\sharp$	0.0084	$0.0063^\sharp$
	(8.36)		(15.82)		(23.43)		(34.64)		(67.82)	
TOPOLOGY I	-0.0265	0.0633	0.0075	0.0125	-0.0023	0.0015	-0.0003	0.0003	0.0008	0.0004
	(-27.13)		(30.19)		(-6.96)		(-1.53)		(8.26)	
TOPOLOGY II					-0.0008	0.0010	-0.0005	0.0006	-0.0001	0.0001
					(-2.76)		(-2.89)		(-0.86)	
BALANCE SHEET I	-0.0052	0.0090	0.0013	0.0016	0.0009	0.0010	-0.0001	0.0002	-0.0011	0.0015
	(-5.57)		(2.99)		(3.05)		(-0.82)		(-13.16)	
BALANCE SHEET II			-0.0025	0.0039	0.0021	0.0026	-0.0005	0.0006	-0.0001	0.0001
			(-6.86)		(7.75)		(-3.11)		(-0.63)	
TIERING	-0.0051	0.0104	-0.0068	0.0154	0.0074	0.0180	-0.0062	0.0150	0.0059	0.0130
	(-5.60)		(-24.86)		(36.92)		(-53.85)		(91.74)	
LOAN STRUCTURE	-0.0012	0.0028			0.0057	0.0087	0.0036	0.0055	0.0015	0.0026
	(-1.04)				(22.47)		(26.29)		(20.29)	
RECOVERY	0.0009	0.0016								
	(0.67)									
TRIGGER	0.0385	0.0669	0.0131	0.0227	0.0058	0.0101	-0.0033	0.0057	-0.0015	0.0027
	(15.73)		(20.87)		(14.43)		(-13.79)		(-12.97)	
R^2	0.3807		0.3163		0.3246		0.3815		0.3563	
Sample size	3317		5022		5682		6096		18618	

Table A.19: OLS regressions for fraction of failing banks split for different ranges of the power law exponent

Appendix B. Detailed results of banking systems with random networks

	Mean	Std deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	5.6972	1.4327	2.9703	13.6638	4.5460	4.9125	5.1273	5.7882	17.2072
CORRELATION	-0.0033	0.0663	-0.1675	10.4247	-0.6286	-0.0357	-0.0027	0.0292	0.5000
DISTRIBUTION	3.2488	1.0043	0.0101	1.7898	1.5024	2.3789	3.2399	4.1384	4.9976
NUMBER BANKS	508.8285	286.1571	-0.0095	1.7953	13.0000	260.0000	512.0000	755.0000	1000.0000
RECOVERY	0.5003	0.2854	0.0054	1.8166	0.0010	0.2538	0.5010	0.7448	0.9999
log(HERF BANKS)	-5.6601	1.7822	0.8886	3.1625	-8.2724	-7.0756	-6.1142	-4.5920	4.3808
EQUITY	0.1968	0.0179	1.4976	9.2286	0.1072	0.1865	0.1938	0.2036	0.3709
RESERVES	0.2643	0.0248	-2.7400	76.9238	-0.4374	0.2539	0.2643	0.2749	0.4798
LOANS GIVEN	0.2292	0.0441	7.0106	238.4496	-0.4016	0.2177	0.2294	0.2403	1.8080
LOANS TAKEN	0.2339	0.0413	-1.6770	8.1229	0.0000	0.2224	0.2445	0.2573	0.4217
NUMBER GIVEN	1.1563	0.1240	0.7045	10.0778	0.5600	1.1042	1.1543	1.2039	2.0667
NUMBER TAKEN	1.1561	0.1245	0.6768	10.2016	0.5000	1.1045	1.1538	1.2043	2.1333
CLUSTERING	0.0029	0.0079	9.1301	129.6970	0.0000	0.0000	0.0010	0.0026	0.1905
HERF TAKEN	0.0048	0.0119	7.0799	77.6751	0.0000	0.0000	0.0017	0.0043	0.2353
HERF GIVEN	0.0048	0.0117	6.7666	70.4926	0.0000	0.0000	0.0017	0.0043	0.2143
DEGREE NEIGHBOR	2.1922	0.3368	0.5733	8.8815	0.6282	2.0445	2.1855	2.3309	4.6797
log(BETWEENESS)	3.9760	1.5108	-0.2142	3.6637	-2.9704	3.0699	3.9960	4.9322	8.4986
log(SHORTEST PATH)	1.3776	0.5081	-0.0134	3.4803	-0.5470	1.0671	1.3633	1.6823	3.0178
log(EV CENTRALITY)	-1.4840	0.4250	0.6600	4.7527	-5.2293	-1.7764	-1.5545	-1.2525	0.9682
TRIGGER	6.5000	3.4521	0.0000	1.7830	1.0000	3.5000	6.5000	9.5000	12.0000

Table B.20: Descriptive statistics of the independent variables investigated for random networks

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion as described in the main text. The numbers in bold are those factor loadings that are highest for each of the variables considered. The heading of the columns provide the name given to each factor resulting from the analysis of those highest factor loadings.

	TOPOLOGY I	LOAN STRUCTURE	BALANCE SHEET II	BALANCE SHEET I	TOPOLOGY II	RECOVERY	TRIGGER	TOPOLOGY III
log(SIZE)	-0.0827	0.0226	**0.4856**	-0.0195	0.0229	-0.0040	0.0000	0.0087
CORRELATION	0.0077	-0.0084	-0.0006	-0.0021	-0.0060	0.0000	0.0000	**0.9966**
DISTRIBUTION	0.1006	-0.0165	**-0.4641**	-0.0753	0.0185	0.0055	0.0000	-0.0067
NUMBER BANKS	0.0085	-0.0284	0.0230	0.0071	**0.6667**	-0.0013	0.0000	-0.0137
RECOVERY	-0.0037	0.0029	0.0007	0.0006	-0.0038	**0.9998**	0.0000	0.0001
log(HERF BANKS)	-0.0741	-0.0341	**0.4713**	0.0015	-0.2027	-0.0059	0.0000	0.0044
EQUITY	0.1476	-0.0184	**0.3829**	-0.0651	0.1022	0.0053	0.0000	-0.0115
RESERVES	-0.0030	0.0041	-0.0031	**0.7092**	-0.0107	0.0003	0.0000	-0.0179
LOANS GIVEN	-0.0222	0.0167	-0.0015	**-0.6956**	-0.0118	-0.0001	0.0000	-0.0166
LOANS TAKEN	-0.1498	-0.0062	**-0.4236**	0.0005	-0.0748	-0.0108	0.0000	0.0102
NUMBER GIVEN	**-0.4567**	-0.0431	-0.0007	-0.0217	-0.0719	-0.0004	0.0000	0.0039
NUMBER TAKEN	**-0.4570**	-0.0406	-0.0006	-0.0190	-0.0724	0.0006	0.0000	0.0007
CLUSTERING	-0.0535	**-0.3774**	-0.0011	0.0202	-0.1316	-0.0103	0.0000	0.0097
HERF TAKEN	0.0197	**-0.6499**	-0.0011	-0.0093	0.0723	0.0053	0.0000	0.0012
HERF GIVEN	0.0151	**-0.6461**	-0.0016	-0.0056	0.0631	0.0058	0.0000	-0.0093
DEGREE NEIGHBOR	**-0.4482**	-0.0407	-0.0021	-0.0098	-0.0738	-0.0028	0.0000	-0.0569
log(BETWEENESS)	**-0.3822**	0.0717	-0.0026	0.0215	0.2320	0.0016	0.0000	0.0316
log(SHORTEST PATH)	**-0.4060**	0.0569	0.0021	0.0271	0.1578	0.0034	0.0000	0.0337
log(EV CENTRALITY)	0.0047	-0.0274	-0.0113	0.0094	**-0.6133**	0.0018	0.0000	-0.0044
TRIGGER	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**-1.0000**	0.0000
Eigenvalue	5.1932	3.5077	3.1741	1.3670	1.0741	1.0002	1.0000	0.9773
Factor mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Factor standard deviation	2.1131	1.5670	1.9045	1.2829	1.4468	1.0001	1.0000	1.0032
Factor skewness	-0.1849	-6.8371	1.4553	-5.1790	-0.5905	0.0051	-0.0001	-0.2516
Factor kurtosis	7.5673	73.7849	5.0918	149.4194	2.8721	1.8178	1.7831	10.6439
Minimal factor value	-12.6292	-29.4959	-3.1784	-38.5287	-7.3430	-1.8252	-1.5933	-9.5799
25% quantile of factor	-0.9815	0.0710	-1.3813	-0.4041	-0.9797	-0.8623	-0.8690	-0.4868
Factor median	-0.0090	0.4202	-0.5798	-0.0043	0.2180	0.0026	0.0000	0.0152
75% quantile of factor	0.9900	0.5967	0.8254	0.4324	1.1455	0.8559	0.8690	0.5011
Maximal factor value	10.4736	1.0955	9.6991	13.8701	4.4262	1.7591	1.5933	7.7407

Table B.21: Rotated factor loadings from a principal components analysis for random networks

Allen, F., Gale, D., 2001. Financial contagion. Journal of Political Economy 108, 1–33.
Bandt, O. D., Hartmann, P., 2000. Systemic risk: a survey, european Central Bank Working Paper 35.
Bank for International Settlements, 1994. 64th annual report. Tech. rep., BIS.
Barabasi, A., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509–512.
Battiston, S., Gatti, D. D., Gallegatti, M., Greenwald, B., Stiglitz, J. E., 2007. Credit chains and bankruptcies avalances in production networks. Journal of Economic Dynamics and Control 31, 2061–2084.
Battiston, S., Gatti, D. D., Gallegatti, M., Greenwald, B., Stiglitz, J. E., 2009. Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk, working Paper.
Becher, C., Millard, S., Soramäki, K., 2008. The network topology of chaps sterling, bank of England Working Paper Series n. 355.
Blavarg, M., Nimander, B., 2002. Interbank exposures and systemic risk. Sveriges Riksbank Economic Review 2, 19–45.
Boss, M., Elsinger, H., Summer, M., Thurner, S., 2004a. The network topology of the interbank market. Quantitative Finance 4, 677–684.
Boss, M., Summer, M., Thurner, S., 2004b. Contagion flow through banking networks. In: Bubak, M., van Albada, G. D., Sloot, P. M., Dongarra, J. J. (Eds.), Computational Science - ICCS 2004. Vol. 3038 of Lecture Notes in Computer Science. Springer Verlag, pp. 1070–1077.
Cajueiro, D., Tabak, B., 2008. The role of banks in the brazilian interbank market: does bank type matter? Physica A 387, 6825–6836.
Canedo, J. M. D., Jaramillo, S. M., 2009a. Financial contagion: A network model for estimating the distribution of losses for the financial system. Working Paper.
Canedo, J. M. D., Jaramillo, S. M., 2009b. A network model of systemic risk: stress testing the banking system. International Journal of Intelligent Systems in Accounting and Finance Management 16, 87–110.
Chan-Lau, J., Espinosa-Vega, M., Giesecke, K., Sole, J., 2009. Assessing the systemic implications of financial linkages, IMF Global Financial Stability Report, Vol. 2.
Cifuentes, R., Shin, H. S., Ferrucci, G., 2005. Liquidity risk and contagion. Journal of the European Economic Association 3, 556–566.
Cocco, J. F., Gomes, F. J., Martins, N. C., 2009. Lending relationships in the interbank market. Journal of Financial Intermediation 18, 24–48.
Craig, B., von Peter, G., 2010. Interbank tiering and money center banks, bIS Working Papers n. 322.
Degryse, H., Nguyen, G., 2007. Interbank exposures: An empirical examination of contagion risk in the belgian banking system. Internatonal Journal of Central Banking 3, 123–171.
Diamond, D., Rajan, R., 2005. Liquidity shortages and banking crises. Journal of Finance 60, 615–647.
Eboli, M., 2007. Systemic risk in financial networks: a graph-theoretic approach, working Paper.
Edson, B., Cont, R., 2010. The brasilian interbank network structure and systemic risk, banco Central Do Brasil Working Paper Series 219.
Eichberger, J., Summer, M., 2005. Bank capital, liquidity, and systemic risk. Journal of the European Economic Association 3, 547–555.
Eisenberg, L., Noe, T., 2001. Systemic risk in financial systems. Management Science 47, 236–249.
Elsinger, H., Lehar, A., Summer, M., 2001. Risk assessment for banking systems. Management Science 52, 1301–1314.
Elsinger, H., Lehar, A., Summer, M., 2006. Systemically important banks: an analysis for the european banking system. International Economics and Economic Policy 3, 73–89.
Estrada, D., Morales, P., 2008. The structure of the colombian interbank market and contagion risk. Working Paper.
Freeman, L. C., 1977. A set of measures based of centrality based on betweenness. Sociometry 40, 35–41.
Freixas, X., Parigi, B. M., Rochet, J.-C., 2000. Systemic risk, interbank relations, and liquidity provison by the central bank. Journal for Money, Credit and Banking 32, 611–638.
Furfine, C., 2000. Interbank exposures: Quantifying the risk of contagion. Journal of Money, Credit and Banking 32, 611–638.
Gai, P., Kapadia, S., 2007. Contagion in financial networks, working Paper, Bank of England.
Graf, J. P., Guerrero, S., Lopez-Gallo, F., 2004. Interbank exposures and contagion: an empirical analysis for the mexican banking sector, working Paper.
Gropp, R., Duca, M. L., Vesala, J., 2006. Cross-border bank contagion in europe, european Central Bank Working Paper 662.
Haldane, A. G., 2009. Rethinking the financial network, bank of England, Speech delivered at the Financial Student Association in Amsterdam on 28 April 2009.
Hirschman, A. O., 1964. The paternity of an index. American Economic Review 54, 761–762.
Iori, G., de Masi, G., Precup, O. V., Gabbi, G., Caldarelli, G., 2008. A network analysis of the italian overnight money market. Journal of Economic Dynamics and Control 32, 259–278.
Iori, G., Jafarey, S., Padilla, F., 2006. Systemic risk on the interbank market. Journal of Economic Behavior and Organisation 61, 525–542.
Iyer, R., Peydro-Alcalde, J. L., 2005. Interbank contagion: Evidence from real transactions. Working Paper.
Joliffe, I. T., 2002. Principal Components Analysis, 2nd Edition. Springer Verlag, New York.
Kaufman, G. G., Scott, K. E., 2003. What is systemic risk, and do bank regulators retard or contribute to it? Independent Review 7, 371–391.
Kaufmann, G. G., 2005. Bank contagion: A review of the theory and evidence. Journal of Financial Services Research 8, 123–150.
Kiyotaki, N., Moore, J., 1997. Credit cycles. Journal of Political Economy 106, 211–248.
Lelyveld, I. V., Liedorp, F., 2006. Interbank contagion in the dutch banking sector: a sensitivity analysis. International Journal of Central Banking 2, 99–134.
Markose, S., Giansante, S., Gatkowski, M., Shaghaghi, A. R., 2010. Too interconnected to fail: Financial contagion and systemic risk in network models of cds and other credit enhancement obligations of us banks, economics Discussion paper Nr. 683, University of Essex.
May, R. M., Arinaminpathy, N., 2010. Systemic risk: the dynamics of model banking systems. Journal of the Royal Society Interface 7, 823–838.
May, R. M., Levin, S. A., Sugihara, G., 2008. Ecology for bankers. Nature 451, 893–895.
Mistrulli, P. E., 2005. Interbank lending patterns and financial contagion, working Paper Banca d'Italia.
Müller, J., 2006. Interbank credit lines as channel of contagion. Journal of Financial Services Research 29, 37–60.
Newman, M. E. J., 2003. The structure and function of complex networks. SIAM Review 45, 167256.
Newman, M. E. J., 2010. Networks. Oxford University Press, New York.
Nier, E., Yang, J., Yorulmazer, T., Alentorn, A., 2007. Network models and financial stability. Journal of Economic Dynamics and Control 31, 2033–2060.

Rochet, J.-C., Tirole, J., 1996. Interbank lending and systemic risk. Journal of Money, Credit and Banking 28, 733–762.
Sheldon, G., Maurer, M., 1999. Interbank lending and systemic risk: An empirical analysis for switzerland. Swiss Journal of Economics and Statistics 134, 685–704.
Soramäki, K., Bech, M., Arnold, J., Glass, R., Beyeler, W., 2007. The topology of interbank payment flows. Physica A 379, 317–333.
Sui, P., 2009. Financial contagion in core-periphery network. Working Paper.
Toivanen, M., 2009. Financial interlinkages and risk of contagion in the finnish interbank market, bank of Finland Research Discussion Papers 06/2009.
Upper, C., 2007. Using counterfactual simulations to assess the danger of contagion in interbank markets, bIS Working Paper 234.
Upper, C., Worms, A., 2004. Estimating bilateral exposures in the german interbank market. European Economic Review 48, 827–849.
Vivier-Lirimont, S., 2004. Interbank networks: towards a small financial world?, working Paper.
Watts, D. J., Strogatz, S. H., 1998. Collective dynamics of 'small-world' networks. Nature 393, 440–442.
Wells, S., 2002. Uk interbank exposures: Systemic risk implications. Financial Stability Review, 175–182.