The Role of Interbank Lending in the Prediction of Individual Bank Failures during a Banking Crisis: Analysis of a Network Model of Systemic Risk☆

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Abstract

We analyze the determinants of individual bank failures arising from solvency and liquidity shortages in a stylized banking system following Krause and Giansante (2012) 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 then investigate the likelihood of an individual bank failing. Most notably we find that the probability of a bank failing depends on the characteristics of the network of interbank loans and the market structure, while balance sheet relationships are of limited influence. We also establish different determinants for failures arising from solvency and liquidity shortages.

Keywords: solvency, liquidity, interbank loans, network topology, banking crises, bank failure

1. Introduction

The credit crisis 2008 has raised questions about the adequacy of financial regulation to ensure the stability of the banking system and preventing the failure of banks. 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 the properties of those banks in a banking system that will fail is still outstanding. In this paper we seek to explore a model of such financial linkages and investigate whether and how they contribute to the failure of banks. 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 assessing bank failures. In addition, rather than focussing solely on the solvency of banks, we also include failures due to liquidity shortages, which was an important aspect of the credit crisis in 2008.

In our assessment of bank failures we employ the model developed in Krause and Giansante (2012) that showed the relevance of interbank loans in the assessment of systemic risk. While the focus of this paper is on the emergence of contagion and its extent, we will here put emphasis on the failure of individual banks and what factors drive their failure. This study thereby complements the former contribution by focussing on the outcome for individual banks rather than the banking system as a whole.

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The following section provides a brief overview of the current research on the prediction of bank failures as well as the importance of interbank loans for systemic risk, together with an outline of the empirical properties of the interbank loan market before we introduce the model investigated 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 investigation 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 banking failures and contagion

This section will provide a brief overview of the current state of the literature on predicting bank failures, the role of interbank loans for systemic risk and finally outline the main empirical characteristics of banking systems and interbank loans.

2.1. The prediction of bank failures

In light of the credit crisis 2008 the focus in banking research has been shifting towards systemic risk and the failure of banks. While most of the emphasis in financial regulation is on the prevention of the failure of a bank as well as the systemic risk, little attention has been paid to which banks are actually failing in a process of contagion. Although not concerned with the effects of contagion per se, there exists a sizeable literature on the prediction of bank failures. This literature has mostly drawn on ideas developed in the prediction of corporate bankruptcies and employs similar techniques. It is most common to employ limited dependent variable regression such as logit or probit to estimate the probability of a bank failing, where the dependent variables are usually accounting ratios derived from balance sheets and income statements of the banks investigated. For example, Abrams and Huang (1987) employ a probit model and find that accounting data obtained from the balance sheet and income statement affect the probability of a bank failing during the US Savings and Loans Crises. Using a similar approach Logan (2001) uses a logit and probit approach to model the failure of small banks in the UK during the early 1990s; he also finds that accounting ratios from the balance sheet and income statement are relevant for the the prediction of bank failures. Kolari et al. (2002) come to the same conclusions for US banks during the late 1980s and early 1990s. This research is complemented by Shen and Hsieh (2004) for Southeast Asian countries around the Asian financial crisis of 1997 through the inclusion of macroeconomic factors that are shown to play a significant role, too. Similarly, Curry et al. (2004) include market data such as abnormal returns of bank stocks into their model of predicting bank failures in emerging markets during the early 1990s. Other contributions with comparible approaches include Godlewski (2004), Oshinsky and Olin (2005), Halling and Hayden (2006), Porath (2006), Cole and Wu (2010), and Distinguin et al. (2009), who employ similar sets of variables.

A range of other techniques have been employed in place of or alongside the logit and probit models, again adopted from the prediction of corporate bankruptcies. Methods found include neural networks, see e. g. Chung et al. (2008)

or Boyacioglu et al. (2009), trait recognition in Kolari et al. (2002), fuzzy sets in Nguyen et al. (2008), proportional hazard models as in Lane et al. (1986) and multi-dimensional scaling as in Mar-Molinero and Serrano-Cinca (2001). Good overviews of a range of methods used to predict bank failures can be found in Demyanyk and Hasan (2010).

A common feature of all of these models is that they view banks as isolated entities through focussing on accounting ratios of these banks. It is not taken into account that banks are highly interconnected with each other through interbank loans, derivatives positions and payment systems. Hence the failure of one bank can have an impact on the default of other banks and even threaten their survival. This *systemic risk* and its implications has been ignored in the literature on bank prediction thus far, although much of the empirical work referred to above is conducted during time periods of sustained systemic risk. Furthermore, it is clear from the data on bank failures that most failures occur as part of banking crises rather than being isolated events. The inclusion of macroeconomic factors seem not to be fully adequate to explain this finding as it only considers common factors that might put a banking system at higher risk of failures overall and has a limited ability to explain why in the same macroeconomic environment some banks fail while others do not fail. It is therefore important to consider the role of systemic risk for the prediction of bank failures. This will in particular necessitate that consideration is given to the role of financial connections between banks.

2.2. The role of interbank loans in systemic risk

Given the importance of systemic risks and of financial links between banks, this section will provide an overview of the of this connection. 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 Krause and Giansante (2012) a model is presented that models the heterogeneity of the balance sheets of banks as well as a realistic network of interbank loans. It is shown that the network structure of interbank loans is the driving factor behind systemic risk and the structure of the balance sheet only has a secondary role.

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.

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).

2.3. The structure of the interbank market

Given the importance of interbank loans for systemic risk and therefore for the failure of banks, this section will briefly investigate the empirical properties of interbank loans and the banking systems as a whole. Empirical studies on interbank loan networks show that connections between banks exhibit a powerlaw tail[1] as established in Boss et al.

[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

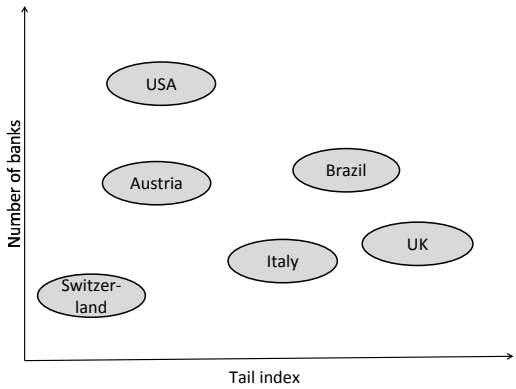


Figure 1: Empirical properties of interbank loan networks of selected countries

(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, Boss et al. (2004a) 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 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 some guidance on the properties of the network structure as well as the size of banks that a model

corresponds to a fatter tail, i. e. more extremely large observations.

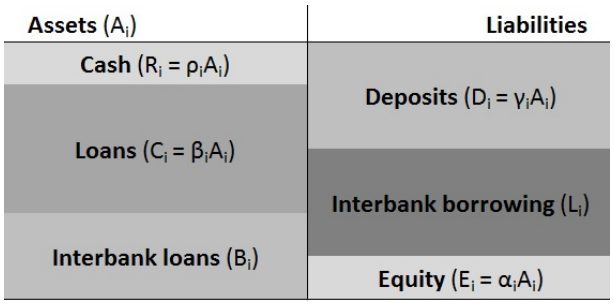


Figure 2: Stylized balance sheet of individual banks

should be using. 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 a model has to rely on additional assumptions to make it operational.

3. The model

We use the model developed in Krause and Giansante (2012) that investigates the importance of interbank loans for systemic risk. Rather than investigating the spread of an initial failure, we will focus on the properties of the banks that are actually failing, contrasting them with those that do not fail. Given the central importance of this model for our investigation, we describe the model in detail in the following sections.

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

[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".

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 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 2.3, 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

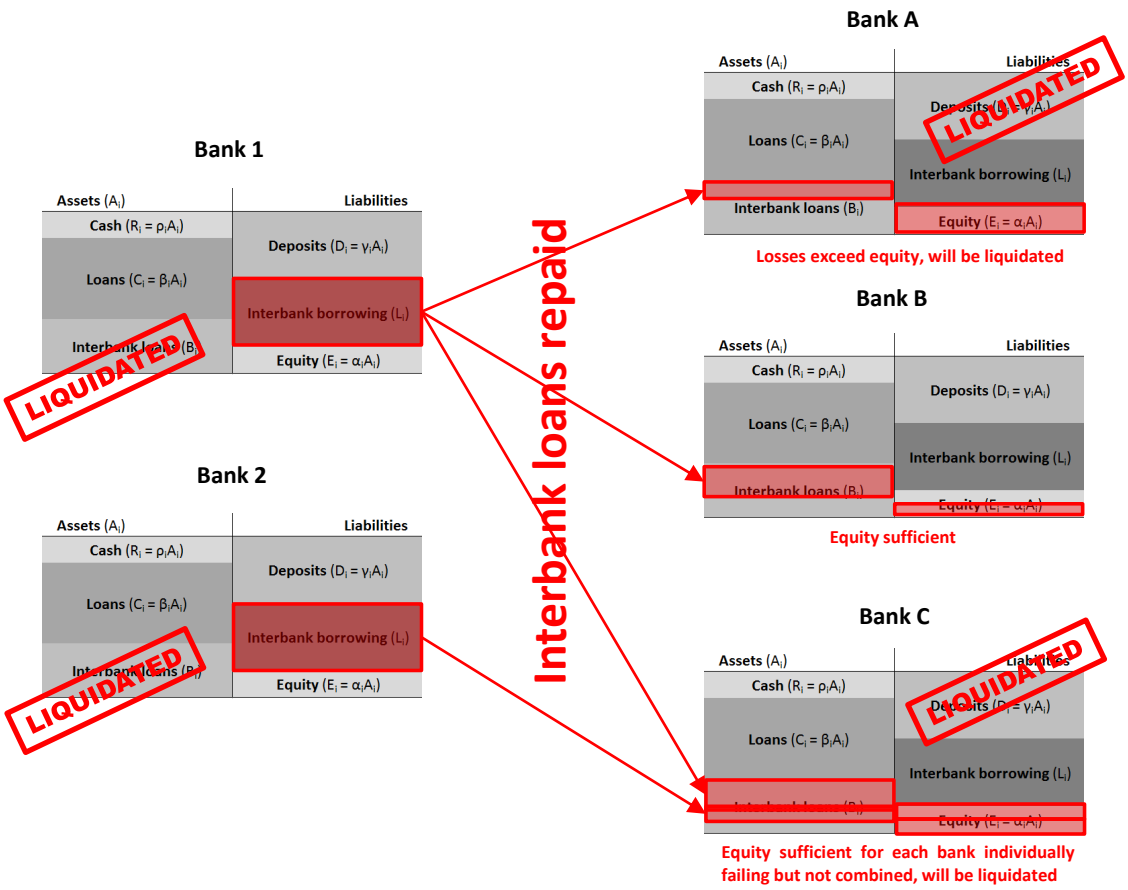


Figure 3: Illustration of the solvency mechanism. Detailed explanations are found in the main text.

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 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 *solvency 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 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 solvency 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 *liquidity mechanism* that arises from a cash shortage. This liquidity 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 liquidity 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. In contrast to Krause and Giansante (2012) we are not interested in the spread of this initial failure itself, but in which banks will be failing and what their properties are. Thus our focus will be on the failure of individual banks in a banking crises.

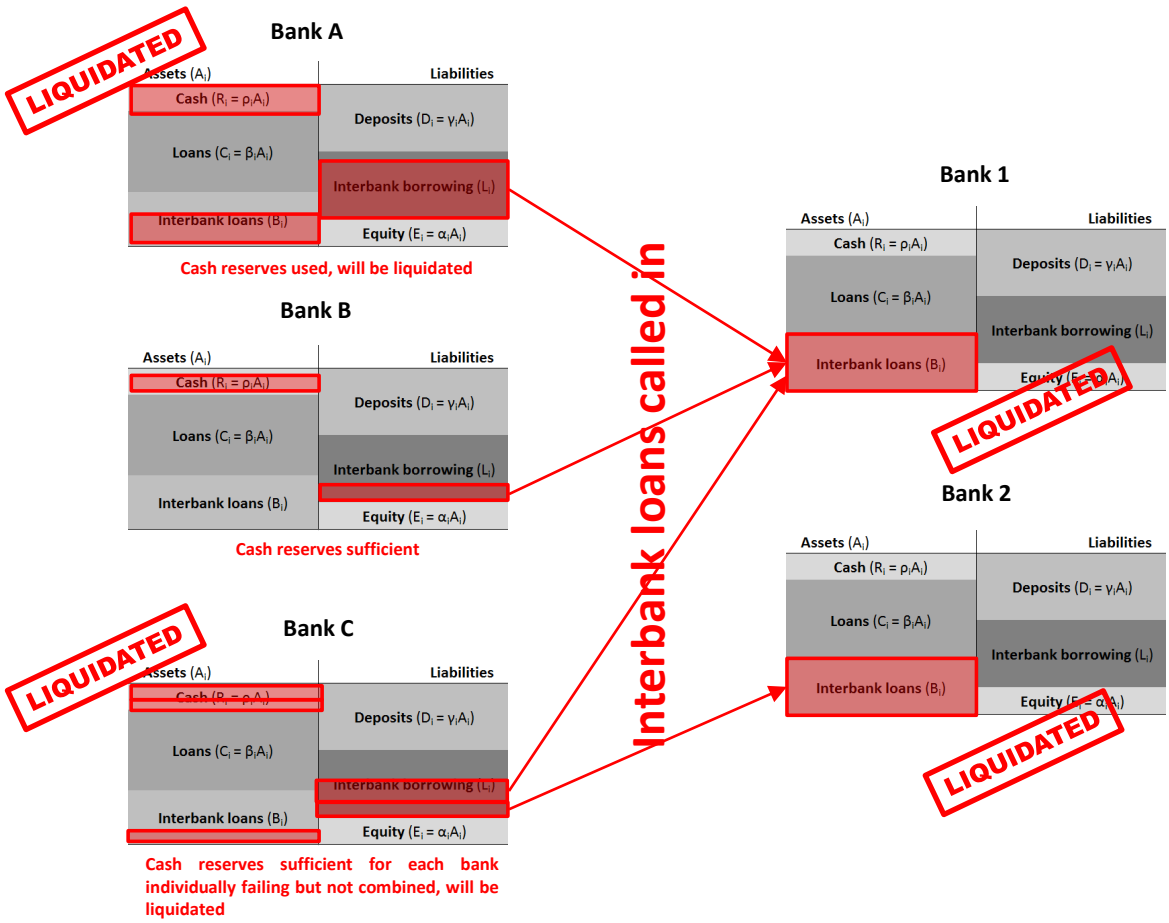


Figure 4: Illustration of the liquidity mechanism. Detailed explanations are found in the main text.

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.

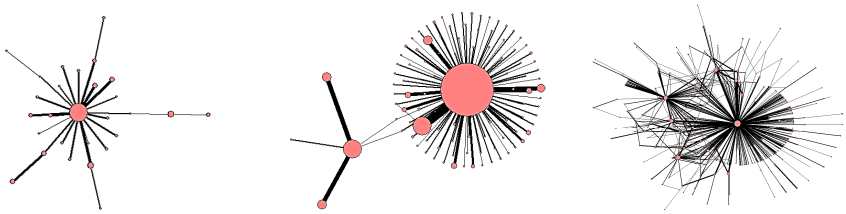
We choose a single bank in the system to fail exogenously. The bank chosen can be the largest bank, the second largest bank in terms of their assets, or a random bank from each of the ten size deciles following these two banks. We let the contagion spread until no more failures are observed and record 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 60,000,000 individual banks. Of these 60,000,000 banks we will randomly select 1,000,000 banks to conduct our analysis; we only select banks that have interbank lending or borrowing, as otherwise no failure of these could be observed in our model as failures are only arising from contagion.

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 2.3.

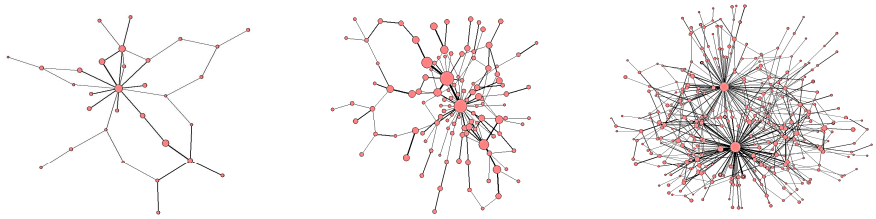
4.2. Variables investigated

We will investigate whether an individual bank fails in our model using a logit estimation with a range of explanatory variables covering balance sheet ratios as well as network properties.

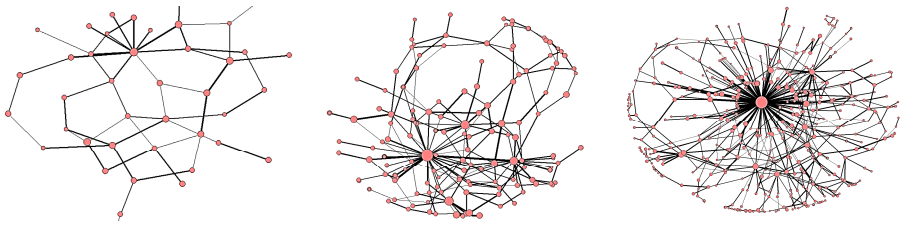
As explanatory variables we use the balance sheet structure of the banks: EQUITY denotes the amount of equity



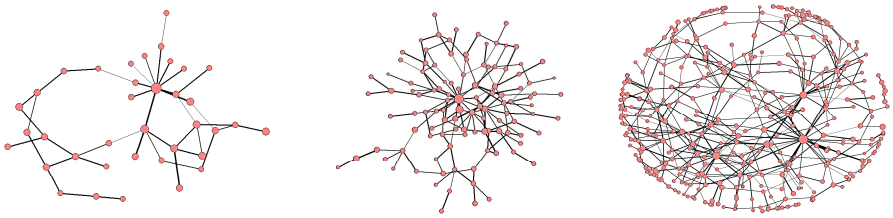
(a) $1.5 \leq \alpha < 2.0$



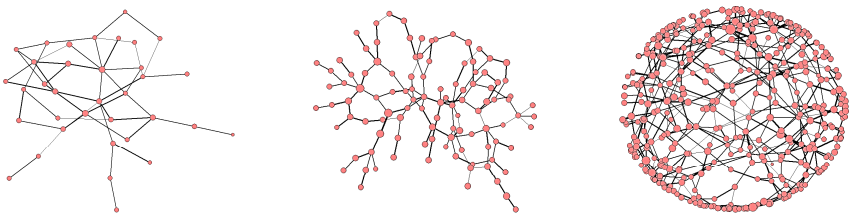
(b) $2.0 \leq \alpha < 2.5$



(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).

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.

	Mean	Standard deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	5.7778	1.3730	2.7321	14.0028	4.5519	4.9125	5.3285	6.0952	23.0078
CORRELATION	-0.1166	0.1630	-1.8441	6.7312	-0.9977	-0.1574	-0.0636	-0.0142	0.7833
DISTRIBUTION	3.0611	0.9796	0.3076	1.9203	1.5008	2.2227	2.9248	3.8698	4.9997
NUMBER BANKS	655.2802	240.2183	-0.5188	2.3304	13.0000	479.0000	693.0000	859.0000	1000.0000
RECOVERY	0.4946	0.2888	0.0130	1.7905	0.0002	0.2434	0.4933	0.7469	1.0000
log(HERF BANKS)	-5.9452	1.7934	0.6767	2.6005	-8.7647	-7.4226	-6.3259	-4.7231	-0.0146
EQUITY	0.1472	0.1023	1.5088	8.4677	0.0000	0.0700	0.1392	0.2075	0.9923
RESERVES	0.2089	0.2228	1.7562	5.5788	0.0000	0.0572	0.1352	0.2592	1.0000
LOANS GIVEN	0.3633	0.2987	0.5875	2.0887	0.0000	0.0998	0.2867	0.5916	1.0000
LOANS TAKEN	0.3735	0.2509	0.3412	2.0400	0.0000	0.1544	0.3445	0.5713	0.9985
log(NUMBER TAKEN)	0.3872	0.5936	2.3161	12.4496	0.0000	0.0000	0.0000	0.6931	6.7708
log(NUMBER GIVEN)	0.5229	0.6134	1.7092	9.6197	0.0000	0.0000	0.6931	0.6931	6.7765
CLUSTERING	0.0213	0.0830	4.7974	27.1825	0.0000	0.0000	0.0000	0.0000	0.9000
HERF TAKEN	0.8509	0.2292	-1.2698	3.3062	0.0075	0.6833	1.0000	1.0000	1.0000
HERF GIVEN	0.7913	0.2524	-0.7639	2.1822	0.0104	0.5467	0.9806	1.0000	1.0000
log(DEGREE NEIGHBOR)	1.7936	1.3464	1.6575	5.1839	0.0000	1.0986	1.3863	1.9459	7.4025
log(BETWEENNESS)	5.6459	2.0615	-0.5680	3.2474	-1.0986	4.6052	5.8278	7.0484	13.5461
log(EV CENTRALITY)	-2.7161	3.0527	1.3785	8.5386	-9.2057	-4.2658	-2.7888	-1.5221	29.0297
log(SHORTEST PATH)	8.1111	7.3265	1.2360	4.3381	1.0000	2.0000	6.0000	12.0000	57.0000
log(TRIGGER)	1.6701	0.7230	-0.9685	2.9774	0.0000	1.0986	1.7918	2.3026	2.4849

Table 1: Descriptive statistics of the independent variables investigated

Table 1 provides an overview of the descriptive statistics of the explanatory variables we investigate. Using these variables as dependent variables we now can investigate what determines whether a bank fails or not. 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 bank that has a high clustering coefficient will usually also have a high eigenvalue centrality. 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.

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 **R** = **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 8 factors as their eigenvalues are above or very close to the threshold of 1 and the ninth eigenvalue is significantly lower. The resulting rotated factor loadings are displayed in table 2. 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 we use for these factors are shown in the top row of table 2.

The variables associated with the first factor are SIZE, CORRELATION, DISTRIBUTION, and HERF BANKS. All these variables are directly or indirectly associated with the market structure. 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 size of the bank and the characteristics of the market it operates in. The node correlation measures the connection of a bank to similarly connected banks, i. e. describes the structure of the market. Therefore we conclude that this factor represents aspects of the market structure and will in the remainder refer to it as MARKET STRUCTURE. We may interpret this as a more concentrated banking system exhibiting a larger factor value.

The second factor provides information on the interbank loans taken by the bank, i. e. their number and concentration, and is therefore referred to as BORROWING. A higher factor value here is associated with borrowing from more banks. Similarly the fifth factor provides information on the interbank loans given to other banks and is referred to as LENDING. The fewer different banks are lent money, the higher the factor value.

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 lower 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 comprises of the number of banks in the banking system, the betweeness centrality measuring the number of shortest shortest paths going through the bank in question, and the shortest path. It therefore provides

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.

	MARKET STRUCTURE	BORROWING	BALANCE SHEET	POSITION	LENDING	RECOVERY	TRIGGER	HUB
log(SIZE)	**0.4357**	0.1677	0.0329	-0.0104	-0.1761	-0.0212	0.0015	-0.1087
CORRELATION	**-0.4076**	0.0502	-0.0107	0.0283	-0.0154	-0.0006	-0.0006	-0.2010
DISTRIBUTION	**-0.5370**	0.0438	0.0312	-0.0832	-0.0777	0.0035	0.0009	0.0606
NUMBER BANKS	0.0412	-0.4031	0.0482	**0.5227**	-0.1230	-0.1267	0.0089	-0.0800
RECOVERY	0.0098	-0.0325	0.0081	0.0255	-0.0195	**0.9888**	0.0008	-0.0118
log(HERF BANKS)	**0.4996**	0.0217	-0.0142	-0.0672	0.0730	0.0217	-0.0015	0.0700
EQUITY	0.0905	-0.1104	**0.4931**	-0.0272	-0.0819	0.0006	0.0021	-0.1371
RESERVES	0.1373	-0.0838	**-0.4560**	-0.0024	-0.0575	-0.0017	0.0021	-0.1480
LOANS GIVEN	-0.0493	0.1304	**0.5279**	0.0479	0.1138	0.0007	0.0013	0.1035
LOANS TAKEN	-0.0607	0.0710	**-0.5031**	0.0341	0.0582	-0.0014	0.0016	0.0798
log(NUMBER TAKEN)	0.0816	**0.5759**	0.0061	0.0596	-0.0819	-0.0212	0.0014	-0.0470
log(NUMBER GIVEN)	0.0327	0.0613	-0.0383	0.0068	**-0.6397**	0.0033	-0.0004	0.0295
CLUSTERING	-0.1433	0.0375	-0.0616	-0.0553	0.0219	-0.0120	-0.0030	**0.6345**
HERF TAKEN	0.0342	**-0.6227**	-0.0131	-0.0736	-0.0255	0.0197	-0.0018	0.0272
HERF GIVEN	0.1126	0.0280	-0.0229	0.0088	**0.6636**	-0.0109	0.0007	-0.0268
log(DEGREE NEIGHBOR)	0.1132	-0.0999	0.0501	0.0908	0.0644	-0.0051	0.0029	**0.4662**
log(BETWEENNESS)	0.0218	0.1250	0.0139	**0.5784**	-0.0816	0.0150	-0.0010	0.0790
log(EV CENTRALITY)	0.1012	0.0026	0.0112	0.0008	-0.1453	0.0092	0.0008	**0.4941**
log(SHORTEST PATH)	-0.0740	0.1060	-0.0600	**0.5955**	0.1617	0.0613	-0.0047	-0.0065
log(TRIGGER)	-0.0016	0.0026	-0.0011	-0.0020	0.0016	0.0007	**0.9999**	0.0015
Eigenvalues	4.6001	3.0212	1.8067	1.3096	1.0751	1.0020	0.9978	0.9655
Mean	-0.0001	0.0003	-0.0001	-0.0001	-0.0009	-0.0002	-0.0009	-0.0002
Standard deviation	1.7823	1.4263	1.3186	1.3181	1.4124	1.0024	0.9995	1.4463
Skewness	0.9670	1.3286	0.3951	0.1712	-1.2491	0.0174	-0.9439	2.4808
Kurtosis	3.7982	5.3144	3.4338	2.7599	5.8897	1.8404	2.9484	11.2708
Minimum	-3.8064	-2.4373	-4.3227	-4.2243	-13.0729	-2.0312	-2.3457	-2.9231
25% quantile	-1.3973	-1.0523	-0.9010	-0.9261	-0.9202	-0.8648	-0.7569	-0.7530
Median	-0.3732	-0.4652	-0.0968	-0.0490	0.3435	-0.0143	0.1994	-0.3339
75% quantile	1.0440	0.8934	0.8254	0.8754	1.1677	0.8641	0.8502	0.2003
Maximum	12.4872	9.9585	6.8380	5.3365	2.3647	2.1360	1.1877	12.1644

Table 2: Rotated factor loadings from a principal components analysis

information on the relative importance of the bank in the network and is referred to as the network POSITION. The more connected the bank is in a network, the higher the factor value.

The eigth factor is associated with the clustering of the network around the bank, the average neighbor degree and the eigenvector centrality, thus representing aspects of the local structure of the interbank loans, in particular how closely integrated the bank is with its neighbors. We therefore call this factor HUB. A bank that is more closely bound into its neighborhood will have a larger factor value.

Factors six and seven are straightforward as they are only associated with a single variable each, the recovery rate and trigger bank (with a negative sign), respectively, and for that reason we retain those names for these factors.

In the remainder of this paper we will simply refer to these factors by the name given in this section. We therefore briefly summarize the identified factors and their interpretation for convenience:

MARKET STRUCTURE measures how large and concentrated the banking system is

BORROWING measures how concentrated borrowing from other banks is (negative sign)

BALANCE SHEET provides a measure for the reliance of the bank on interbank loans (negative sign)

POSITION measures how well connected a bank is in the network

LENDING measures how concentrated lending to other banks is

RECOVERY is representing the recovery rate in case of bank failures

TRIGGER measures the size of the initially failing bank (negative sign)

HUB measures how closely integrated a bank is in its immediate neighborhood

Having established these factors, we can now proceed to analyze the results of our model in the coming section.

6. Results of the model

We analyze our model using 1,000,000 banks chosen randomly from our simulations as described above. Our aim is to evaluate the determinants of a bank failing and to this effect will employ firstly a logit regression using as explanatory variables the factors identified above. We also use some of the original variables investigated in our analysis as a robustness check of our specification. Furthermore, we seek to establish the determinants of the reason of failure, i. e. solvency or liquidity problems. To this end we employ a multinomial logistic regression, distinguishing between those two possibilities and whether they are driven by different factors or variables.

We find that out of the 1,000,000 banks considered 4,832 failed, of which 4,174 failed from to the solvency mechanism and 658 from the liquidity mechanism.[3] Given the small fraction of observations that are categorized as ”fail”

[3] We excluded those banks from our analysis that failed simultaneously from the solvency and liquidity mechanism. As there are only about 5 such banks per 1,000,000 there exclusion does not affect our results and including them as a separate category in the multinomial logit regression below would not be useful given the small number of observations of this event.

in the subsequent regressions, we also conducted an analysis using the correction of the potential underestimation of fails as suggested in King and Zeng (2001), but found the results to be indistinguishable from those presented here due to our large sample size. We therefore restricted ourselves to reporting the uncorrected Maximum Likelihood Estimations of parameters in this section.

6.1. Determinants of bank failures

The results of our logit regressions are shown in table 3.[4] We firstly note that most coefficients are stable across different specifications of independent variables with a comparable goodness of fit; this is true of those regressions that use the individual variables, the factors or a combination of these. Some differences in signs and significance levels can easily attributed to the inclusion of correlated variables and factors that mask the true relationships.

Focussing on the specification consisting only of the factors identified, column 4 in table 3, we easily see that the factors consisting of balance sheet items and the recovery rate are the only factors not being statistically significant or showing a lower significance level. However, given the sample size of 1,000,000 the relevance of statistical significance is greatly diminished and we instead focus on the size of the marginal effects. Given that marginal effects and the size of the coefficient are proportional due to us using normalized regressors in our analysis, we can focus solely on the coefficient size. Inspecting those values, we see that in order of importance the factors relevant are TRIGGER, MARKET STRUCTURE, HUB, POSITION, LENDING, BORROWING, BALANCE SHEET and RECOVERY. Even when including balance sheet items explicitly into the regression as in column 5, we see that they exhibit relatively small marginal effects and thus do not have a significant influence on whether a bank fails or not; only the size of the bank is also important in this specification. Furthermore, not including TRIGGER, does not change the results significantly, although the goodness of fit reduces substantially, as shown column 6.

Thus our results suggest that the main determinant of whether a bank fails is the bank's location in the network of interbank loans rather than balance sheet structures, in addition to the market concentration as represented by MARKET STRUCTURE. This result is in marked contrast to current banking regulation that seeks to regulate balance sheet structures more tightly but does not address the financial links between banks in a meaningful way. Our results clearly show that it is important to consider these aspects in assessing the systemic risk embedded in a banking system.

The obvious result, confirmed in our logit regression, is that a larger trigger bank increases the probability of a bank failing. The larger the failing bank is, the larger the losses it will spread and it will spread among more banks (recall that the size of a bank and the number of links are correlated by construction in our model), thus potentially leading to more banks failing and cause more subsequent cascades of failures through the interbank loan network. Thus, irrespective of network properties or balance sheet structures, a bank is more likely to fail in this case.

The second most important factor is the market structure, i. e. how concentrated the banking market is. A more concentrated market is one that is dominated by a small number of relatively large banks; here the risk of failures are

[4] We run all regressions using normalized variables in order to make the estimated coefficients comparable across variables and specifications.

This table shows the estimates of a logit regression on the failure of the banks for a variety of model specifications. We show the estimates of these regressions with numbers in parentheses denoting the t-values. The LR statistics for testing of the statistical significance of the model as a whole and the Pseudo R^2 denotes McFadden's R^2. Estimates with ***,**,* denote statistical significance of the estimate at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CONSTANT	-7.0748 ***	-6.7188***	-6.7455***	-7.0243***	-7.0573***	-5.6796***
	-(202.97)	-(209.30)	-(209.01)	-(204.60)	-(203.97)	-(308.12)
Individual Variables						
log(SIZE)	-0.0671***	0.3312***	0.3119***		-0.2609***	
	-(4.09)	(35.42)	(31.84)		-(12.51)	
CORRELATION	-0.0295					
	-(1.05)					
DISTRIBUTION	0.1108***					
	(2.91)					
NUMBER BANKS	-0.1402***					
	-(8.60)					
log(HERF BANKS)	0.6833***					
	(15.79)					
EQUITY	-0.0145	0.0687***	0.0118		-0.0277**	
	-(1.11)	(5.37)	(0.90)		-(2.05)	
RESERVES	0.0148	-0.1571***	-0.0393**		-0.0186	
	(0.82)	-(9.28)	-(2.17)		-(1.02)	
LOANS GIVEN	0.0767***		0.2134***		0.0783***	
	(4.37)		(12.99)		(4.33)	
LOANS TAKEN	-0.0283*		-0.07824***		-0.0100	
	-(1.65)		-(4.68)		-(0.58)	
log(NUMBER TAKEN)	0.0437					
	(1.56)					
log(NUMBER GIVEN)	0.0876***					
	(3.33)					
CLUSTERING	0.0163*					
	(1.71)					
HERF TAKEN	0.0443*					
	(1.69)					
HERF GIVEN	0.1397***					
	(5.44)					
log(DEGREE NEIGHBOR)	0.0897***					
	(4.50)					
log(BETWEENNESS)	-0.0621**					
	-(2.47)					
log(EV CENTRALITY)	0.1750***					
	(8.07)					
log(SHORTEST PATH)	0.0201					
	(0.81)					
RECOVERY	-0.0170	-0.0017	-0.0014	0.0168	0.0057	0.0189
	-1.1500	-(0.12)	-(0.10)	(1.14)	(0.38)	(1.31)
log(TRIGGER)	-1.4833***	-1.4624***	-1.4631***	-1.4838***	-1.4822***	
	-(89.38)	-(89.15)	-(89.16)	-(89.38)	-(89.38)	
Factors						
MARKET STRUCTURE				0.3153***	0.4577***	0.3007***
				(33.86)	(31.43)	(33.36)
BORROWING				0.0341***	0.0768***	0.0313***
				(2.84)	(5.85)	(2.67)
BALANCE SHEET				0.0243**		0.0208**
				(2.28)		(2.02)
POSITION				-0.1377***	-0.1593***	-0.1316***
				-(10.24)	-(11.58)	-(10.00)
LENDING				0.0962***	0.0190	0.0947***
				(7.81)	(1.37)	(7.87)
HUB				0.1756***	0.1388***	0.1634***
				(21.76)	(15.44)	(21.18)
LR statistics	16383.77***	12790.04***	13050.01***	16031.47***	16202.09***	4260.06***
Pseudo R^2	0.2678	0.2091	0.2133	0.2621	0.2649	0.0696

Table 3: Logit regression for the determinants of bank failures

relatively large as the failure of a large bank easily spreads to smaller banks and might also affect another large bank, causing their failure. This increased risk is reflected in the positive coefficient of the logit regression.

The two main coefficients above are not directly related to properties of the individual banks themselves, but rather another bank (the trigger bank) and a market characteristic (the market concentration). However, the next factors all capture aspects that are specific to individual banks. A bank acting as a local hub is more likely to fail. The reasoning for this result is that when acting as a local hub a bank will be well connected to other banks in its neighborhood and therefore is exposed to a large number of other banks. This increases the possibility of experiencing contagion from their interbank loan connections, either through the solvency or liquidity mechanism, thus leading to a positive coefficient.

On the other hand, banks that have a more central position in the network are less likely to fail. The reason for this observation is that while these banks might be central for the network structure, e. g. by many shortest paths connecting two banks going through this bank, they are typically not well connected with other banks, exhibiting only few connections themselves. Therefore they will only fail if by chance other banks in their neighborhood fail and given that their neighborhood is small, this is unlikely to happen.

The lending concentration increases the risk of a bank failing. This is an obvious result as fewer loans of larger sizes given, the risk of failure in case of one of the borrowers failing is increased. The opposite effect can be observed for the borrowing concentration, although the associated regression coefficient is lower.[5] A less concentrated borrowing exposes the bank to multiple potential call ins of these interbank loans from other banks, thus increasing the risk of not being able to meet all those demands.

The balance sheet, i. e. degree of reliance on interbank lending, plays only a very limited role in the determination of bank failures. In most cases the amount of equity or cash is sufficient to withstand the failure of a single bank, unless the failing bank relatively large. Once multiple banks to which connections exist fail, the total losses easily exceed the equity or cash holdings, regardless of the amount of equity held. This balance sheet structures have only a limited impact on the probability of failure, although as expected a more widespread reliance on interbank loans increases the probability of default. Interestingly, the recovery rate is not statistically significant as losses quickly accumulate regardless of the recovery rate.

Adding additional variables does not change results substantially and replacing the balance sheet with the individual variables summarized in this factor (column (5) in table 3), shows consistent results. The amount of interbank lending and equity being the only statistically significant balance sheet items, implying again that an increased exposure to interbank lending increases the risk of failure while not surprisingly equity reduces it, a result consistent with that using the factors alone. The other variable that is statistically significant is the size of the bank. The larger a bank is, the less likely its failure is. This result is to be expected as larger banks will be less susceptible to losses given their larger absolute amount of equity and cash to absorb any losses.

[5] Recall that the factor BORROWING decreases the more concentrated the borrowing is.

These result clearly implies that, apart from the trigger bank, the important determinants of bank failure are the market structure and network properties of the interbank loan market, a result consistent with Krause and Giansante (2012), who found similar properties for the likelihood of observing contagion and the fraction of banks failing. It clearly shows the need for taking into account the network structure of financial linkages between banks in order to fully assess and understand systemic risks in banking systems.

The logit regressions conducted above only analyze the determinants of the failure of banks, regardless of the mechanism leading to this failure. It would be of interest to evaluate whether the two different mechanisms that can lead to failures, the solvency and liquidity mechanism, are influenced by different variables. To this effect the coming section will employ a multinomial logit regression making this distinction between the reasons of bank failures.

6.2. Determinants of the reason for failure

In order to analyze whether the two failure mechanisms employed in our model are influenced by different factors, we conducted a multinomial logit regression, consistent with the logit regressions above, as shown in table 4; the categories used were ”no fail” (the base case), ”failure due to the solvency mechanism” and ”failure due to the liquidity mechanism”.[6] Firstly, we observe that results are broadly consistent with the previous logit regressions, in terms of significance of variables as well as signs and sizes. However, there are some significant and important differences in the parameter estimates between the two failure mechanisms that we will discuss in this section.

Again, we focus mainly on the regressions using the factors only, as shown in column 4 of table 4. If we concentrate on those factors whose parameters are statistically significantly different from each other across the failure mechanisms, we have to pay attention to the market structure, borrowing, position and the trigger bank. Table 5 provides the test statistics for the test of equality of coefficients across the two categories. The interpretation of the signs of those variables that do not change significantly between failure mechanisms will be identical to that in the logit regression above and are therefore not repeated here.

Firstly we observe that the influence of the trigger bank is much smaller for banks succumbing to the liquidity mechanism compared to the solvency mechanism. The influence in solvency problems is significantly larger as the failing bank directly imposes losses on any bank lending to this bank, which might cause their failure. On the other hand, the calling in of interbank loans via the liquidity mechanism will not result in a bank’s instant failure, but only if it cannot raise sufficient cash itself. Hence, while the larger sized loans that are called in will increase the likelihood of a liquidity problem, this is much less certain than for a solvency problem as it will also depend on the amount of loans that can be called in whether a bank fails. Hence the link between the size of the trigger bank and failure is less strong.

We secondly observe that the sign of market structure changes from positive for solvency problems to negative for liquidity problems. Hence a more concentrated market increases the risk of failure due to solvency but reduces the

[6] As in the logit regression above, we normalized the original variables for ease of comparison and excluded any banks that were failing simultaneously due to the solvency and liquidity mechanism.

This table shows the estimates of a multinomial logit regression on the failure mechanism of the banks for a variety of model specifications. The categories used are failure due to the solvency mechanism (Solvency) and failure due to the liquidity mechanism (Liquidity). We show the estimates of these regressions with numbers in parentheses denoting the t-values. The LR statistics for testing of the statistical significance of the model as a whole and the Pseudo R^2 denotes McFadden's R^2.. We show the estimates of these regressions, with numbers in parentheses denoting the t-values. Estimates with ***,**,* denote statistical significance of the estimate at the 1%, 5%, and 10% level, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)	
	Solvency	Liquidity	Solvency	Liquidity	Solvency	Liquidity	Solvency	Liquidity	Solvency	Liquidity	Solvency	Liquidity
CONSTANT	-7.6971***	-7.8875***	-7.2161***	-7.6755***	-7.2497***	-7.6779***	-7.6331***	-7.7968***	-7.6799***	-7.8169***	-5.9425***	-7.4598***
	(-174.71)	(-139.74)	(-179.89)	(-151.00)	(-179.85)	(-150.80)	(-176.51)	(-143.82)	(-176.14)	(-142.56)	(-279.67)	(-169.42)
Individual Variables												
log(SIZE)	-0.0757***	-0.1449*	0.3748***	-0.2064***	0.3541***	-0.2140***			-0.2973***	-0.2768***		
	(-4.46)	(-1.89)	(38.99)	(-4.05)	(35.11)	(-4.09)			(-13.64)	(-3.14)		
CORRELATION	-0.0932***	0.5080***										
	(-3.06)	(6.17)										
DISTRIBUTION	-0.0815*	0.2689***										
	(-1.83)	(3.08)										
NUMBER BANKS	-0.0952***	-0.4685***										
	(-5.39)	(-9.28)										
log(HERF BANKS)	0.6271***	0.5362***										
	(13.33)	(4.19)										
EQUITY	-0.0216	0.0486	0.0713***	0.0532	0.0081	0.0416			-0.0459***	0.0976**		
	(-1.55)	(1.17)	(5.28)	(1.32)	(0.59)	(1.01)			(-3.19)	(2.28)		
RESERVES	0.0029	0.0702*	-0.2053***	0.0546	-0.0651***	0.0736*			-0.0439**	0.1232***		
	(0.15)	(1.73)	(-10.80)	(1.44)	(-3.23)	(1.82)			(-2.16)	(2.90)		
LOANS GIVEN	0.0720***	0.0774			0.2338***	0.0747			0.0694***	0.0228		
	(3.80)	(1.59)			(13.23)	(1.62)			(3.55)	(0.44)		
LOANS TAKEN	-0.0391**	0.0282			-0.0983***	0.0334			-0.0117	0.0035		
	(-2.08)	(0.68)			(-5.37)	(0.81)			(-0.62)	(0.08)		
log(NUMBER TAKEN)	0.0595**	-0.0710										
	(2.02)	(-0.69)										
log(NUMBER GIVEN)	0.0994***	0.0984										
	(3.57)	(1.10)										
CLUSTERING	0.0165*	0.0541										
	(1.67)	(1.21)										
HERF TAKEN	0.0560**	-0.0696										
	(1.99)	(-0.84)										
HERF GIVEN	0.1789***	0.0106										
	(6.40)	(0.14)										
log(DEGREE NEIGHBOR)	0.0894***	0.0993										
	(4.24)	(1.42)										
log(BETWEENNESS)	-0.0573**	-0.0115										
	(-2.08)	(-0.18)										
log(EV CENTRALITY)	0.1583***	0.0171										
	(6.77)	(0.25)										
log(SHORTEST PATH)	0.0126	0.0244										
	(0.45)	(0.45)										
RECOVERY	-0.0162	-0.0161	-0.0019	-0.0005	-0.0016	-0.0004	0.0114	0.0614	-0.0021	0.0562	0.0153	0.0616
	(-1.01)	(-0.41)	(-0.12)	(-0.01)	(-0.10)	(-0.01)	(0.71)	(1.58)	(-0.13)	(1.44)	(0.99)	(1.58)
log(TRIGGER)	-1.6688***	-0.7553***	-1.6404***	-0.7547***	-1.6414***	-0.7549***	-1.6712***	-0.7599***	-1.6686***	-0.7601***		
	(-83.42)	(-22.56)	(-83.16)	(-22.55)	(-83.18)	(-22.55)	(-83.42)	(-22.70)	(-83.43)	(-22.70)		
Factors												
MARKET STRUCTURE							0.3922***	-0.1527***	0.5606***	-0.0704	0.3702***	-0.1561***
							(38.65)	(-5.28)	(35.50)	(-1.53)	(38.12)	(-5.41)
BORROWING							0.0073	0.2503***	0.0582***	0.3035***	0.0055	0.2498***
							(0.56)	(8.35)	(4.05)	(8.92)	(0.43)	(8.34)
BALANCE SHEET							0.0151	-0.0214			0.0104	-0.0214
							(1.33)	(-0.64)			(0.96)	(-0.64)
POSITION							-0.0880***	-0.3377***	-0.1151***	-0.3362***	-0.0821479***	-0.3366***
							(-5.88)	(-10.58)	(-7.49)	(-10.45)	(-5.64)	(-10.55)
LENDING							0.1235***	0.0412	0.0320**	0.0067	0.1213***	0.0408
							(9.05)	(1.36)	(2.09)	(0.19)	(9.16)	(1.35)
HUB							0.1773***	0.0985***	0.1324***	0.0988***	0.1624***	0.0935***
							(20.87)	(3.05)	(13.88)	(2.81)	(20.17)	(2.90)
LR statistics	17785.92***		13528.67***		13819.15***		17339.53***		17567.18***		5041.92***	
Pseudo R^2	0.2735		0.2081		0.2125		0.2667		0.2702		0.0775	

Table 4: Multinomial logit regression for the determinants of bank failures due to the solvency and liquidity mechanism

This table shows the χ^2 test statistics for a test whether the coefficients for the regressors in different categories from the multinomial regression in table 4 are equal. Statistics with ***,**,* denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Individual Variables						
log(SIZE)	0.78	125.63***	113.89***		0.05	
CORRELATION	47.11***					
DISTRIBUTION	12.84***					
NUMBER BANKS	48.81***					
log(HERF BANKS)	0.04					
EQUITY	0.45	0.18	0.59		10.14***	
RESERVES	2.57	37.75***	9.45***		12.66***	
LOANS GIVEN	2.21		10.42***		0.72	
LOANS TAKEN	0.01		8.52***		0.11	
log(NUMBER TAKEN)	2.20					
log(NUMBER GIVEN)	1.49					
CLUSTERING	0.00					
HERF TAKEN	0.68					
HERF GIVEN	2.05					
log(DEGREE NEIGHBOR)	4.27**					
log(BETWEENNESS)	0.02					
log(EV CENTRALITY)	0.43					
log(SHORTEST PATH)	3.84*					
RECOVERY	0.00	0.00	0.00	1.42	1.91	1.22
log(TRIGGER)	550.05***	521.05***	522.00***	546.92***	544.05***	
Factors						
MARKET STRUCTURE				317.57***	169.50***	299.65***
BORROWING				55.33***	44.20***	56.37***
BALANCE SHEET				1.07		0.82
POSITION				50.37***	38.60***	52.67***
LENDING				6.14**	0.45	5.93**
HUB				5.60**	0.85	4.30**

Table 5: Test statistics for equality of coefficients of coefficients across categories in the multinomial regression

risk of failure due to liquidity problems. The reason for this observation is that in a concentrated market most banks, larger as well as smaller banks, are lending to larger banks. Calling in a loan from a large bank is more likely to be successful and thus failure is avoided. Hence a more concentrated market reduces the risk of failure due to liquidity problems. In contrast, failures due to solvency problems are more likely in concentrated markets as the failure of any large bank can easily spread to other banks given its size and there are no opportunities to mitigate this effect through calling in interbank loans as in the case of liquidity problems.

We also observe that the borrowing concentration becomes statistically significant for liquidity issues as should be expected because borrowing a large number of different banks increases the risk of failure due to any of these few loans being called in, while for solvency problems this is of no consequence. Similarly the lending concentration is statistically insignificant for liquidity problems and statistically significant for solvency problems, although the difference in coefficients is less statistically significant.

The impact of the position of a bank in the network is much increased for liquidity problems compared to solvency problems, thus a more central position in the network reduces the risk of failure from liquidity problems more than for solvency problems. This difference can again be attributed to the different way the two mechanisms work, namely the ability to call in interbank loans to avoid a liquidity problem. The ability of banks to call in interbank loans is

improved if they are in a central position as the small number of connections these banks have will generally with banks of a relatively large size, thus making the calling in of loans more successful.

When including balance sheet variables directly into the regression rather than the resulting factor, we observe that for solvency problems equity and cash are statistically significant. We find not unsurprisingly that more equity results in a lower risk of failure, although the impact is quite small; for failures due to liquidity problems this impact is much reduced. The same is true for the amount of cash held, where in the case of a liquidity problem the failure rate increases as the amount of cash held increases. However, it has to be noted that the confidence level of all parameter estimates are not very high given the sample size in our regression and coefficients are small, hence the results may well be spurious.

These results clearly show that both, failures due to solvency and liquidity problems, are driven mainly by network properties with only limited input from balance sheet structures. We found that some differences between the strength of the impact between the two failure mechanisms exist and that in case of the market concentration the impact was reversed between them. Our results have implications for the regulation of banking systems that are explored in the coming section.

7. Policy implications

Current banking regulations, including Basel III, attempt to limit bank failures by putting particular emphasis on the amount of equity and, more recently, 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. The Dodd-Frank Act in the US also establishes the need for limits for the concentration of exposures, including interbank lending, but falls short of addressing wider aspects of the network structure of interbank loans and other financial linkages between banks.

It has become clear in our analysis that the size of the bank initially failing is the main determinant whether the failure spreads (”too-big-too-fail”), 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 considered that our results also show that other factors, primarily associated with the network structure of interbank loans, have a significant influence, too.

Interestingly, the balance sheet structure, the main focus of current regulation with minimum capital requirements, maximum leverage and liquidity constraints, has only a limited impact on the likelihood of a bank failing from contagion. 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 a very limited impact on any further failures during a banking crisis itself.

The implications of our findings are that regulators seeking to address bank failures, especially the spread of bank failures during banking crises, should pay particular attention to the network structure of financial relationships

between banks. It is beyond the scope of this contribution to develop specific policy propositions that allow regulators to affect banking failures in such a situation. Our results nevertheless suggest that in order to reduce the extent of any banking crisis and affect the likelihood of a bank failing, regulators should seek measures that address the exposure of banks in the interbank loan market. We found that the way a bank is integrated into the network, e. g. through its position in the network of interbank loans and whether it acts as a hub, is an important determinant of its probability of failure, thus not (only) the amount of interbank loans is of importance but the whole network of interbank loans needs to be taken into account.

Our results also suggest that the market concentration is an important aspect to consider for the likelihood of a bank failing. While reducing the market concentration through the split-up of large banks will reduce the likelihood of banks failing due to insolvency, it would on the other hand increase the likelihood of a failure due to liquidity problems. Furthermore, the more numerous but smaller banks would then in itself be more vulnerable to failures due to their reduced 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 and is left for future research.

8. Conclusions

We have evaluated 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 continued to investigate what determines the failure of individual banks through contagion from an initial exogenous failure of a single bank. We find that the important determinants of whether a specific bank fails includes various aspects of the network structure of interbank loans. On the other hand, the balance sheet of a bank seems only to have a very limited influence.

Our findings clearly suggest that aspects of the network structure are a determinant for the likelihood of a bank failing . 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 implies that such conventional measures have only a very limited impact on the likelihood of a bank failing in a banking crisis, although it might be more important to determine whether a bank fails initially and causes such a banking crisis. This deficit in current regulation has been shown to have a potentially significant effect on bank failures that is not addressed at present.

Future research arising from this paper is manifold. It would be worth to investigate real banking systems by using actual balance sheets, even if the interactions themselves are not known, with the aim to investigate how the likelihood of banks failing has been changing over time as well as whether it correctly predicts those banks that have become distressed. We could use 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 the likelihood of a bank failing. 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. Finally it would be beneficial to explore some more advanced forecasting techniques with the aim to improve the quality of the failure forecast.

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