DEUTSCHE BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 23/2020

Interbank risk assessment – A simulation approach

Maximilian Jager
(University of Mannheim)

Thomas Siemsen

Johannes Vilsmeier
(European Central Bank)

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978–3–95729–704–4 (Printversion)
ISBN 978–3–95729–705–1 (Internetversion)

Non-technical summary

Research Question

The interbank market offers banks the possibility to exchange liquidity without having to rely on other sources, such as central banks or retail deposits. While this is in general beneficial to the financial system, it fosters the connectedness and the synchronization of banks, thus making them more vulnerable. This paper aims at quantifying the risks borne by the system, the risks borne by single banks and the risks emitted from single banks. For this purpose, the interbank network structure is analyzed and a simulation method is applied to elicit the desired information. To show the functionality and implications of our framework, we apply it to the German interbank market as of end 2016.

Contribution

We contribute to the literature by simulating distributions of possible events which allow to study the probability of arbitrary events, for example the probability of having a loss exceeding a certain threshold. Most studies in this strand of literature focus on deriving probabilities for particular events, which are all nested by our approach. Lastly, our framework further gives information about which banks emit the most risks through the interbank market, a widely-discussed concept often called "systemic relevance" in the literature.

Results

We find that the examined portion of the German banking system appears generally resilient to domestic exogenous interbank shocks. Even if large or well connected banks default, the system can absorb the losses rather easily due to its sufficient capital buffers. For single institutions, however, we find indications for elevated vulnerabilities and the need for a close supervision.

Nichttechnische Zusammenfassung

Fragestellung

Der Interbankmarkt bietet Banken die Möglichkeit, ihre Liquidität zu managen, ohne auf andere Quellen, wie z.B. Zentralbanken oder Privatkundeneinlagen, zurückgreifen zu müssen. Während dies im Allgemeinen nützlich für das Finanzsystem ist, verstärkt es die Verbundenheit und den Gleichlauf von Banken, was zu einer erhöhten Verletzbarkeit führt. Dieses Papier verfolgt das Ziel, die Anfälligkeit des gesamten Banksystems, einzelner Banken, als auch die Gefahr einzelner Bank für das gesamte System zu quantifizieren. Zu diesem Zweck wird die Interbanknetzwerkstruktur analysiert und die benötigten Informationen mit Hilfe einer Simulationsmethode berechnet. Um die Funktionalität und die Implikationen unseres Modellrahmens aufzuzeigen, wenden wir die Methode auf die Daten des deutschen Interbankmarkts aus dem Jahr 2016 an.

Beitrag

Wir tragen zur Forschungsliteratur bei, indem wir Wahrscheinlichkeitsverteilungen möglicher Ereignisse simulieren, welche es ermöglichen, die Wahrscheinlichkeit beliebiger Ereignisse, beispielsweise des Ereignisses einer Überschreitung eines bestimmten Verlustes, zu berechnen. Die meisten Studien in dieser Literatur beschränken sich auf die Berechnung der Wahrscheinlichkeit für einzelne Ereignisse, während unser Ansatz all diese und noch beliebige weitere Ereignisse beinhaltet. Zu guter Letzt ermöglicht unser Modellrahmen die Analyse der Risiken, die einzelne Institute auf das restliche System ausstrahlen; ein Konzept, das in der Literatur viel diskutiert und als 'systemische Relevanz' bezeichnet wird.

Ergebnisse

Die Ergebnisse zeigen, dass der betrachtete Ausschnitt des deutschen Bankensystems exogenen Interbank-Schocks gegenüber stabil zu sein scheint. Selbst die Verluste, die der Ausfall großer oder eng vernetzter Banken hervorruft, kann das System dank seiner ausreichenden Kapitalpuffer abfangen. Für einzelne Banken finden wir Hinweise für erhöhte Anfälligkeiten und die Notwendigkeit einer sorgfältigen Überwachung durch die Bankenaufsicht.

Bundesbank Discussion Paper No 23/2020

Interbank Risk Assessment – A Simulation Approach*

Maximilian Jager
University of Mannheim

Thomas Siemsen

Johannes Vilsmeier
European Central Bank

Abstract

We introduce a novel simulation-based network approach, which provides full-fledged distributions of potential interbank losses. Based on those distributions we propose measures for (i) systemic importance of single banks, (ii) vulnerability of single banks, and (iii) vulnerability of the whole sector. The framework can be used for the calibration of macro-prudential capital charges, the assessment of systemic risks in the banking sector, and for the calculation of banks' interbank loss distributions in general. Our application to German regulatory data from End-2016 shows that the German interbank network was at that time in general resilient to the default of large banks, i.e. did not exhibit substantial contagion risk. Even though up to four contagion defaults could occur due to an exogenous shock, the system-wide 99.9% VaR barely exceeds 1.5% of banks' CET 1 capital. For single institutions, however, we found indications for elevated vulnerabilities and hence the need for a close supervision.

Keywords: Interbank contagion, credit risk, systemic risk, loss simulation

JEL classification: G17, G21, G28

*Contact address: European Central Bank, Kaiserstrasse 29, 60314 Frankfurt am Main, Germany, e-mail: *johannes.vilsmeier@ecb.europa.eu*. Discussion Papers represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

1 Introduction

The Basel Committee on Banking Supervision outlines five central factors of systemic relevance of banks in its assessment methodology for global systemically important banks (G-SIBs): cross-jurisdictional activity, size, interconnectedness, substitutability, and complexity (Basel Committee on Banking Supervision, 2013). Each of those components is deemed equally vital in judging a bank's importance for the global financial system. Three out of the five determinants can be assessed using straightforward indicators, namely size through total exposures, cross-jurisdictional activity through cross-jurisdictional balance sheet positions, and substitutability through contribution to (domestic) financial infrastructure, which comprises, e.g., the amount of assets under custody. The remaining two are harder to gauge since, by its nature, the importance of single elements in huge networks is hard to assess and the complexity of financial institutions is a rather abstract concept. Currently, the Basel Committee uses amounts of OTC derivatives, level-3 assets, and trading securities as proxies for the complexity of a financial institution. Moreover, interconnectedness is measured by intra-financial system balance sheet positions.

The latter approach, though easy to implement, falls short of accounting for the structure of the network. It is clearly not sufficient to look at the mere amount of, e.g., interbank lending; instead, one needs to investigate the specific linkages through which the liabilities spread through the system. A medium-sized bank may have a comparably low outstanding amount of interbank positions, but may at the same time serve as the primary lender for a considerable number of small(er) banks. Hence, the default of this medium-sized bank can have a higher system-wide impact than the default of a large bank with a high volume of interbank positions which is, however, evenly spread among a lot of other large and sound banks.

We propose a new method for measuring the systemic risk component which is due to interconnectedness to resolve the described problem of ignoring the network structure. Our simulation-based contagion approach uses information that is readily available to any supervisory authority, which is exactly the kind of institution for which this type of analysis is of use, since supervisors need to take a stance on the stability of their domestic banking system, as well as the systemic relevance of single institutions (e.g. when calibrating domestically systemic important bank (D-SIB) buffers).

Many studies are concerned with measuring contagion effects on the basis of the network structure in the (domestic) interbank lending market, e.g. for Austria (Elsinger, Lehar, and Summer, 2006), Belgium (Degryse and Nguyen, 2007), the Netherlands (Lelyveld and Liedorp, 2006), Italy (Mistrulli, 2011), the US (Furfine, 2003), or even for the global market (Kanno, 2015). For German data, which we will use in this paper, Upper and Worms (2004), Memmel and Sachs (2013) and Fink, Krüger, Meller, and Wong (2016) can be named as references. Most of these studies rely on the sequential default algorithm as proposed by Furfine (2003) which allows to trace the network effects of single defaults. They use this algorithm to simulate the default of one bank after another to measure the impact every single bank has on the network. Our approach is more in the spirit of Elsinger et al. (2006), as we approximate all possible network events by simulation, i.e. also events where more than one bank defaults at the same time, which allows us to study the whole distribution of potential interbank losses for each institution.[1] We go beyond the seminal analysis of Elsinger et al. (2006) by endogenizing the probability of default during the scenario simulation, i.e. we track not only the losses induced by the exogenous defaults but also the PD effect of off-writes that do not cause an immediate default of the affected bank. Closest to our analysis are those by Drehmann and Tarashev (2013) and Fink et al. (2016), although both only look at effects at the expected loss level while we provide the whole distribution of possible outcomes. Moreover, Fink et al. (2016) analyse the system by shocking banks' capital, respectively the risk-weights of banks' portfolios. These shocks are exogenously set and meant to simulate an economic downturn. Our analysis, however, focuses on the status quo of the German interbank market.

We are additionally embed in the strand of literature that is concerned with deriving systemic risk indicators and assessing the stability of financial networks. Recent and seminal contributions to the field are CoVaR (Adrian and Brunnermeier, 2016), SRISK (Brownlees and Engle, 2016), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Acharya, Pedersen, Philippon, and Richardson (2017) and Hautsch, Schaumburg, and Schienle (2014). The CoVaR is a reduced-form measure focusing on the tail-dependence of an institution's loss distribution. This ignores large parts of the stress dynamics, as it disregards the remainder of the respective distribution's probability mass. Acemoglu et al. (2015) develop a theoretical model that helps in understanding the importance of the network structure for systemic risk but that cannot, due to its stark theoretical assumptions, be implemented easily as a practical assessment tool. It is, however, of interest to compare our empirical results to the implications stated in Acemoglu et al. (2015). The approach by Hautsch et al. (2014) infers network interdependencies from public data. Their model, however, only captures systemic risk of single banks at the quantile level (e.g. contribution at the 95% VaR level), while our approach yields the whole distribution of potential losses for both single banks and the system, thus nesting the idea of Hautsch et al. (2014). Acharya et al. (2017) do not explicitly take into the account the structure of the network and neither does the SRISK, which is, moreover, market-based, making it subject to noise as well as to the standard critique of only capturing risk that has already materialized.[2] Therefore, our methodology goes beyond these studies by deriving network-based measures for (i) systemic importance of single banks, (ii) vulnerability of single banks, and (iii) vulnerability of the whole sector, exclusively on the basis of regulatory data.

We therefore contribute to the literature in three ways: (i) we provide a comprehensive framework for regulatory authorities to supervise the systemic importance of single institutions as well as the vulnerabilities in their respective banking sector; (ii) we make use of a novel simulation-based approach to derive full-fledged distributions of potential interbank losses; (iii) we offer a tractable alternative to the G-SIB methodology for assessing the systemic importance of banks that can be used for G-SIB, D-SIB, and other systemically important banks (O-SIB) classifications.

We apply our model to the German interbank market data as of end-2016. We find that the German interbank market was at that time generally resilient to bank defaults with

[1] For a review of simulation-based approaches in modeling contagion in interbank networks, see Upper (2011).

[2] For a recent critical assessment of market-based tools, see, for example, Löffler and Raupach (2017).

a system-wide 99% (99.9%) Value at Risk of 789 (2,813) million euro, which corresponds to 0.4% (1.4%) of the common equity tier 1 capital of the examined banks. In general, regardless of the structural shock, no more than four contagion defaults were found.

For single institutions, however, we find substantial contagion risks, where the most vulnerable banks in our sample had 99.9% Values at Risk, equaling up to 19% (45%) of their (excess) capital. Hence, despite there being a stable system, supervisors need to carefully assess the situation of single institutions from a microprudential perspective to avoid an excessive exposure to interbank contagion risks.

Our systemic risk indicator has a correlation of 61% with the assessment of the systemic risk component due to interconnectedness proposed by the Basel Committee, which considers the volume of interbank balance sheet positions only. Thus, even though a larger exposure is clearly positively related to a larger systemic risk contribution, there is obviously more to the picture, which can only be covered by taking into account the structure of the network.

Finally, we show the importance of obtaining unconditional fully-fledged interbank loss distributions as opposed to scenario-specific losses by highlighting non-linearities of interbank losses at distributions' tails. Our distributional approach allows to evaluate the dependence of our risk measures to the chosen confidence level and thereby extends our scope beyond that of comparable exercises undertaken in the literature.

The remainder of the paper is structured as follows: Section 2 depicts the methodology of the simulation-based approach, Section 3 introduces the data set and its peculiarities, Section 4 describes the results. Lastly, Section 5 contains concluding remarks.

2 Methodology

In this section we will describe our simulation mechanism, with the main structure being summarized in Figure 1. Before we can simulate default scenarios in our network, we first have to initialize a PD for every bank. For this purpose we use the profit and loss history of each bank and its current level of common equity tier 1 capital. We define default as a situation where the CET 1 ratio drops below an exogenous threshold θ. Hence, each bank's excess capital is defined as $EC_i = (CET1_i - \theta \cdot RWA_i)$. We fit a generalized skewed t-distribution onto the profit history by maximum likelihood technique, i.e.

$$maxL(\mu, \sigma, \lambda, p, q|PL_i) = \frac{p}{2v\sigma q^{1/p} B(\frac{1}{p}, q)(\frac{|PL_i - \mu + m|^p}{q(v\sigma)^p(\lambda sign(PL_i - \mu + m) + 1)^p} + 1)^{\frac{1}{p} + q}} \quad (1)$$

where PL_i refers to the profit/loss history of the bank i.[3] We use the cumulative distribution function to obtain the probability of having a loss equal to or larger than the bank's excess

[3] The generalized skewed t-distribution, which was first introduced by Theodossiou (1998), enjoys great popularity among practitioners in risk management. Its advantage over a standard t-distribution are that one can individually control the first four moments via the parameters $\mu, \sigma, \lambda, p, q$, which enables a very flexible way of modelling financial data, which is often strongly leptokurtic and left-skewed. Since these properties also apply to the profit loss time series, which we feed in the maximum likelihood estimation, the usage of the generalized skewed t-distribution seems justified.

capital, which we define as the probability of default:

$$PD = F_i(-EC_i), \tag{2}$$

where F_i is the cumulative distribution function for the skewed t-distribution of bank i with the parameters obtained by equation 1. In alignment with the European standard for counterparty risk evaluation as set out in CRR 160(1), we floor the PDs at 3 bps to avoid underestimating PDs due to the backward-looking nature of the estimation. The German interbank profit and loss history was hardly, if at all, influenced by contagion effects in the past, since almost no defaults of major banks occurred. We therefore label the PDs which we obtain by this approach as the "structural PDs", as they indicate how likely a bank will default due to any exogenous shock that is orthogonal to contagion effects. In contrast, we label the PDs that we obtain after the network simulation as the "contagion-augmented PDs", as they account not only for exogenous shocks but also for the endogenous network-contagion effects. The difference between those PDs indicates how much a bank is exposed to contagion risk.

Starting in round t=0

1. Initialize $PD_{i,t}$ for each bank $i \in \{1, 2, ..., K\}$ using equations 2.1 and 2.2

2. Draw $outcomes_{i,n}$ for each bank i from $Bern(PD_{i,t})$ to generate N scenarios

3. For each $n \in \{1, 2, ..., N\}$:
   3.1. If $outcome_{j,n}$ = "default" $\rightarrow IBloss_{i,j} = IBexposure_{i,j} \; \forall i$
   3.2. Each $CET1_i$ reduces by $\sum_{j=1}^{K} IBloss_{i,j}$
   3.3. If $\frac{CET1_i}{RWA_i} < \theta$ for at least one $i \rightarrow$ set $PD_{i,t+1} = 1$
   3.4. If $\sum_{i=1}^{K} \sum_{j=1}^{K} IBloss_{i,j} = 0 \rightarrow$ terminate algorithm for this n
   3.5. Set $t = t + 1$ and repeat steps 1, 2, and 3, with $PD_{i,t}$ in step 2 being
   the difference between $PD_{i,t-1}$ and $PD_{i,t}$

Figure 1: Baseline Contagion Algorithm

After obtaining the PDs, we simulate N sets of outcomes for which we can analyze the repercussions throughout the network. Each of the N sets consists of a vector that summarizes the binary events for each bank. These events are drawn individually from the Bernoulli distribution $Bern(p)$, with p being equal to the respective PD of each bank. We thus have N scenarios, where in every scenario we observe a number of defaults between 0 and K, where K is the number of banks in the sample. For each of those scenarios, we then track the losses ($IBloss$) that are induced by interbank exposure ($IBexposure$) which has to be written off due to defaults of debtors. Because of this so-called first round effect, the equity of each bank is reduced by the losses it suffered and so, in turn, is the excess capital.[4] Hence, a new PD for each bank has to be calculated via equation 2. In the upcoming rounds, which no longer consider banks that have already defaulted, new scenarios are generated using the difference between the PD of the last finished round and the current round. This means only the *increase* in the PDs caused by contagion and the defaults this potentially provokes are studied in the higher rounds. The algorithm stops without analyzing further rounds if no more defaults/losses occur.

After running the simulation, one can quantify the "contagion-augmented" PD for each bank by

$$PD = PD_0 + \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T}\left(\prod_{j=0}^{t-1}(1-\Delta PD_j)\right)\Delta PD_t, \tag{3}$$

where PD_i is the PD of round i during the simulation, making PD_0 the initial "structural" PD and PD_1 the probability of defaulting in round 1 after surviving the structural shock in round 0, and $\Delta PD_t = PD_t - PD_{t-1}$ with special case $\Delta PD_0 = PD_0$.

To assess the vulnerability one can, moreover, take a look at the simulated loss distribution for each bank, which reads

$$C\hat{D}F^{i}_{Loss} = \hat{P}^{i}(Loss \leq x) = \frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{K}\mathbb{1}\{IBloss^{j}_{i,k} \leq x\}, \tag{4}$$

where $IBloss^{j}_{i,k}$ is the interbank loss realized for bank i due to default of bank k in simulation run j.

Beyond the single bank level, we provide the possibility to evaluate the vulnerability of the whole system. For this purpose, we can quantify the system-wide risk as the Value at Risk or Expected Shortfall at a given confidence level by using the aggregate loss distribution of all banks. That is, the VaR can be computed as:

$$C\hat{D}F_{Loss} = \hat{P}(Loss \leq x) = \frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{K}\mathbb{1}\{\sum_{i=1}^{K} IBloss^{j}_{i,k} \leq x\} \tag{5}$$

$$VaR^{\alpha}_{full} = C\hat{D}F^{-1}_{Loss}(\alpha) \tag{6}$$

To analyze whether the system-wide vulnerabilities are driven by single banks or are instead widely spread across a large set of banks, we calculate for every bank the share of its Value at Risk in the sum of Value at Risks across the system:

$$VS^{\alpha}_{i} = \frac{VaR^{\alpha}_{i}}{\sum\limits_{j=1}^{N} VaR^{\alpha}_{j}}, \tag{7}$$

[4] In the baseline analysis we assume the RWA to be fixed across the simulation.

where VS_i^α corresponds to the vulnerability share of bank i at the α level.
Beyond this simple metric, we can quantify the systemic risk caused by single banks by re-running the whole procedure outlined above K times, dropping one bank at a time. This allows us to decompose moments of the interbank loss distribution obtained in a run with all K banks onto the sub-runs with $K-1$ banks to quantify the contribution of a respective bank to the system-wide losses.[5] In rigorous terms:

$$SI_i^\alpha = \frac{VaR_{full}^\alpha - VaR_{-i}^\alpha}{VaR_{full}^\alpha}, \tag{8}$$

with SI_i^α being the systemic importance of bank i at confidence level α, VaR_{full}^α being the system-wide Value at Risk at level α for the run with all banks, and VaR_{-i}^α the same Value at Risk for the sub-run without bank i.
Let us emphasize that even though we call the variable Value at Risk, our approach is not limited to looking at tail events. By using different α values, one can assess the vulnerabilities and risks at any given level. This is an important feature, as some banks may contribute strongly to the "normal" state of the network while they contribute far less to possible tail events, and vice versa.

3 Data

We apply the framework to the German interbank market. The German banking sector consists of a large number of highly heterogeneous banks in terms of both size and business models. Of the about 1,700 credit institutions, 21 banks are labeled as systemically important. The remainder mostly consists of small and medium sized banks (so-called less significant institutions), which mostly pursue a plain vanilla savings-and-loans business model and have only limited interbank exposures. To derive the matrix of interbank exposures, we use the Bundesbank's Credit Register, which contains loan-level data for any exposures larger than €1.0 million at a quarterly frequency. While the floor on loan size is likely to filter out large shares of the retail business, we believe the constraint to be less binding for interbank loans. We use the data as of 2016Q4. Table 1 summarizes descriptive statistics for interbank exposures derived from the Credit Register. In the baseline scenario – to economize on computation time – we constrain our analysis to the interbank network of the 50 banks with the largest interbank exposure, which cover 85% of the interbank exposure in the market.[6]
Figure 2 shows a showcase snapshot of the constrained interbank network. The network can be described by a standard core-fringe relationship: it features a core of a few, highly interconnected banks and a fringe that relies on interbank loans from core banks, without

[5]Even though the underlying mechanism differs strongly, the conceptual idea is close to the Systemic Expected Shortfall (SES) by Acharya et al. (2017).

[6]Given the binary nature of the default variable, there are 2^K possible outcomes, where K is the number of banks considered. Therefore, the number of outcomes that have to be simulated to sufficiently approximate the actual distribution of possible outcomes rises exponentially with the number of banks. In order to assess the appropriate number of simulated outcomes, we gradually increased the number of N keeping K fixed and stopped at the point where the interbank loss distribution converged, i.e. did not change further for a higher N. The number obtained by this approach for $K = 50$ is $N = 950,000$.

supplying loans themselves.

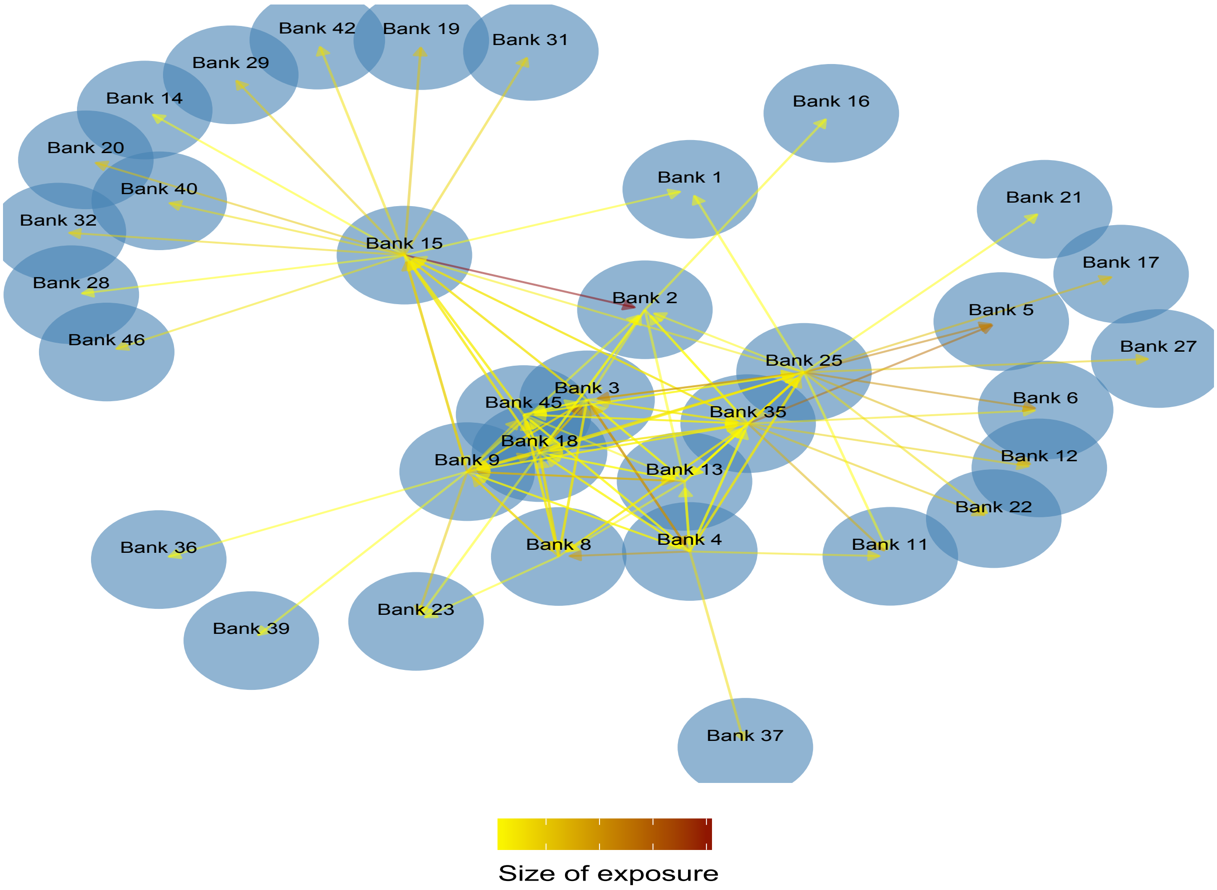
Bank-specific starting values for common equity tier 1 capital, capital ratios and risk-weighted assets are taken from the 2016Q4 Common Reporting Framework (COREP). The history of profit and losses, used to calculated implied probability of default, is taken from the annual banking statistics for the years 1992 to 2016 at the bank level.

Table 1: Interbank loans data - Descriptive statistics

	Mean	25% Quantile	50% Quantile	75% Quantile
Interbank loan size (mln €)	170.7	1.0	10.9	67.7
No. of loans per lender	28	9	12	45
No. of loans per borrower	2.4	1	1	2

No. of interbank loans	924
No. of lenders	33
No. of borrowers	382

Notes: Interbank loans data taken from the Bundesbank's Credit Register as of 2016Q4.



Notes: The color of the link indicates the size of the interbank exposure relative to borrower's assets.

Figure 2: Snapshot from constrained interbank network

4 Results

The following section summarizes the results obtained by running our model for the subsample of the $K = 50$ banks with the highest interbank exposure. The presentation is split into the three concepts of (i) single-bank vulnerability, (ii) system-wide vulnerability, and (iii) single bank systemic risk contribution. Due to the confidential nature of the data, the results are mostly presented in an aggregated manner so as to ensure that banks cannot be identified through the results. For the baseline analysis we set $\theta = 0.085$.[7]

4.1 Single-bank vulnerability

For an impression of the vulnerabilities that single banks face, Figure 3 shows the distribution of the interbank losses normalized by equity averaged over the banks in our sample. The

[7]We arrive at 8.5% by considering both Pillar 1 and Pillar 2 requirements as well as the capital conservation buffers.

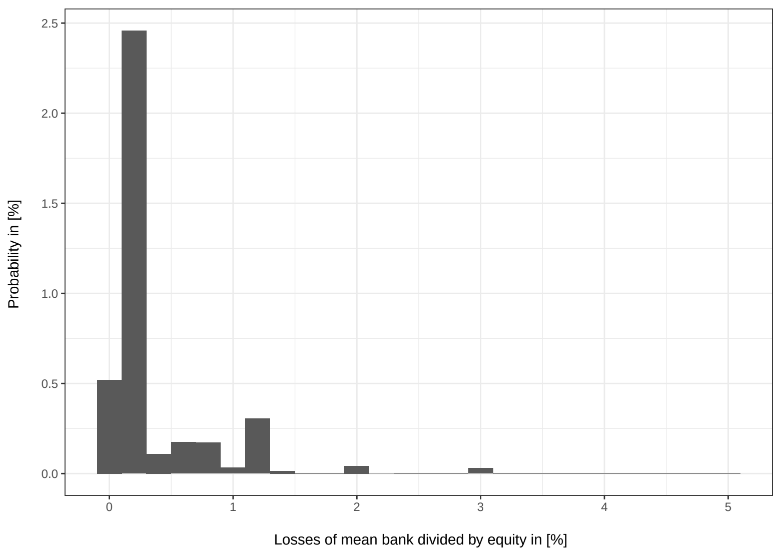
vulnerabilities appear mild, with a substantial probability for the average bank of 3.9% of losing between 1% and 2% of its equity, but with only a 0.34% probability of losing more than 2% of equity due to contagion effects. Thus, on average, German banks appeared not particularly vulnerable to contagion risk as of end-2016.

To obtain a broader picture, we next take a look at the loss distributions for banks at different percentiles across our sample. That is, we rank the banks by the average loss they suffer during the contagion simulations and present the results for the banks that are below the γ-percentile in this ranking in Figure 4.

This inspection reveals a strong heterogeneity across banks. While banks below the 25% quantile hardly suffer any economically meaningful losses, the probability of such losses rises sharply at the median and even more so at the 75% and 90% quantile. To be more precise, the probability of obtaining a loss higher than 5% of the disposable equity rises from 0.15% over 0.74% and 1.43% to 2.43% along the quantiles.

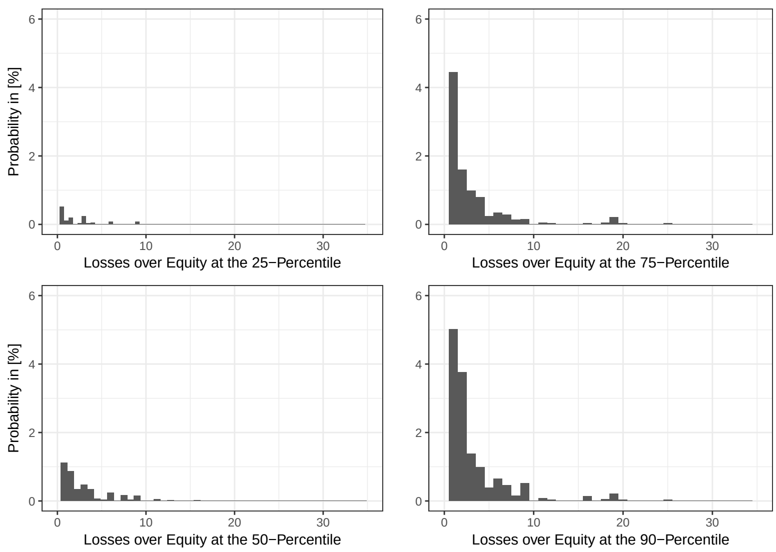
Since this suggests that specific institutions had a very strong exposure to contagion risk, we investigate the 99.9% Value at Risk of banks divided by their CET1 capital. Quantiles of these values (excluding zeros, as for some banks the risk of obtaining losses larger than 0 is extremely small) can be seen in Table 2. A considerable set of banks would lose between 6.5% and 8.9% of their capital if the 99.9% VaR materialized, whereas the most vulnerable banks would even lose more than 12.2%. These values may give rise to concern, as one has to keep in mind that this would be the effect of the interbank contagion only. Suffering a shock that causes contagious spillovers would most likely induce further losses via the non-MFI loan channel, the asset channel, and others, making the respective bank strongly vulnerable.

Next, we take a look at the "contagion-augmented" PDs and examine how much they differ from the "structural" PD. Generally, the "contagion augmented" PDs are not substantially higher than the "structural" PDs with growth rates of between 0.02% and 0.7% and a mean rise of 0.1 bp. This is related to the fact that the PD only reacts to the most extreme tail events, with losses exceeding 100% of the excess capital, which are extremely rare cases (cf. Table 2).



Notes: Only losses larger than zero are shown.

Figure 3: Simulated interbank loss distribution of average bank - normalized by equity



Notes: Only losses larger than zero are shown.

Figure 4: Simulated interbank loss distributions divided by equity at different percentiles across the bank sample

Table 2: Quantiles for Value at Risk

Quantile	10%	25%	50%	75%	90%
$\frac{VaR^{99.9}}{CET1}$	1.92%	3.30%	6.48%	8.86%	12.18%

Note: Only banks with Value at Risk larger than zero are considered.

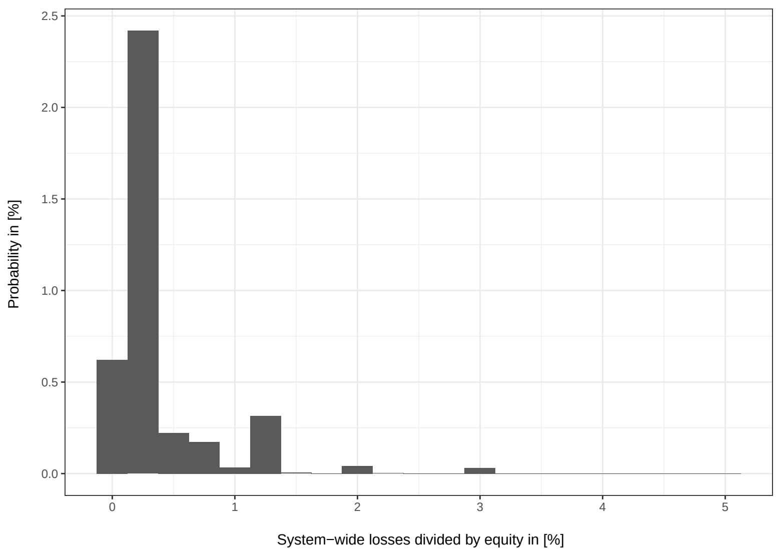
4.2 System-wide vulnerability

Similar to the metrics above, we will look at the system-wide loss distribution, the system-wide α-Value at Risk, and the system-wide α-Value at Risk standardized by the available capital of the banking sector. Figure 5 shows the distribution of the system-wide losses standardized by equity, revealing a similar picture to that of the mean bank. The probability of having a loss larger than 0 but smaller than 1% of available capital amounts to 3.4%, while the probability of obtaining a loss larger than that is around 0.42%, respectively.
The Values at Risk for the system on the 99% and 99.9% level are 789 million and 2,813 million euro, respectively. This represents 0.40% (0.83%) and 1.43% (2.97%) of the system's (excess capital), respectively.
Moreover, regardless of the structural shock scenario, the number of contagion defaults in the simulation run never exceeds four. It can therefore be concluded that the system appears resilient to contagion risk. Even a severe tail event would not induce a loss of more than 3% of the excess capital available to banks to cover the losses. Lastly, an inspection of the vulnerability shares of each bank at the 99.9% level shows that there are 12 banks whose $VS_i^{99.9\%}$ exceeds 3%. Hence, a wide range of banks adds to the system-wide vulnerability which is, in turn, not clustered at a single institution. An overview of the quantiles of vulnerability shares across banks can be found in Table 3.

Table 3: Quantiles for banks' share in system-wide vulnerability

Quantile	10%	25%	50%	75%	90%
$VS_i^{99.9}$	1.34%	2.06%	4.00%	7.58%	10.54%

Notes: Only banks with Value at Risk larger than zero are considered.



Notes: Only losses larger than zero are shown.

Figure 5: Simulated interbank loss distribution of whole system - normalized by equity

4.3 Single bank systemic risk contribution

We now review the results of the main part of the analysis, which is the assessment of the systemic risk contribution, since we propose our tool as an alternative to the recommendations by the Basel Committee (BC from here on). Table 4 shows the quantiles for systemic risk contribution of banks. The mean value of the $SI_i^{99.9}$ of the banks with significant contributions is roughly 2.44%, meaning that an average bank in this sub-sample is responsible for around 2.5% of the system-wide risk.[8] While banks' importance can rise up to 20% of the system-wide risk, one can see that the risk is rather well diversified in the German banking market, as there are 10 banks with contributions higher than 2.5% to the systemic risk. However, the three banks with the highest systemic risk contribution are responsible for around 40% of the system-wide contagion risk showing some signs of risk clustering.

To benchmark the assessment of the systemic risk contribution, we calculate (rank) correlations between our measure and the sum of interbank balance sheet positions (as proposed by the Basel Committee) as well as the sum of risk-weighted assets (as a natural benchmark, since larger banks usually emit larger risks). The (rank) correlation between our measure and that of the BC is 61.7% (56.74%) and the (rank) correlation between our measure and the sum of risk-weighted assets is 79.8% (51.1%).[9] This shows that even though a clear positive relationship exists between the volume of interbank balance sheet positions and systemic relevance for the network, the structure of the network is highly important. Disregarding the

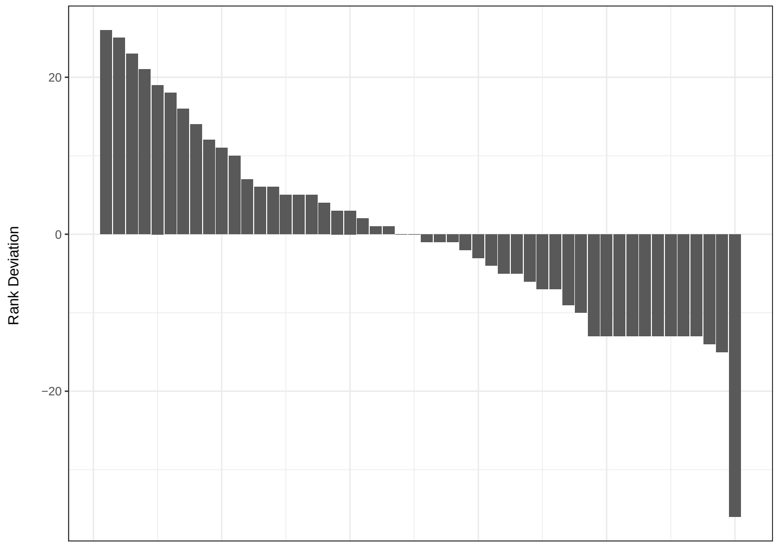
[8]Including all banks, this number shrinks to 2%.

[9]These correlations were obtained using the $SI_i^{99.9}$. As can be seen in the following analysis of the tail behaviour of the loss distributions, these correlations could look different for other α-levels. From a regulatory perspective, the 99.9-level seems representative, however.

structure as proposed by the Basel Committee can lead to serious misjudgments. To give an example of this, Figure 6 shows the deviations of the ranks for our 50 banks obtained from ranking via $SI_i^{99.9}$ and from ranking via the BC. These deviations can go in both directions and can be as high as 26 positions. Considering the size of the sample for the G-SIB exercise, the impact of such a mis-ranking can be substantial.
These results emphasize the importance of taking the network structure into account when assessing systemic importance. Our approach provides a traceable method to measure network-structure-sensitive systemic importance relying solely on regulatory data.

Table 4: Quantiles for banks' systemic risk contribution

Quantile	10%	25%	50%	75%	90%
$SI_i^{99.9}$	0%	0.78%	0.92%	1.16%	5.21%



Notes: Positive deviation means that the rank obtained via SI_i^{α} is higher than the one obtained by the BC. A higher rank corresponds to lower risk.

Figure 6: Deviations between the ranking by SI_i^{α} and the ranking by the BC

4.4 Importance of fully-fledged distributions

To provide an insight into the importance of obtaining unconditional fully-fledged distribution as opposed to scenario-specific losses (as is common in the literature), the sensitivity of the results to the choice of α are depicted in the following.
To this end, Table 5 lists the respective quantiles for VaR^{α}, the VS^{α}, and the SI^{α} for the α levels of 95%, 99%, 99.9%, and 99.99%. When looking at the VaR levels, one can clearly see how the severity of the losses divided by equity sharply rises in a non-linear fashion along the α-dimension. For example, the VaR for the most vulnerable banks rises from 0 over 2% and 12% up to 21% of their respective equity when increasing the α. Thus, depending on

the supervisor's desired confidence level, the risks can be seen as negligible (95%, 99%) or as severe (99.9%, 99.99%).
When looking at the shares of single banks' vulnerability in the system-wide vulnerability, the picture remains relatively stable across the α-levels. The vulnerability share steadily increases from the low to the high percentiles, indicating a well-spread vulnerability share throughout the system. In fact, the vulnerabilities are more evenly spread at higher levels (99.9%, 99.99%) than at lower levels (99%).
Lastly, the systemic risk contribution of single banks, which already showed some clustering in the main analysis at the 99.9% level, reveals even stronger clustering at different confidence scales. Especially for $\alpha = 99.99\%$, the risk clustering is enormous, as below the median there is no risk contribution at all, at the 75% quantile there still is almost none contribution, and the 90% quantile has a contributional value of 5%, indicating that the remaining 95% of the systemic risk contribution are clustered at the very small subset of banks above the 90% quantile. This clearly highlights the importance of looking at the whole distribution, since certain figures and evaluations are strongly driven by the α level of the assessment, and an encompassing analysis is only feasible by looking at the distributional behavior, especially at the tails.

Table 5: Quantiles for all metrics – different α levels

Quantile	10%	25%	50%	75%	90%
$\frac{VaR^{95}}{CET1}$	0%	0%	0%	0%	0%
$\frac{VaR^{99}}{CET1}$	0.03%	0.12%	0.43%	0.86%	1.99%
$\frac{VaR^{99.9}}{CET1}$	1.92%	3.30%	6.48%	8.86%	12.18%
$\frac{VaR^{99.99}}{CET1}$	4.80%	7.48%	9.21%	16.05%	20.80%
VS_i^{95}	0%	0%	0%	0%	0%
VS_i^{99}	0.17%	2.36%	7.96%	14.20%	18.35%
$VS_i^{99.9}$	1.34%	2.06%	4.00%	7.58%	10.54%
$VS_i^{99.99}$	0.74%	1.60%	4.00%	7.86%	11.33%
SI_i^{95}	0%	0%	0%	0%	0%
SI_i^{99}	0%	0%	0%	3.04%	5.60%
$SI_i^{99.9}$	0%	0.78%	0.92%	1.16%	5.21%
$SI_i^{99.99}$	0%	0%	0%	0.06%	5.03%

Notes: Only banks with Value at Risk larger than zero are considered for VaR and VS.

4.5 Discussion

Our simulation setup gets by almost without any statistical or parametric assumptions; some economic assumptions are inherent, however. The baseline setup keeps the sum of RWAs for each bank constant across the simulation. If banks fail, however, the risk weight of assets may change and banks might be incentivized to rebalance their portfolio, both of which could have a significant impact on the RWA. It is, however, hard to predict, especially at the bank level, which direction and magnitude the effects will have, which is why we decide to keep the RWA constant.[10] Moreover, one could consider collateral, since in our data set 8.4% of the total interbank loan amount is collateralized. Taking this into account does not qualitatively affect the results and is not preferred, as the banks' own valuation of collateral appears doubtful in some cases in the data set. The full default threshold is, as many other (implicit) assumptions, set to be as conservative as possible with $\theta = 8.5\%$ in the baseline scenario. Even though lowering this threshold has very little effect on the qualitative results, we prefer the 8.5% specification as it represents a point at which regulatory action for the particular bank seems inevitable, thus corresponding to a serious incision in banks' business despite not having formally defaulted.

Regarding the PD calculation, the assumption of a skewed t-distribution is backed by statistical tests showing the highest fit for the skewed t as compared to other standard distributions when applied to our profit/loss data. Moreover, the 3bp floor is based on regulatory standards and is binding for a majority of banks in the sample, which makes our scenario as conservative as possible (without compromising reasonability). A further possible amendment would be to assume that banks can still pay back parts of their loans even though they "defaulted", but this would again make the scenario less conservative.

Lastly, one has to keep in mind that we only observe interbank linkages within Germany even though, especially for large, internationally connected banks, exposure to foreign banks may make up a substantial part of their interbank loan portfolio. One might consider a factor that rescales the vulnerability and risk measures on the basis of the share of foreign interbank exposure, which would, however, be imprecise.

Our simulation of interbank loss scenarios has shown that the German interbank market appeared very resilient as of end-2016, with an evenly spread contribution to systemic risk among a considerably large set of banks, and only very few single institutions with vulnerabilities. Whereas this is a robust and unambiguous finding, it is important to discuss the scope of the conducted analysis. By construction, in our approach, which focuses on contagion risk, only banks that are lenders can actually reveal vulnerabilities by having borrowers who default or whose probability of default rises, which naturally limits us in making statements about banks that are borrowers only. It can, however, be the case that the default of a bank such as "Bank 15" in Figure 2 can have severe consequences for the banks that are its borrowers as they may run into liquidity problems. Such a feature cannot be captured by our approach and is hard to gauge in general, even though the substitutability measure as proposed by the Basel Committee might serve as a possible way of implementing the importance of defaults on liquidity risk in the network.

Generally speaking, the focus of our tool is to provide a basic, comprehensible, and tractable way to assess contagion risks in a domestic banking sector. On the other hand, there are no limits whatsoever as to which additional features and/or risk classes can be added to the framework. The recent literature offers a vast list if possible amendments, such as modeling changes to the LGD Memmel and Sachs (2013), taking into account market risk (Elsinger et al., 2006) or augmenting the model by market data (Hautsch et al., 2014). Furthermore, while we present a static analysis for the status quo in 2016 Q4[11], one could also look at

[10] One possible way of modeling this can be found in Fink et al. (2016).

[11] Recent evidence in the literature (Garcia-de Andoain, Heider, Hoerova, and Manganelli, 2016) has shown

the development of the results over time and/or study specific events, as is done in Iyer and Peydro (2011).
All these features and risk classes naturally add to the overall picture of understanding vulnerabilities and systemic risk contributions of banks and are thus worth studying. Nevertheless, this paper focuses on providing a tool to supervisors and policy makers which helps them to easily assess contagion risks without disregarding the network structure. To facilitate applications, we will provide the code of our framework to supervisors upon request. The framework requires as inputs a interbank exposure matrix, CET1-ratios and history of profit and losses for all banks in the network, which is information available to most supervisors. The framework can be used to classify banks as (domestically) significant, to calibrate (D-)SIB buffers, or to obtain an adequate sum to equip a rescue fund with.

5 Conclusion

This study presents an assessment tool for interbank lending networks. The simulation-based framework allows to study (i) the vulnerabilities of single banks, (ii) the vulnerability of the banking sector as a whole, and (iii) the systemic risk contribution of single banks. The proposed method relies on very few assumptions and is thus very tractable and stable. Application to the German interbank market reveals that the market as a whole appeared resilient to shocks as of end-2016, as the potential contagion losses was almost negligible with the 99.9% system-wide Value at Risk being 2,813 million euro (i.e. 1.43 % of the available equity). Single institutions, however, seemed quite vulnerable to domestic interbank shocks with a 99.9% Value at Risk of up to 19% of their equity. The systemic risk was made up of significant contributions of a set of approximately 10 banks, hence showing that the risk was well diversified in the banking system, even though some clustering can be observed at the very top, as three banks are responsible for 40% of the system-wide contagion risk. When comparing our approach, which explicitly takes into account the structure of the network, with the interconnectedness measure as proposed by the Basel Committee, which simply looks at the magnitude of banks' interbank balance sheet positions, we find that the deviations can be substantial. Ranking the banks according to our systemic risk contribution measure SI_i^{α} and ranking them according to the Basel Committee approach yields differences in the ranks of up to 26 positions. That is, a bank which is among the top five systemic risk contributors may be judged as being only in the range of the top 30 by the Basel Committee, thus implying huge drawbacks. We, moreover, highlight the importance of obtaining fully-fledged distributions of losses, as the risk assessment strongly depends on the particular confidence level and only a distribution allows to study the magnitude and structure of this dependence.
On request, we will provide the code for our tool to supervisors and policy makers to facilitate the application of our approach.

that the interbank lending volumes have plummeted due to massive liquidity injections by the ECB, which could hint towards a comparably low usage of the interbank lending channel in our sample.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic risk and stability in financial networks. *The American Economic Review 105*(2), 564–608.

Acharya, V., L. H. Pedersen, T. Philippon, and M. Richardson (2017). Measuring systemic risk. *The Review of Financial Studies 30*(1), 2–47.

Adrian, T. and M. K. Brunnermeier (2016). CoVaR. *The American Economic Review 106*(7), 1705–1741.

Basel Committee on Banking Supervision (2013). Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement. Technical report, Bank for International Settlements.

Brownlees, C. and R. F. Engle (2016). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies 30*(1), 48–79.

Degryse, H. and G. Nguyen (2007). Interbank exposures: An empirical examination of contagion risk in the Belgian banking system. *International Journal of Central Banking 3*(2), 123–171.

Drehmann, M. and N. Tarashev (2013). Measuring the systemic importance of interconnected banks. *Journal of Financial Intermediation 22*(4), 586–607.

Elsinger, H., A. Lehar, and M. Summer (2006). Risk assessment for banking systems. *Management Science 52*(9), 1301–1314.

Fink, K., U. Krüger, B. Meller, and L. H. Wong (2016). The credit quality channel: Modeling contagion in the interbank market. *Journal of Financial Stability 25*, 83–97.

Furfine, C. (2003). Interbank exposures: Quantifying the risk of contagion. *Journal of Money, Credit, and Banking 35*(1), 111–128.

Garcia-de Andoain, C., F. Heider, M. Hoerova, and S. Manganelli (2016). Lending-of-last-resort is as lending-of-last-resort does: Central bank liquidity provision and interbank market functioning in the euro area. *Journal of Financial Intermediation 28*, 32–47.

Hautsch, N., J. Schaumburg, and M. Schienle (2014). Financial network systemic risk contributions. *Review of Finance 19*(2), 685–738.

Iyer, R. and J. L. Peydro (2011). Interbank contagion at work: Evidence from a natural experiment. *The Review of Financial Studies 24*(4), 1337–1377.

Kanno, M. (2015). Assessing systemic risk using interbank exposures in the global banking system. *Journal of Financial Stability 20*, 105–130.

Lelyveld, I. V. and F. Liedorp (2006). Interbank contagion in the Dutch banking sector: a sensitivity analysis. *International Journal of Central Banking 2*, 99–133.

Löffler, G. and P. Raupach (2017). Pitfalls in the Use of Systemic Risk Measures. *Journal of Financial and Quantitative Analysis 53*(1), 269–298.

Memmel, C. and A. Sachs (2013). Contagion in the interbank market and its determinants. *Journal of Financial Stability 9*(1), 46–54.

Mistrulli, P. E. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of Banking & Finance 35*(5), 1114–1127.

Theodossiou, P. (1998). Financial data and the skewed generalized t distribution. *Management Science 44*, 1650–1661.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability 7*(3), 111–125.

Upper, C. and A. Worms (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review 48*(4), 827–849.