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Network-based computational techniques to determine the risk drivers of bank failures during a systemic banking crisis

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***Abstract*—This paper employs a computational model of solvency and liquidity contagion assessing the vulnerability of banks to systemic risk. We find that the main risk drivers relate to the financial connections a bank has and the market concentration, apart from the size of the bank triggering the contagion, while balance sheets play only a minor role. We also find that market concentration might facilitate banks to withstand liquidity shocks better while exposing them to larger solvency chocks. Our results are validated through an out-of-sample forecasting that shows that both type I and type II prediction errors are reduced if we include network characteristics in our prediction model.**

Keywords*—Solvency, liquidity, interbank loans, network topology, banking crises, systemic risk, systemic crisis, bank failure

I. Introduction

Almost a decade after the financial crisis of 2007-2008 regulators, along with academics and practitioners, are debating the risk drivers responsible for systemic risk events in the banking sector. Systemic risk is defined as a negative externality of a financial institution's failure on the resilience of other institutions, leading to system-wide instabilities. An important factor of risk propagation is the high degree of interconnections between financial institutions, for example via interbank loans (mainly very short term borrowing and lending among banks) or derivative positions (from basic futures and swaps to more sophisticated credit derivatives). Such complex bilateral interconnections make the assessment of financial contagion and systemic risk a complex task. Recent developments in banking regulation around the world, Basel III internationally and the Dodd-Frank act in the U.S., to name only the most prominent ones, have explicitly included the concept of interconnectedness as important risk drivers to assess bank resilience to distress.

In this paper we aim to shed light on the probability of bank failures by directly testing their vulnerability within a model of an interconnected banking system. [1] showed the relevance of the network structure of interbank loans in the assessment of systemic risk. While the focus of that paper was on the emergence of contagion and its extent at the macro-level, we employ their interbank model to evaluate the vulnerability of individual banks to systemic risk. This study thereby complements the former contribution by focusing on the outcome for individual banks rather than the banking system as a whole. This allows us to assess more explicitly those aspects that drive systemic risk and work towards proposals for banking regulations that aim at improve banks resilience to systemic risk.

Our model represents a complex human system of banks connected via a network of interbank loans. Although the topology of the network and the balance sheet mechanism during times of market distress are pre-defined conditions, i.e no learning or adaptations are allowed, our computational solutions unravel the complexity of the propagation of shocks during financial distress by exposing the main risk drivers responsible for the failure of banks.

In particular, we find that the failure of banks is determined mainly by the connectedness of a bank in the network of interbank loans as well as the market concentration; balance sheet structures have a limited impact on the bank failure rate. When distinguishing between failures arising from insolvency and illiquidity we find that these results remain valid.[1] We assess the validity of our results in an out-of-sample forecasting of the failure of individual banks through the examination of type I and type II errors, showing that the inclusion of network characteristics reduces both error types.

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 before we briefly outline the main features of the model in section III. The way our computer experiments are conducted and the resulting data processed for analysis is described in section IV. The main results of our investigation are discussed in section V with policy implications of these results being outlined in section VI. Finally section VII concludes our findings and makes numerous suggestions for further research.

II. Literature Review

This section provides a brief overview of the current state of the literature on predicting bank failures and the role of interbank loans for systemic risk.

A. The prediction of bank failures

In light of the financial crisis of 2007-2008 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 an individual

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[1] Insolvency refers to a situation where a bank accumulates losses exceeding its capital and illiquidity where its liquid assets (e. g. cash) are insufficient to meet all instant obligations (e. g. the repayment of loans due).

bank as well as systemic risk, little attention has been paid to which banks are actually failing in a process of contagion. The latter denotes the loss propagation of a failing institution to other banks.

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 regressions (where dependent variables are 1 for a bank failing and 0 otherwise) such as logit or probit to estimate the probability of a bank failing, where the independent variables are usually accounting ratios derived from balance sheets and income statements of the banks investigated[2]. For example, [3] 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 U.S. Savings and Loans Crises. Using a similar approach, [4] uses logit and probit models to evaluate the failure of small banks in the U.K. during the early 1990s; he also finds that accounting ratios from the balance sheet and income statement are relevant for the prediction of bank failures. [5] come to the same conclusion for U.S. banks during the late 1980s and early 1990s.

More recent studies focused on the financial crisis of 2007-2008 and used balance sheet and income statement proxies to obtain a CAMELS rating, among them [6] for U.S. banks, [7] for EU banks, and [8] in a more international setting. All of them confirm the importance of CAMELS ratings[3] in predicting banking failures. This research is complemented by [9] for Southeast Asian countries around the Asian financial crisis of 1997 through the inclusion of macroeconomic factors are shown to play a significant role, too. Similarly, [10] include market data such as abnormal returns of bank stocks into their model of predicting bank failures in emerging markets during the early 1990s.

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. Methodologies include neural networks in [11] and [12], trait recognition in [5], fuzzy sets in [13], proportional hazard models in [14], and multi-dimensional scaling in [15]. It is noteworthy that the above computational intelligence techniques explore elements of learning and/or adaptation in corporate behaviour during financial distress, whereas our computational solutions aim at unravelling the complexity of shock propagation within a network of connected banks. A good overview of a range of methods used to predict bank failures can be found in [16].

A common feature of all these models is that they view banks as isolated entities by focusing on their accounting ratios. 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 profits of other banks and even threaten their very survival. Those systemic risk implications have been ignored in the literature on bank failure 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 an isolated event. The inclusion of macroeconomic factors seems 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 failure. This approach has a limited ability to explain why in the same macroeconomic environment some banks fail while others do not. 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.

B. *The role of interbank loans in systemic risk*

Recently studies have explicitly analyzed the financial connections between banks in several interbank markets, including Italy [17], Germany [18], and the U.K. [19], among others. Simulation techniques are usually employed to assess the spread of any bank failures and quantify the threats that systemically important institutions can pose to the whole system[4]. The main balance sheet aspects investigated, liquidity in [21], [22], and [17] as well as capital in [23], are considered the most important risk drivers for the failure of individual banks. Other studies focused more on the optimal network structure [24] and the endogenous bank behavior in interbank networks, such as [25] and [26], and are therefore of limited value to understand the risk driver of bank failures.

Although the number of assumptions made in the above literature on the network structure (properties of the banks and how failures spread) can limit the assessment of systemic risk, the main shortfall is represented by the contagion mechanism employed in that it assesses liquidity and solvency shocks in isolation.[5] The model presented in [1] fills this methodological gap by combining both liquidity shortfalls (from a lender that stops lending to its borrowers) and solvency shocks (from a borrower that fails to repay its debt), and design it as a computational dynamical system. Their numerical experiments on a variety of realistic financial networks provide evidence of the importance of the network structure of interbank loans in driving systemic risk while the structure of the balance sheet has only a secondary role. However, their analysis focused on the probability and extent of contagion at the system level only. This paper seeks to fill the gap in the literature on the risk drivers of individual bank failure by employing this dual-channel (liquidity-solvency) contagion mechanism of [1] within a framework that looks at the banks' individual characteristics to determine the risk drivers of bank failure during systemic risk crises.

[2] See [2] for an extensive review on market based systemic risk metrics.

[3] CAMELS is a measure for the solvency of a bank as used by the U.S. deposit insurance company (FDIC) and is based on balance sheets as well as income statements.

[4] A general overview of the issues surrounding such modeling techniques is given by [20].

[5] The most widely used contagion mechanisms are those proposed by [27] and [28].

III. The model

In contrast to most contributions on systemic risk investigating the spread of an initial failure, we focus here on the properties of the banks that are actually failing in this process, contrasting them with those that do not fail. While the details of the model we use are given in [1], we here provide a brief synopsis of its main aspects to aid the understanding of the setting of our results.

Each bank has a balance sheet with total assets exogenously given, consisting of cash reserves (cash holdings and other highly liquid and risk-free assets such as treasury bonds), loans to external customers, and loans to other banks (interbank lending). The liabilities of each bank are made up of deposits by customers, loans received from other banks (interbank borrowing) and equity.[6] This highly stylized balance sheet captures all the key aspects relevant for the model employed here. We can easily extend the interpretation of interbank borrowing and lending to encompass any financial connections between banks, such as those arising from derivatives positions or payment systems.

All interbank lending and borrowing consists of overnight loans that can be recalled instantly and we can thus focus on a single time period. In the case of an interbank loan being recalled, banks are only able to recover a fraction of their value to account for any costs associated with such recalls or we can interpret this as the liquidity impact from selling bank assets quickly.[7] All balance sheet items are assumed to be fixed in this single time period model. Making such restrictive assumptions enables us to focus on the impact financial connections between banks have on the failures rather than other factors that might result from the behaviour of depositors or borrowers.

To model the interbank loans between banks we generate a directed Albert-Barabasi scale-free network [30], where the number of links are correlated with the total assets of the banks. In such a network large banks have a large number of links and are connected to most larger banks (as they also have to find many other banks to link to) and a sizable fraction of smaller banks. Smaller banks are more likely connected to larger banks than smaller banks given the higher number of links these banks have to fill. This network structure is commonly used to model realistic social and financial networks and is found to be empirically adequate. It induces a significant degree of heterogeneity into the network as observed in real interbank markets, namely a power-law distribution of the number of connections a bank has. We analyze the impact this network structure has on the propagation of failures.

The size of each interbank loan is determined to be proportional to the size of both the lender and borrower: $L_{ij} = \frac{L_j B_i}{\sum_i L_i}$, where L_{ij} denotes the loan from bank i to bank j, L_j the total interbank borrowing of bank j, and B_i the total interbank lending of bank i.

[6] In accounting terms equity is classified as a liability and is thus positioned on the liabilities side of any balance sheet. For convenience we retain this convention also widely used in the economics and finance literature.

[7] [29] reports average recovery rates of around 70% during the Savings and Loans Crises in the U.S. of the late 1980s, with a sizeable variation between banks, thus suggesting that substantial, although not complete losses, are a realistic prospect.

Notation used:

$\mathfrak{F}^t$	Set of banks that fail at step t
$\mathfrak{S}^t$	Set of banks that fail from the solvency mechanism at step t
E_i^t	Equity of bank i at time t
L_{ij}^t	Interbank loan of bank i to bank j at time t
R_i^t	Cash reserves of bank i at time t
κ	Recovery rate
$1_{j\in\mathfrak{F}^{t-1}}$	Indicator function which is 1 if j$\in \mathfrak{F}^{t-1}$ and zero otherwise

PROCEDURE **Solvency**$(\mathrm{E}_i^{t-1}, L_{ij}^{t-1}, R_i^{t-1}, \mathfrak{F}^{t-1}, \kappa)$

1 $\mathrm{S}^t = \left\{ i \mid E_i^{t-1} - \sum_{j\in\mathfrak{F}^{t-1}} L_{ij}^{t-1}(1-\kappa) \le 0 \right\}$

2 $\mathrm{E}_i^t = \max\left\{ E_i^{t-1} - \sum_{j\in\mathfrak{F}^{t-1}} L_{ij}^{t-1}(1-\kappa), 0 \right\}$

3 $\mathrm{L}_{ij}^t = L_{ij}^{t-1} - \mathbf{1}_{j\in\mathfrak{F}^{t-1}} L_{ij}^{t-1}$

4 $\mathrm{R}_i^t = R_i^{t-1} + \sum_{j\in\mathfrak{S}^t} \kappa L_{ji}^{t-1}$

END

Fig. 1. Pseudo code of the solvency mechanism

We employ two mechanisms through which these financial linkages between banks can transmit any shock. A bank experiencing a loss from its borrowers that exceeds its equity will become insolvent (solvency shock). This loss arises from the failure of other banks and the losses associated with the interbank loans granted to them. Any interbank loans from failing banks are repaid, exclusive of the non-recoverable part, and the recovered amount added to the cash reserves of the granting bank (lender).

Figure 1 formalizes this *solvency mechanism* in a pseudo code. We indicate by superscript t the different steps contagion will generally go through. Initially we consider whether the equity E_i^{t-1} a bank has is sufficient to cover the losses arising from the failure of banks in the previous step and record any banks S^t whose losses exceed their equity as failing (line 1). We adjust the equity E_i^t of all banks for losses (line 2), where those banks whose losses are less than their equity see their equity reduced by the corresponding amount and those banks failing having it reduced to zero. The interbank loans L_{ij}^t of those banks that have previously failed are removed as the bank is liquidated (line 3). Finally the amount recovered from interbank loans κL_{ji}^{t-1} is paid to the loan granting bank (lender) and added to its reserves R_i^t (line 4).

A bank that fails will call in, as lender, all their interbank loans to its borrowers, causing potential liquidity shortfalls. Repaying these called-in loans will reduce the cash reserves of the affected banks (borrowers); if the cash reserves are not sufficient to repay the called-in loans, the banks will themselves call in a fraction of all their interbank loans from their borrowers, proportional to the total amount of cash required. If not enough cash can be raised by calling in loans, the interbank loans are repaid proportionally to their size until

Notation in addition of that used previously:

$\mathfrak{F}^t$	Set of banks that fail at step t
$\mathfrak{L}^t$	Set of banks that fail from the liquidity mechanism at step t
$\mathbf{1}_{j\in\mathfrak{F}^{t-1}}$	Indicator function which is 1 if $j \in \mathfrak{F}^{t-1}$ and zero otherwise
C_i^t	Amount of loans to be called in by bank i at time t
E_i^t	Equity of bank i at time t

PROCEDURE **Liquidity**$(L_{ij}^{t-1}, R_i^{t-1}, \mathfrak{F}^{t-1})$

1 $C_i^t = \max\left\{\sum_{j\in\mathfrak{F}^{t-1}} L_{ji}^{t-1} - R_i^{t-1}, 0\right\}$

2 $\widehat{L}_{ij}^t = \min\left\{\frac{C_i^t}{\sum_j L_{ij}^{t-1}}, 1\right\} L_{ij}^{t-1}$

3 $A_{ij}^t = \min\left\{\frac{R_j^{t-1}}{\sum_i \widehat{L}_{ij}^t}, 1\right\} \widehat{L}_{ij}^t$

4 $\mathfrak{L}^t = \left\{ i \mid R_i^{t-1} + \sum_i A_{ij}^t - \sum_j A_{ij}^t - \sum_{j\in\mathfrak{F}^{t-1}} L_{ji}^{t-1} < 0\right\}$

5 $R_i^t = \max\left\{R_i^{t-1} + \sum_i A_{ij}^t - \sum_j A_{ij}^t - \sum_{j\in\mathfrak{F}^{t-1}} L_{ji}^{t-1}, 0\right\}$

6 $L_{ij}^t = L_{ij}^{t-1} - A_{ij}^t - \mathbf{1}_{i\in\mathfrak{F}^{t-1}} L_{ij}^{t-1}$

END

Fig. 2. Pseudo code of the liquidity mechanism

Notation:

$\mathfrak{F}^t$: Set of banks that fail at t

$\mathfrak{L}^t$: Set of banks that fail at t due to the liquidity

$\mathfrak{S}^t$: Set of banks that fail at t due to the solvency

PROCEDURE **Contagion** $\left(E_i^{t-1}, L_{ij}^{t-1}, R_i^{t-1}, \mathfrak{F}^{t-1}, \kappa\right)$

1 $\mathfrak{F}^0 = \{\text{trigger bank}\}$

2 FOR $\mathfrak{F}^t \neq \emptyset$ DO

3 Solvency$(E_i^{t-1}, L_{ij}^{t-1}, R_i^{t-1}, \mathfrak{F}^{t-1}, \kappa)$

4 Liquidity$(L_{ij}^{t-1}, R_i^{t-1}, \mathfrak{F}^{t-1})$

5 $\mathfrak{F}^t = \mathfrak{S}^t \cup \mathfrak{L}^t$

6 $\mathfrak{F} = \bigcup_t \mathfrak{F}^t$

7 $\mathfrak{S} = \bigcup_t \mathfrak{S}^t$

8 $\mathfrak{L} = \bigcup_t \mathfrak{L}^t$

9 $\mathfrak{B} = \mathfrak{S} \cap \mathfrak{L}$

END

Fig. 3. Pseudo code of the complete contagion mechanism

all cash reserves are used up.[8] If the cash reserves and the amount received from the called-in loans are not sufficient, the bank will be deemed illiquid and therefore failing. This liquidity mechanism can thus trigger the solvency mechanism if the recovery of interbank loans from such failing banks is too small.

The above *liquidity mechanism* is formalized in a pseudo code as shown in Figure 2. Banks that previously failed will be wound up and during this liquidation they will call in the interbank loans they have granted (as lender). A bank whose interbank loans are called in (borrower) will have to repay this amount from its cash reserves and raise any missing amount from itself calling in interbank loans from its borrowers. The amount of loans a bank needs to call in in excess of its reserves C_i^t is given in line 1. This amount is spread proportionally over all interbank loans this bank has granted as lender to other banks (borrowers) $\widehat{L}_{ij}^t$ (line 2).[9] A bank receiving this and similar requests from other banks to repay loans, will repay these loans to the extent its reserves are sufficient and will pay the requested amounts in proportion of these requests, the amount being A_{ij}^t (line 3).[10] Taking into account the current reserves R_i^t, the monies received from calling in loans A_{ij}^t, the monies paid out to other banks calling in their loans A_{ji}^t and the amount recalled from failing banks L_{ji}^{t-1}, we can determine which banks L^t are not able to repay their interbank loans in full and will thus fail and be liquidated in the next stage (line 4). We then adjust the amount of reserves held by all banks R_i^t, failing and surviving, accordingly (line 5) and finally adjust the interbank loans L_{ij}^t by the amounts recalled A_{ij}^t and eliminate those of failing banks $\mathbf{1}_{i\in\mathfrak{F}^{t-1}} L_{ij}^{t-1}$ (line 6).

We can now combine these two mechanisms to obtain the full contagion mechanism as employed in this paper, see Figure 3. As pointed out in the coming section, we exogenously trigger a banking crisis by failing a trigger bank (line 1). We then continue to apply the solvency and liquidity mechanisms through as many steps as required until no further failure is observed (lines 2-5). As banks can fail from the solvency or liquidity mechanism, a failure from the solvency mechanism can trigger a subsequent failure from the liquidity mechanism or vice versa (line 5) and we observe that solvency and liquidity mechanisms are highly interactive. We can finally determine all those banks that throughout the process failed from either mechanism or both (lines 6-9).

We have thus established a contagion mechanism that allows for the propagation of liquidity shortfalls as well as solvency failures, which are strongly interacting with each other. A potential banking crisis is triggered exogenously by failing one bank. In our model we do not allow banks to react to an unfolding crisis by unilaterally withdrawing interbank loans from other banks. Such an extension is left for future research.

We would expect that a larger exposure to the interbank market as borrower or lender would increase the likelihood of failure as would reduced capital and cash reserves. Obviously

[8]We do not allow for a longer chains of interbank recalls, assuming that the delay in completing this procedure would be too long before creditors would require the bank to file for bankruptcy. For simplicity we do not assume that banks unable to fulfill the full request of repaying interbank loans in this secondary stage will be declared bankrupt and be wound up. We can easily justify this assumption by proposing that interbank loan specifications allow for some delay in early repayments, while in case of a bank filing for bankruptcy such clauses in the interbank loan specifications are assumed to be void.

[9]Formally a bank can only call in interbank loans from other banks that have not defaulted. As our algorithm sets the interbank loans given to previously failed banks to zero, we can for simplicity consider all possible banks in our algorithm.

[10]For simplicity we do not allow for banks to call in loans in excess of their actual requirements. Such strategic behavior of banks and its impact on systemic risk is left for future consideration.

a larger exposure to interbank borrowing (lending) makes, *ceteris paribus*, losses that exceed the capital (cash reserves) more likely. Similarly lower capital or cash reserves reduce the cushion available to absorb losses and repayments, thus increasing the risk of the bank failing. Our analysis below investigates the validity of this straightforward conjecture, alongside properties of the network of interbank loans, as well as the influence of these aspects on the failure rate of banks.

IV. The computer experiments

Due to the individual interactions between banks through interbank loans, we cannot solve the model analytically but have to rely on computer experiments on a large number of banking systems with varying properties to assess our model. Each banking system is initialized using a random set of parameters as shown in Table I. The parameters range has been specifically calibrated following the universal banking model [31] to generate bank balance sheets representing the main business models adopted by banks.[11] Given the randomness of parameters used, we induce a large degree of heterogeneity into our banking system, both in terms of bank sizes, their balance sheet compositions and the number of banks included. This allows us to investigate the effect these aspects have on the propagation of bank failures. Note that any bank with low equity or cash reserves could have been affected by an idiosyncratic shock or be exposed to a macroeconomic shock that may have affected this bank more than others.

We then apply the same mechanism to adjust these balance sheets as in [1] to ensure that the balance sheets and the network of interbank loans are consistent with each other. For the triggering of a banking crisis, a single bank is chosen to fail, taken to be either the largest bank (denoted by TRIGGER =1), the second largest bank (TRIGGER = 2), or a bank randomly chosen from each decile by asset size (TRIGGER = 3-12), excluding the largest two banks.[12]

In total we generate 10,000 different banking systems, each triggered by 12 different banks, allowing us to investigate approximately 60,000,000 individual banks. Of these 60,000,000

Parameter	Distribution	Range
Number of banks	Uniform	$[13; 1000]$
Assets	Power law	$[100; 10bn]$
Power law exponent	Uniform	$[1.5; 5]$
Recovery rate	Uniform	$[0; 1]$
Equity relative to assets	Uniform	$[0; 0.25]$
Cash reserves relative to assets	Uniform	$[0; 0.25]$
Loans to public relative to assets	Uniform	$[0; 1]$
Deposits relative to assets	Uniform	$[0; 1]$

TABLE I. Parameter ranges of variables in computer experiments

banks we will randomly select 1,000,000 banks to conduct our analysis such that regressions remain feasible and statistical tests meaningful; we only select banks that have interbank lending or borrowing, as otherwise no failure of these could be observed in our model given that failures are only arising from contagion.

We 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. These explanatory variables briefly characterized in Table II in the online appendix, together with their descriptive statistics. In the following we will make use of these variables and identify them as required in our analysis.

The potential explanatory variables considered are often highly correlated, while still providing slightly different information on the network or balance sheet structure. Using such variables in a regression analysis does not only raise the problem of multi-collinearity but also makes the interpretation of any results difficult. To overcome this difficulty, we performed a principal components analysis and using the eigenvalue criterion identified eight factors. These factors are identified and the resulting rotated factor loadings are displayed in Table III of the online appendix. [33] provides a comprehensive overview of this technique and [1] provide more details of the technique used in this setting.

For the remainder of our analysis we will focus on these eight factors identified. The factors identified are MARKET STRUCTURE which measures the size and concentration of the the banking system, BORROWING which measures the concentration of borrowing from other banks, LENDING which measures the concentration of interbank lending, POSITION which measures the connectedness of a bank in the network, HUB which measures the integration of a bank in its immediate neighborhood, BALANCE SHEET which measures how reliant the bank is on interbank loans, RECOVERY which is the recovery rate in case of bank failures, and TRIGGER which measures the size of the initially failing bank.

V. 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 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

[11] The number of banks, asset sizes, and power law exponents are consistent with modern banking systems around the world as reported in Section II-B. The recovery rate captures all potential liquidation scenarios, ranging from full recovery to full losses after liquidation. Finally, the range of the last four parameters spans the major banks business models, such as traditional retail-oriented banks (mainly deposit funding and investments into loans to the public with low capital and liquidity buffers, usually less than 10% of total assets), to more modern strategies including wholesale oriented models (a mix of deposit and interbank loans on the liability side with well diversified asset side as well as being well liquid and capitalized, usually above 10% of total assets) up to investment oriented strategies (mainly wholesale debt coming from interbank loans and other non-deposit debt) as reported in [32].

[12] While in some cases the failure of a single bank for exogenous reasons can be realistic, e.g Barings Bank 1995 or Herstatt Bank 1974, it is more common that banks fail due to a wider macroeconomic shock affecting a wide range of banks. However, it is the purpose of this paper to focus on the propagation of any failure that might occur. This way we avoid loosing the focus of our analysis by having to consider the magnitude and cross-sectional distribution of any macroeconomic shocks. Furthermore, even in the case of a macroeconomic shock affecting all banks, it is often that only a single bank will initially fail before this failures spreads, e. g. Lehman Brothers in the U.S. or Northern Rock in the U.K. during the financial crisis of 2007-2008.

of our specification.[13] 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.[14] Table IV in the online appendix shows the fraction of banks failing, depending on the size of the triggering bank, and we note that the smaller the triggering bank is the less likely a bank is to fail.

A. Risk drivers of bank failures

We conduct a logit regression of the failure of a bank, the results of which are detailed in Table V of the online appendix using a range of specifications by changing the variables included. This includes the factors identified in the principal components analysis above, the original variables of the balance sheet structure and network characteristics, as well as a combination of these and find that results are very consistent across different specifications, suggesting that results are not sensitive to the exact variables we include in our analysis.

Given the consistency of results, our analysis focuses on the factors identified in the principal components analysis. We find that the factors consisting of balance sheet items and the recovery rate are the only factors not being statistically significant or showing a low significance level. However, given the sample size of 1,000,000, the relevance of statistical significance is greatly diminished and instead we focus on the size of the marginal effects (magnitude of the coefficients). 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 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 as a variable does not change the results significantly, although the goodness of fit reduces substantially, suggesting that the size of the bank initiating the contagion is an important determinant.

Our results imply that the main risk driver for a bank to fail 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 contrast to current banking regulation that seeks to regulate balance sheet structures more tightly but does not monitor the financial links between banks in a meaningful way. Our results clearly show that it is important to consider these aspects of systemic risk embedded in a banking system for the failure of individual bank. Of course, the initial failure of the triggering bank for exogenous reasons will most likely be the result of a weakness in the balance sheet as implied here. Hence a focus on balance sheet variables, as in the traditional and current regulation, has its merits in reducing the likelihood of any such failures. Our analysis here is concerned with the spread of this initial failure and would therefore complement any requirements to address the initial failure of a bank.

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

The two main risk drivers 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 remaining risk drivers 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 part of many paths in the money flow 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 with fewer loans of larger sizes, 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. 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

[13]In future research it would be interesting to apply other methods of assessing failure risks such as using models employing neural networks or fuzzy systems to see whether the predictions can be improved further.

[14]We excluded those banks from our analysis that failed simultaneously from the solvency and liquidity mechanism. As there were only 5 such banks in our sample of 1,000,000, their 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 for this event.

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 is 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. Thus 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 factor with the individual variables summarized in this factor shows consistent results. The amount of interbank lending and equity are 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.

These results on the importance of network properties as risk drivers of individual bank failure are consistent with [1], but we can also see which network properties make individual banks particularly vulnerable to systemic risk rather than only increase the risk to the system as a whole. We can deduct that in order to protect itself from systemic risk, a bank should not only reduce the amount of interbank lending and increase its capital as would be expected (which will have a quite limited effect), but also avoid being a hub in the network of interbank loans while still retaining a central position. Changing these properties would have a stronger impact than adjusting the balance sheet. While it may be difficult for the bank to directly influence their position in the network, which will also depend on the behavior of other banks, it may also achieve some reduction in its exposure to systemic risk by reducing the concentration of its interbank lending while increasing the concentration of its interbank borrowing.

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, designed to control for this distinction between the reasons of bank failures.

B. Risk drivers of the reason for failure

In order to analyze whether the two failure mechanisms employed in our model are influenced by different risk drivers, we conducted a multinomial logit regression, consistent with the logit regressions above, as shown in Table VI of the online appendix; the categories used were ”no fail” (the base case), ”failure due to the solvency mechanism” and ”failure due to the liquidity mechanism”.

We observe that results are broadly consistent with the previous logit regressions, in terms of the 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 on the regressions using the factors only. 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 VII of the online appendix 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 the triggering 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 pronounced 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 the 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 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 from 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 significance level is lower than for the borrowing concentration.

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 be with banks of a relatively large size, thus making the calling in of loans more successful on average.

When including balance sheet variables directly into the regression rather than the balance sheet 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. In case of the market concentration, the impact was reversed between them. We see that apart from the market structure all variables affect the failure rates of banks similarly, whether they fail through the solvency or liquidity mechanism. Thus banks reduce their exposure to systemic risk through either mechanism by the same measures as outlined above. However, any regulation on the market structure would have to consider the different effect of reducing market concentration on the risks arising from the solvency and liquidity mechanisms. As before, the influence of balance sheet structures such as the exposure to interbank borrowing and lending, as well as capital and cash reserves, is relatively small compared to the network properties of the interbank lending market.

The next section evaluates the out-of-sample forecasting ability of the risk drivers in order to asses the importance of network characteristics for the quality of predictions our model is able to make.

C. Out-of-sample prediction of failure

While the above results suggest that the inclusion of network properties of the interbank loan network increases not only the goodness of fit of our models as measured by the pseudo-R^2, but also by the LR-test of the model specification, we will in this section look explicitly at the ability of our model to predict which banks are failing in order to assess the quality of the models we used. To this end we selected another 1,000,000 banks randomly according to the same constraints as before and conducted an out-of-sample forecasting of their failure

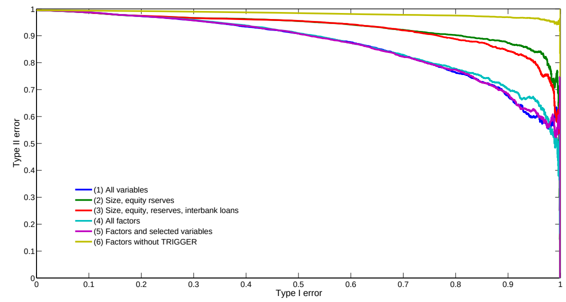

Fig. 4. Type I (false negative) and type II (false positive) errors of a failure prediction using a logit model. Model specifications (1) to (6) are characterized by a different list of regressors reported in Table VI of the online appendix.

based on our model estimates. We construct the value of the factors and use the parameter estimates of our regressions to obtain an estimate of the probability of default, and in the case of the multinomial logit also an estimate of the probability for failure from each mechanism.

These probabilities of failure have then to be transformed into a discrete prediction of "fail" and "no fail" ("fail from solvency", "fail from liquidity" and "no fail" for the multinomial logit model that we discuss further below). We denote the predicted probability of a failure of bank i by p_i and in the case of the logit model the predicted outcome X_i is given as

$$X_i = \begin{cases} \text{fail} & \text{if} \quad p_i > \pi \\ \text{no fail} & \text{if} \quad p_i \leq \pi \end{cases} \tag{1}$$

for some parameter $\pi \in [0; 1]$. The choice of this parameter π will be important for the quality of our prediction, most notably the type of prediction errors we obtain. We define *type I error*s as the fraction of banks that are actually failing but are predicted to not fail (false negative). On the other hand, *type II error*s are defined as the fraction of banks that are predicted to fail but are actually not failing (false positive). As we change π we will affect these two types of errors; the higher π the higher type I errors become and type II errors reduce. Figure 4 shows this trade-off between the two error types as we change π from 0 to 1.

From this Figure we clearly see that for those models that include network characteristics of the interbank loans as risk drivers, i. e. models (1), (4), and (5), type I and type II errors are reduced compared to those excluding these variables, i. e. models (2) and (3). This clearly suggests that the inclusion of network characteristics improves the performance of the model, giving an additional strong indication for the relevance of these aspects in the prediction of individual bank failure during times of systemic risk. We furthermore see that when excluding the trigger bank from the model, the quality of predictions reduces significantly as implied by the regressions.

The choice of π will have to be made exogenously. A regulator will have to make a decision based on his own criteria, e. g. by weighing the cost of not identifying a failing bank (type I error) against the costs of providing assistance to a bank that will eventually not fail (type II error). The choice will be determined depending on the relative costs of these two errors. The regulator will choose a π that corresponds to a lower type I error (higher type II error) if the former costs are relatively high and higher type I errors (lower type II errors) if the latter costs are higher.

We can now conduct a similar analysis for our multinomial logit model that distinguishes between the two mechanisms leading to failure. Here the analysis is complicated by the fact that we have three possible outcomes and can thus not base the prediction on a single threshold. Therefore, we use a two-step method. In a first step we decide whether a bank is predicted to fail; this is achieved by aggregating the two different types of failure at this stage. The decision whether a bank is predicted to fail is made by applying a threshold π^F as in our logit model. In a second step all those banks that are predicted to fail are then predicted to either fail due to solvency problems or liquidity problems by using a similar methodology: we apply another threshold π^S to decide which of these two possibilities are chosen. We can summarize this forecasting mechanism here as follows:

$$X_i = \begin{cases} \text{fail from solvency} & \text{if} \quad p_i^{NF} < \pi^F \text{ and } p_i^S > \pi^S \\ \text{fail from liquidity} & \text{if} \quad p_i^{NF} < \pi^F \text{ and } p_i^S \leq \pi^S \\ \text{no fail} & \text{if} \quad p_i^{NF} \geq \pi^F \end{cases}, \tag{2}$$

where p_i^{NF} and p_i^S denote the predicted probabilities of not failing and failing due to solvency problems, respectively.

Similarly as above we can now define type I and type II errors. Only in this model we will have two different type I and type II errors, those for the prediction of failure and then those for the prediction of the reason for failure. Let us firstly focus our attention only on the prediction of failure, ignoring the reason of failure, thus providing the same framework as the logit regression analyzed before. We observe results consistent with those for the logit regression. If we compare the type I and type II errors between the predictions of failure of the logit model and the multinomial logit model in Figure 5, we clearly see that the multinomial model outperforms the logit model through showing lower type I and type II errors for the same variables chosen in the regressions. Although at this stage we have not made the distinction between the reasons of failure, the multinomial logit model takes better into account that the two mechanisms are working differently and thus allows for a more tailored approach in predicting the failure of banks by not averaging the determinants across failure mechanisms as the logit regression necessarily does. This result provides additional evidence to the regressions that failures by the two mechanisms can be predicted using different variables and different degrees of influences of the same risk drivers.

As a final analysis we also determined the type I and type II errors of the prediction of the failure type, i. e. the mechanism leading to a bank failing. Type I errors are defined as the fraction of banks that are failing from the solvency mechanism but are predicted to fail from the liquidity mechanism (false liquidity) and type II errors are the fraction of banks that are predicted to fail from the solvency mechanism but are

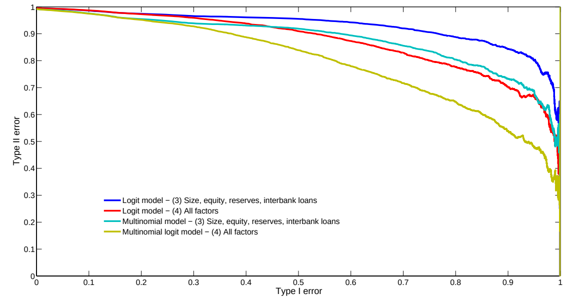

Fig. 5. Comparison of the Type I (false negative) and Type II (false positive) errors of a prediction of failure using the logit and mulinomial logit models. Model specifications (3) and (4) are characterised by different list of regressors as described in Tables V and VI of the online appendix, respectively.

actually failing from the liquidity mechanism (false solvency). As before in the case of errors arising from the prediction of failure, a regulator would need to choose the threshold π^S such that the costs arising from type I and type II errors are optimally balanced. Obviously the size of these errors will depend on the first step, i. e. the prediction of failure as this determines the banks that are being analyzed in the second step.

Figure 6 shows these two errors from the prediction of the failure type, together with the type I error of the initial prediction of failure (using type II errors would provide a similar picture). We clearly see once again that including network characteristics reduces both type I and type II errors as the surface of the model using network characteristics in form of the factors is entirely below the surface of the model using only selected variables from the balance sheet. Using the other models that included individual variables would give us results consistent with those presented here. Hence including these network characteristics as risk drivers improves the quality of our forecasts. Therefore we can conclude that network characteristics of the interbank loans are not only useful to predict which banks are failing but also allows us to better distinguish the mechanism they are more likely to succumb to.

Summarizing the results of our out-of-sample predictions we can confirm that including network characteristics into our model significantly improves the quality of forecasting bank failures as well as the type of mechanism that leads to its failure, consistent with our analysis of the logit and multinomial logit regressions above. Thus in the analysis of bank failures arising from systemic risk it is important to consider the characteristics of the interbank loan network between banks, or other similar exposures between banks. The next section briefly explores the implications of our findings for policy makers.

VI. Policy implications

Current banking regulations, including Basel III and the Dodd-Frank Act, attempt to limit bank failures by putting particular emphasis on the amount of equity and, more recently,

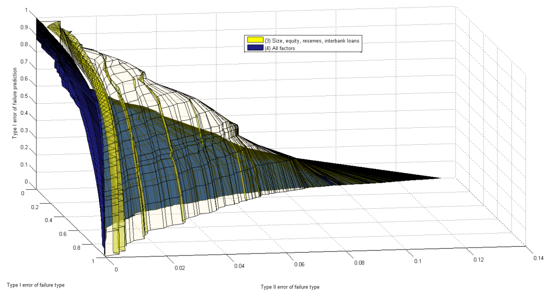

Fig. 6. Type I (false liquidity) and Type II (false solvency) errors of a prediction of failure types using the multinomial logit model, plotted against Type I (false negative) error of prediction of failure. Model specifications (3) and (4) are characterised by different list of regressors as described in Table VI of the online appendix.

aspects of liquidity, i. e. balance sheet structures, seeing them as the main risk drivers of bank failures. 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 to limit the exposure to systemic risk. The Dodd-Frank Act in the U.S. also establishes the need for the concentration of exposures limits, including interbank lending, but falls short of addressing wider aspects of the network structure of interbank loans and other financial linkages between banks, which we have seen in our model to be a very important risk driver of bank failures.

It has become clear in this study 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 not surprisingly shown in our model to be a valid concern. It has, however, to be considered that our results also show that other risk drivers, 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 systemic crisis itself. This aspect has been neglected in the literature on the prediction of bank failures as discussed in section II-A and our analysis has clearly shown its importance as a risk driver.

The implications of our findings are that regulators seeking to address bank failures in a systemic crisis scenario 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, those numerous small banks would themselves 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 into 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. It would be worth investigating how capital and cash reserves of individual banks might be varied taking the results of this paper into account, e. g. through increasing minimum requirements in line with the network properties of the bank. Such a regulation with different requirements for banks might then lead to reduced systemic risk for the entire banking system. It is, however, beyond the scope of this paper to evaluate this proposal and it is left for future research.

VII. CONCLUSIONS

We investigated the main risk drivers of individual bank failures in a computational model of systemic risk. A model was employed that explicitly considers the financial connections between banks arising from interbank loans, derivatives positions, and payments systems. The exogenous failure of a single bank can spread through these financial connections by solvency shocks and liquidity shortfalls. Rather than focusing on the spread of such failures, the focus of this paper is on the failure of individual banks and their characteristics as main risk drivers. Traditionally, models of bank failure have seen banks as isolated entities rather than integrated with other banks in a complex network of financial connections. Our paper showed the relevance of these financial connections for the prediction of bank failures.

The findings shown here, in contrast to results in the literature, support our claim that the main risk drivers of bank failures during a systemic banking crisis are not balance sheet relationships, but the position of a bank in the network of financial connections with other banks. This result is robust also when controlling for the reason a bank fails, either through insolvency or illiquidity, showing that the inclusion of risk drivers related to the network position of a bank reduces type I and type II forecast errors. We also discuss some policy implications for the regulation of banks arising from the results obtained here.

Future research emerging from this paper is manifold. While an empirical investigation of our model using actual banking systems would be desirable, the lack of publicly available data on the financial connections between banks would limit any such analysis to central banks or regulators. Given the importance of network positions by banks to predict their failure during a systemic banking crisis, it would be useful to assess how regulatory measures, such a capital and liquidity requirements, might be set such that they take into account this risk driver to mitigate the likelihood of a bank failing and extending a systemic crisis. Banks being subjected to a common macroeconomic shock that induces significant losses on banks and leads to weakened balance sheets of banks might also be considered to assess how a banking system reacts to any such triggers of a banking crisis. Finally it would be worth considering how banks would grant, extend, and withdraw interbank loans in response to an unfolding banking crises; this would allow to investigate how the actual behavior of banks contributes to or mitigates the onset of a banking crisis using an adaptive complex systems approach.

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Appendix

Online tables

	Description	Mean	Standard deviation	Skewness	Kurtosis	Minimum	25% quantile	Median	75% quantile	Maximum
log(SIZE)	Assets of a bank	5.7778	1.3730	2.7321	14.0028	4.5519	4.9125	5.3285	6.0952	23.0078
CORRELATION	Node correlation [34]	-0.1166	0.1630	-1.8441	6.7312	-0.9977	-0.1574	-0.0636	-0.0142	0.7833
DISTRIBUTION	Power law exponent of assets	3.0611	0.9796	0.3076	1.9203	1.5008	2.2227	2.9248	3.8698	4.9997
NUMBER BANKS	Number of banks in the banking system	655.2802	240.2183	-0.5188	2.3304	13.0000	479.0000	693.0000	859.0000	1000.0000
RECOVERY	Recovery rate in case of failure	0.4946	0.2888	0.0130	1.7905	0.0002	0.2434	0.4933	0.7469	1.0000
log(HERF BANKS)	Herfindahl index of assets	-5.9452	1.7934	0.6767	2.6005	-8.7647	-7.4226	-6.3259	-4.7231	-0.0146
EQUITY	Ratio of capital and assets of a bank	0.1472	0.1023	1.5088	8.4677	0.0000	0.0700	0.1392	0.2075	0.9923
RESERVES	Ratio of cash and assets of a bank	0.2089	0.2228	1.7562	5.5788	0.0000	0.0572	0.1352	0.2592	1.0000
LOANS GIVEN	Ratio of interbank loans given and assets of a bank	0.3633	0.2987	0.5875	2.0887	0.0000	0.0998	0.2867	0.5916	1.0000
LOANS TAKEN	Ratio of interbank loans taken out and assets of a bank	0.3735	0.2509	0.3412	2.0400	0.0000	0.1544	0.3445	0.5713	0.9985
log(NUMBER TAKEN)	Number of interbank loans taken out (indegree)	0.3872	0.5936	2.3161	12.4496	0.0000	0.0000	0.0000	0.6931	6.7708
log(NUMBER GIVEN)	Number of interbank loans given (outdegree)	0.5229	0.6134	1.7092	9.6197	0.0000	0.0000	0.6931	0.6931	6.7765
CLUSTERING	Local clustering coefficient [35]	0.0213	0.0830	4.7974	27.1825	0.0000	0.0000	0.0000	0.0000	0.9000
HERF TAKEN	Herfindahl index of the interbank loans taken out [36]	0.8509	0.2292	-1.2698	3.3062	0.0075	0.6833	1.0000	1.0000	1.0000
HERF GIVEN	Herfindahl index of the interbank loans given [36]	0.7913	0.2524	-0.7639	2.1822	0.0104	0.5467	0.9806	1.0000	1.0000
log(DEGREE NEIGHBOR)	Average degree of neighbors	1.7936	1.3464	1.6575	5.1839	0.0000	1.0986	1.3863	1.9459	7.4025
log(BETWEENNESS)	Betweenness centrality [37]	5.6459	2.0615	-0.5680	3.2474	-1.0986	4.6052	5.8278	7.0484	13.5461
log(EV CENTRALITY)	Eigenvalue centrality	-2.7161	3.0527	1.3785	8.5386	-9.2057	-4.2658	-2.7888	-1.5221	29.0297
log(SHORTEST PATH)	Maximum distance between two banks in the largest component	8.1111	7.3265	1.2360	4.3381	1.0000	2.0000	6.0000	12.0000	57.0000
log(TRIGGER)	Decile of the size of the bank failed exogenously	1.6701	0.7230	-0.9685	2.9774	0.0000	1.0986	1.7918	2.3026	2.4849

TABLE II. DESCRIPTIVE STATISTICS OF THE INDEPENDENT VARIABLES INVESTIGATED

This table shows the rotated factor loadings from conducting a principal components analysis using the varimax-criterion. 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 III. ROTATED FACTOR LOADINGS FROM A PRINCIPAL COMPONENTS ANALYSIS

TRIGGER	1	2	3	4	5	6	7	8	9	10	11	12
Mean	0.0294	0.0119	0.0048	0.0033	0.0027	0.0020	0.0018	0.0017	0.0014	0.0012	0.0007	0.0004
Standard deviation	0.0680	0.0256	0.0150	0.0118	0.0115	0.0091	0.0107	0.0090	0.0080	0.0066	0.0056	0.0067

TABLE IV. MEAN AND STANDARD DEVIATION OF THE FRACTION OF BANKS FAILING WHEN TRIGGERED BY BANKS OF DIFFERENT SIZES

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. Estimations (1)-(3) use the variables RECOVERY and TRIGGER, while estimations (4)-(6) use the corresponding factors. Estimates with ***,**,* denote statistical significance of the estimate at the 1%, 5%, and 10% level, respectively.
We run all regressions using normalized variables in order to make the estimated coefficients comparable across variables and specifications.

	(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)/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 V. LOGIT REGRESSION FOR THE DETERMINANTS OF BANK FAILURES

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. Estimations (1)-(3) use the variables RECOVERY and TRIGGER, while estimations (4)-(6) use the corresponding factors. 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)/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 VI. 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 VI are equal. Estimations (1)-(3) use the variables RECOVERY and TRIGGER, while estimations (4)-(6) use the corresponding factors. 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 VII. TEST STATISTICS FOR EQUALITY OF COEFFICIENTS ACROSS CATEGORIES IN THE MULTINOMIAL REGRESSION