Ranking Consistency of Systemic Risk Measures: A Simulation-Based Analysis in a Banking Network Model

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This version: 15. September 2016

Abstract:
In a banking network model, the ranking consistency of various popular systemic risk measures (SRMs) is analyzed. In contrast to previous studies, this model-based analysis offers the advantage that the sensitivity of the ranking consistency with respect to bank and network characteristics can easily be checked. The employed network model accounts, among others, for bank insolvencies as well as illiquidities, stochastic dependencies of non-bank loans as well as of liquidity buffer assets across various banks, bank rating-dependent volumes of deposits and interbank liabilities, and the funding liquidity reducing effect of fire sales of other banks. Within the assumed banking network model, it can be shown that, in general, the ranking consistency (measured by the rank correlation) of various SRMs is rather low. Furthermore, the ranking consistency can significantly vary, for example, for an increasing correlation between the returns of the liquidity buffer assets across banks, for an increasing degree of heterogeneity in the banks' balance sheets or with a changing network structure of the banking system. However, forecasting which effect a specific change in parameters, bank behavior or network characteristics has on the ranking consistency of SRMs in general seems to be rather difficult because the sign of the effect can be different for different pairs of SRMs.

Key words: banking network model, credit risk, funding risk, market risk, systemic risk

JEL classification: G01, G21, G28

[1] I thank Michael Abendschein for excellent research assistance. For helpful comments, I thank Alois Knobloch, Andreas Pfingsten and Bernhard Schwetzler as well as participants of the annual meeting of the German Academic Association for Business Research in Munich 2016.

1 Introduction

The question on how the aggregate systemic risk (i.e., the risk that many banks simultaneously suffer large losses and that these losses are then spread through the system (see Benoit et al. (2016, p. 2)) and the exposure and contribution to systemic risk of single banks could be measured has intensively been discussed in the academic world and by regulatory authorities in the past few years. During the financial crisis of 2007-2009, it became obvious that a purely microprudential regulation of banks is not sufficient to ensure the stability of the financial system as a whole, but that this method has to be supplemented by a macroprudential approach. Since then, as one element of a macroprudential supervision, systemic risk measures (SRMs) have been developed, on the one hand, to identify those financial institutions whose collapse would have the most harmful effect on the financial system, and, on the other hand, to identify those financial institutions who would be most significantly affected by a financial distress on the system level.

The regulatory authorities use an indicator-based approach to classify banks according to their systemic importance. The indicators are related to five broad categories: size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global (cross-jurisdictional) activity and complexity (see BCBS (2013)). In contrast, many of the popular SRMs proposed by academics rely on market and – partly additionally – on accounting data (see Section 3 for examples). Based on a theoretical banking network model, the goal of this paper is to analyse to which extent these SRMs yield comparable results with respect to the systemic risk of a financial institution and, in particular, on which determinants the degree of consistency of the classification by the various SRMs depends.

With respect to the literature on SRMs, various strands can be identified. First, there are papers in which the SRMs are introduced, motivated and empirically estimated the first time. Examples are Acharya et al. (2010, 2012), Adrian and Brunnermeier (2014) or Brownlees and Engle (2016). Acharya et al. (2010) introduce the Marginal Expected Shortfall (MES) which is defined as the expected equity return of bank i conditional on the market return being smaller than some low quantile. The ΔCoVaR measure of a bank i proposed by Adrian and Brunnermeier (2014) corresponds to the increase of the conditional Value-at-Risk (VaR) of bank i, given that the market return of the whole banking system switches from its median to values at (below) some low quantile.[2] This value is called the "exposure CoVaR" of bank i by Adrian and Brunnermeier (2014); it measures the extent to which an individual bank is affected by systemic financial distress. To measure the influence that financial stress of one bank i has on the whole banking system, Adrian and Brunnermeier (2014) also define the ΔCoVaR of the system where the conditioning is reversed. The SRISK-index proposed by Acharya et al. (2012) and Brownlees and Engle (2016) corresponds the expected capital shortfall of a bank i conditional on a system crisis.[3]

Second, in a large body of follow-up papers, existing SRMs are taken (more or less) as they are and empirically estimated on various kinds of data sets. Partly, it is tried to identify determinants that have a significant influence on the SRMs (e. g., features of the individual bank, such as size or leverage, or of the regulatory framework in which a bank operates). Examples of papers belonging to this second group are Döring et al. (2015), Engle et al. (2015), López-Espinosa et al. (2012) or Weiß et al. (2014a, 2014b). Döring et al. (2015) and Giglio et al. (2016) are also examples in which, the other way round, the prognostic power of SRMs for financial market and macroeconomic downturns is checked. Acharya et al. (2013) and Huang et al. (2012) analyse the relationship between macroeconomic stress test results and SRMs.

[2] Originally, Adrian and Brunnermeier (2014) proposed as conditioning event that the market return is at some low quantile. Later, Girardi and Ergün (2013) proposed to define as conditioning event that the market return is below some low quantile. The suitability of this modification compared to the original proposal of Adrian and Brunnermeier (2014) has also been discussed, among others, by Jiang (2012).

[3] Further alternative SRMs that have been proposed in the literature are, for example, systemic risk indices based on assets (SIV), on the number of banks (SIN) or on structural credit risk models (see Lehar (2005)), the DebtRank (see Battiston et al. (2012c)), the distressed insurance premium (DIP) (see Huang et al. (2009)), joint bank default probabilities and the bank stability index (see Segoviano and Goodhart (2009)), the index put option-based tail risk gamma (see Knaup and Wagner (2012)), measures based on the multivariate option iPoD methodology (see Matros and Vilsmeier (2014)), upper tail dependencies between pairs of returns of bank-specific credit default swap spreads (see Trapp and Wewel (2013)), lower tail dependencies between bank-individual and market equity returns (see Weiß et al. (2014a, 2014b)) or the realized systemic risk beta (see Hautsch et al. (2015)). For an extensive, early survey of SRMs, see Bisias et al. (2012), and for a more recent survey Benoit et al. (2016), who differ between global measures of systemic risk (such as MES, SRISK or ΔCoVaR) and those SRMs that are designed to measure specific sources of systemic risk (systemic risk-taking, contagion and amplification).

Third, in another group of papers, modifications, extensions or enhanced strategies for empirical estimation of existing SRMs are proposed. Examples are Girardi and Ergün (2013), Gravelle and Li (2013) or López-Espinosa et al. (2012, 2015). While, for example, Girardi and Ergün (2013) modify the conditioning event in the ΔCoVaR measure, López-Espinosa et al. (2012, 2015) modify the ΔCoVaR measure to capture asymmetric comovements between system-wide and individual bank returns in case of a positive and a negative shock.

Fourth, a much smaller group is formed by recent papers in which the ability of the proposed SRMs to consistently measure the systemic risk of financial institutions, their robustness and their relationship to historical systemic events are analyzed. Examples are Benoit et al. (2013), Brownlees et al. (2015), Danielsson et al. (2015, 2016), Jiang (2012), Löffler and Raupach (2013) and Zhang et al. (2016). First results in the literature show that correlations between SRMs are pretty much below one and that for different SRMs, different sets of variables are significant drivers of their variation over banks and time (see, e. g., Benoit et al. (2013), Bostandzic et al. (2014), Brownlees et al. (2015), Jiang (2012), Nucera et al. (2016)). Thus, from a theoretical point of view as well as from a practical perspective (for example, for the concerned bank itself), it is interesting to know how consistent different SRMs rank a financial institution according to its systemic risk and, in particular, to which extent this consistency depends on characteristic features of the individual bank balance sheets, the banking system and the market conditions. These questions can be addressed, for example, in an empirical way (see, e. g., Jiang (2012) or Benoit et al. (2013)). Alternatively, a theoretical research design is possible to analyse the ranking consistency of SRMs (see, e. g., Benoit et al. (2013) or Löffler and Raupach (2013)). For example, Benoit et al. (2013) assume in the theoretical part of their paper a bivariate GARCH process for the bank equity and market returns and analytically derive sufficient conditions for a ranking consistency between various popular SRMs. In this paper, an alternative theoretical approach is pursued. The ranking consistency of various SRMs is analyzed in a network model with interacting banks, in which the individual balance sheets dynamically evolve.[4] Hence, for example, equity returns can endoge-

[4] The idea to compute SRMs in a network model has also been expressed by Tom Hurd in a presentation at the C.R.E.D.I.T. 2013 conference in Venice.

nously be computed and no distributional assumptions on equity returns have to be made as in other papers on theoretical SRM comparisons. The main advantage of the theoretical network approach employed in this paper over a pure empirical analysis is that characteristic features of the banking network structure, the individual bank balance sheets or the market and regulatory environment in which banks operate can easily be modified to check their influence on the ranking consistency of SRMs. Furthermore, the results are not affected by sample composition/sample period issues (see Benoit et al. (2013, p. 4)). However, of course, the approach exhibits the disadvantage that model risk is prominent.

The modelling of networks of interacting banks and the analysis of financial stability in these network-based financial systems have intensively been debated in recent years (for an excellent overview on theoretical analyses of systemic risk and contagion in financial networks, see Chinazzi and Fagiolo (2015)). Meanwhile, modelling frameworks exist in which individual, interacting bank balance sheets are modeled and illiquidity as well as insolvency can cause a bank's default (see, e. g., Gai and Kapadia (2010), Gai et al. (2011) or Hurd et al. (2014)). For example, Gai and Kapadia (2010) show that the risk of the occurrence of a systemic crisis is smaller in networks in which the number of connections between banks is high, but, at the same time, the magnitude of a crisis is larger in such networks. Further related papers are, for example, Acemoglu et al. (2015), Allen and Gale (2000), Battiston et al. (2012a, 2012b, 2012c, 2016), Eisenberg and Noe (2001), Elliott et al. (2014), Freixas et al. (2000), Frey and Hledik (2014), Georg (2013), Glasserman and Young (2015), Iori et al. (2006), or Krause and Giansante (2012). The focus of the above mentioned papers is either on the derivation of rigorous mathematical results characterising the default dynamics in a bank network or on a simulation-based analysis of the default dynamics' dependence on the network parameters and its topology. Thus, in general, only the cascade of insolvencies and/or illiquidities after one or several banks are hit by a shock is modeled, but the 'life' of the financial institutions before a crisis is ignored. However, for analysing the ranking consistency of SRMs, both perspectives are needed. That is why existing models have to be extended by some important elements that describe the behavior of the banks and their interaction as well as the evolution of the balance sheet items in normal times.[5]

The main contributions of this paper to the literature are twofold. First, existing banking network models in the spirit of Gai and Kapadia (2010), Gai et al. (2011) and Hurd et al. (2014) are extended to describe the behavior of individual banks and their interaction in crisis as well as in non-crisis times sufficiently realistic (and, at the same time, to keep it numerically tractable). For this, important transmission channels for systemic risk, such as interbank linkages, common exposures to risk factors or fire sales, are incorporated.[6] Second, this banking network model is used to study the ranking consistency of various popular SRMs. In particular (and this is the main difference to related empirical papers, such as Nucera et al. (2016)), it is also studied which characteristic features of the bank-individual balance sheets, the network structure or the markets in which banks operate can significantly influence the ranking consistency of the SRMs.

Summarizing, the main results of the paper are: Within the assumed banking network, it can be shown that, in general, the ranking consistency (measured by the rank correlation) of various SRMs is rather low. This confirms empirically observed inconsistencies of SRMs reported in the literature. However, going beyond the pure description of inconsistencies found in previous studies, it can also be shown that the ranking consistency can significantly vary, for example, for an increasing correlation between the returns of the liquidity buffer assets across banks, for an increasing degree of heterogeneity in the banks' balance sheets or with a changing network structure of the banking system. Unfortunately, forecasting which effect a specific change in parameters, bank behavior or network characteristics has on the ranking con-

[5] Doing these extensions, network models in the spirit of Gai and Kapadia (2010), Gai et al. (2011) or Hurd et al. (2014) get closer to complex (partly macroeconomic) integrated risk management approaches, such as Aikman et al. (2011), Barnhill and Schumacher (2014) or Wong and Hui (2011), which are used for example for macro stress testing purposes.

[6] Benoit et al. (2016) group systemic risk sources in the three broad categories 'systemic risk taking', 'contagion' and 'amplification'. In the employed banking network model described in Section 2, mechanisms to create systemic risk out of all three categories are incorporated.

sistency of SRMs in general seems to be rather difficult because the sign of the effect can be different for different pairs of SRMs.

The remainder of the paper is structured as follows: In Section 2, the banking network model is presented. In Section 3, the employed SRMs are described and, in Section 4, the parameterization of the banking network for various model versions is introduced. In Section 5, the results are presented and discussed. Robustness checks of the results are done in Section 6. Section 7 discusses policy implications of the results and Section 8 concludes.

2 Banking Network Model

The construction of the banking network model in this paper is mainly inspired by Hurd et al. (2014), who themselves make use of the work of Gai and Kapadia (2010), Gai et al. (2011) and others. However, their approach is significantly extended to incorporate a normal times and a crisis perspective (see Section 1). It is assumed that the network initially consists of $N < \infty$ banks and that the length of a time period $\left(t-1, t\right]$ is one day. The number of days considered is T.

To keep things simple, it is assumed that each bank has three kinds of assets, two kinds of liabilities and equity. At time t, each bank i has lent an amount of $A_{i,t}^{NB}$ to defaultable entities outside the banking system (non-bank (NB) loans) and an amount of $A_{i,t}^{IB}$ to other (defaultable) banks within the system (unsecured overnight interbank (IB) loans). Furthermore, each bank i possesses a liquidity buffer of volume $A_{i,t}^{L}$ (e. g., cash, trading assets, collateral for repos with the central bank and with other entities outside the system, such as money market funds). Issuers and secondary market buyers of assets out of the liquidity buffer are from outside the banking system. On the liability side, each bank i has private and corporate deposits $L_{i,t}^{D}$ from creditors outside the banking system and interbank liabilities inside the system of volume $L_{i,t}^{IB}$.[7] To balance both sides of the balance sheet, the bank's equity is defined at each time t as:

[7] For the assumption of a similar balance sheet structure see, for example, Hurd et al. (2014) and Krause and Giansante (2012).

$$E_{i,t} = A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L} - L_{i,t}^{D} - L_{i,t}^{IB}. \tag{1}$$

The shareholders of all banks $i \in \{1,...,N\}$ are from outside the banking network. For simplicity, dividend payments to the shareholders as well as tax payments are not modeled. Denoting by $A_{ij,t}^{IB}$ bank i's debt claim with respect to bank $j \neq i$ (i: creditor, j: debtor) at time t and by $L_{ij,t}^{IB}$ bank i's liability with respect to bank $j \neq i$ (i: debtor, j: creditor) at time t, the following relationships must hold in the network:

$$A_{i,t}^{IB} = \sum_{j=1, j\neq i}^{N} A_{ij,t}^{IB} \ (i \in \{1,...,N\}), \tag{2}$$

$$L_{i,t}^{IB} = \sum_{j=1, j\neq i}^{N} L_{ij,t}^{IB} \ (i \in \{1,...,N\}), \tag{3}$$

$$L_{ij,t}^{IB} = A_{ji,t}^{IB} \ (i, j \in \{1,...,N\}, \ i \neq j). \tag{4}$$

With respect to the relationship structure of the banks among each other, many degrees of freedom exist. For example, there might be some large banks in the core of the network that are highly interconnected both with each other and with smaller banks in the periphery whereas the latter banks are only sparsely connected with each other via the interbank market (core-periphery structure; see, e. g., Craig and von Peter (2014) for the German unsecured interbank market or in't Veld and van Lelyveld (2014) and Blasques et al. (2015) for the corresponding Dutch market). In the model-based literature (see, e. g., Battiston et al. (2012a, 2012b), Cifuentes et al. (2005), Elliott et al. (2014), Gai and Kapadia (2010), Georg (2013) or Krause and Giansante (2012)), it is shown that, among others, the network topology has a crucial (and frequently non-monotonic) influence on the default dynamics in the network in the case of a crisis. Thus, presumably, this network topology also has an influence on the SRMs and it could affect the ranking consistency of the SRMs. That is why various network structures are considered for the simulations (for details, see Section 4).

For illustrative purposes, Figure 1 shows for a 2-bank-network the proposed simple balance sheet structures and the relationships inside the network and with (not further specified) entities outside the system. The direction of an arrow shows the flow direction of money.

- insert Figure 1 about here -

Two default mechanisms are modeled, insolvency and illiquidity. Bank i is insolvent at time t when its equity value is negative:

$$E_{i,t} < 0. \tag{5}$$

It is illiquid when it has no cash or assets in its liquidity buffer that can be transformed into cash (either by sales or by repo transactions) and, at the same time, its interbank loans are zero so that no additional cash can be generated by further reducing the granted interbank loans:[8]

$$A_{i,t}^{L} \leq 0 \wedge A_{i,t}^{IB} \leq 0. \tag{6}$$

If a bank is either insolvent or illiquid, it defaults and leaves the system. It is assumed that no bail-outs take place.

I assume that the volume of bank i's defaultable non-bank loans evolves over time as follows:

$$A_{i,t}^{NB} = g_i \cdot A_{i,t-1}^{NB} - l_{i,t}^{NB} = g_i \cdot A_{i,t-1}^{NB} - d_{i,t}^{NB} \cdot LGD_i \cdot A_{i,t-1}^{NB} = \left(g_i - d_{i,t}^{NB} \cdot LGD_i\right) \cdot A_{i,t-1}^{NB} \tag{7}$$

where g_i is one plus a constant growth rate (per period $(t-1,t]$) of bank i's non-bank loans, LGD_i is the average loss given default of bank i's non-bank loans and $d_{i,t}^{NB}$ is bank i's Va-

[8] More precisely, in the numerical implementation, the second condition is $A_{i,t}^{IB} \leq 0.001 \cdot A_{i,1}^{IB}$ because due to the reduction of the granted interbank loans by a factor λ in case of funding liquidity problems of bank i (see the following), $A_{i,t}^{IB}$ cannot reach zero in finite time.

sicek-distributed default rate in the non-bank loan portfolio for the time period $(t-1,t]$ (see Vasicek (1987, 2002)):

$$d_{i,t} = \frac{1}{250} \cdot \Phi\left(\frac{\Phi^{-1}(PD_i) - \sqrt{\rho_i} \cdot Z_{i,t}}{\sqrt{1-\rho_i}} \right) \tag{8}$$

with i.i.d. $Z_{1,t},\ldots,Z_{N,t} \sim N(0,1)$ and $\Phi(\,\cdot\,)$ ($\Phi^{-1}(\,\cdot\,)$) being the (inverse of a) cumulative density function of a standard normally distributed random variable. At each time t, the stochastic dependence between the variables $Z_{1,t}$, …, $Z_{N,t}$ (due to the banks' exposure to common or dependent risk factors influencing the value of their non-bank loan portfolios) is assumed to be governed by a Gauss copula with correlation parameters ρ_{ij}^{bank} ($i, j \in \{1,\ldots,N\}$). By means of ρ_{ij}^{bank}, the degree of stochastic dependencies between the default rates in the non-bank loan portfolios across the N banks (and, hence, a first transmission channel for systemic risk) can be modeled.[9] The parameter ρ_i in (8) (which can be interpreted as the average correlation between the asset returns of the bank's non-bank obligors) determines the stochastic dependence between the default events of the obligors in the individual non-bank loan portfolios. With larger values for ρ_i, there is a stronger tendency for joint credit quality movements of the obligors of bank i and, hence, a larger probability for a smaller and larger number of default events. The parameter PD_i is the average unconditional one-year default probability for obligors in bank i's non-bank loan portfolio. From (8) it follows $E[d_i] = PD_i/250$. The times to maturity of the non-bank loans are not modeled, but rather it is assumed that each loan that is due is immediately rolled over. The credit loss $l_{i,t}^{NB} = d_{i,t} \cdot LGD_i \cdot A_{i,t-1}^{NB}$ in period $(t-1,t]$ negatively affects bank i's net income and, hence, reduces its equity $E_{i,t}$. The constant increase $(g_i - 1) \cdot A_{i,t-1}^{NB}$ of the volume of bank i's non-bank loan portfolio is assumed to be refinanced in each period $(t-1,t]$ by an increase in the non-bank deposits $L_{i,t}^{D}$. Furthermore, it is assumed that the non-bank loan portfolio of bank i generates a constant cash inflow (causing an increase of the liquidity buffer $A_{i,t}^{L}$) and revenue (causing an increase of the equity $E_{i,t}$) of $e_i^{NB} \cdot A_{i,t-1}^{NB}$ in each period $(t-1,t]$. Finally, it is assumed that non-bank loans cannot be secu-

[9] Of course, the assumption of copulas with non-zero and asymmetric tail dependencies would also be possible (see Section 6.2).

ritized to transform them into liquidity buffer assets and that they cannot be called to satisfy funding liquidity needs.

The liquidity buffer assets of each bank i are assumed to be marked-to-market. Extending Gai and Kapadia (2010) who refer to Cifuentes et al. (2005), it is assumed that their value $A_{i,t}^{L}$ at time t is given by:[10]

$$A_{i,t}^{L} = \exp\left(-\tau \cdot x_{t-1} + r_{i,t}\right) \cdot A_{i,t-1}^{L} \tag{9}$$

where $\tau > 0$ is some constant and $x_{t-1} = \Delta_{t-1}^{L} \Big/ \sum_{i=1}^{N} A_{i,t-1}^{L}$ is an indicator (where Δ_{t-1}^{L} is defined in the following) which shows which fraction of the system-wide liquidity buffer assets has been sold (or used as collateral in a repo transaction) in the previous period $\left(t-2, t-1\right]$ due to cash needs.[11] In addition to the assumption of Gai and Kapadia (2010), the stochastic i.i.d. log-returns $r_{i,t} \sim N\left(\mu_i, \sigma_i^2\right)$ are introduced in (9) to model price fluctuations due to new information arriving in the market. By the choice of the copula function describing the multivariate distribution of the random returns $r_{1,t}, \ldots, r_{N,t}$, the strength of the stochastic dependence between the price fluctuations of the liquidity buffer assets across banks can be determined. This dependence contributes to the first transmission channel for systemic risk mentioned above. In the following, a Gauss copula with correlation parameters $Corr\left(r_{i,t}, r_{j,t}\right) = \rho_{ij}^{market}$ ($i, j \in \{1,...,N\}, i \neq j$) is assumed.[12] The multiplier $\exp\left(-\tau \cdot x_{t-1}\right)$ in (9) accounts for value depreciations of the liquidity buffer assets and, hence, a deterioration of the funding liquidity position of bank i that is caused by previous sales of liquidity buffer assets by all banks. The parameter τ governs the depth of the market for these assets; every $\tau > 0$ implies a finite

[10] Contrary to the approach in this paper, Gai and Kapadia (2010) assume that the mark-to-market value of illiquid assets depends on the system-wide fraction of illiquid assets that have been sold in the market. They assume that only if a bank defaults, its illiquid assets are sold in the market. This can reduce the mark-to-market value of the illiquid assets of all surviving banks and, hence, their equity value. In their model, price variations of the illiquid assets cannot happen without any bank defaults. This is somehow problematic because, for example, this neglects the effect of fire sales that banks carry out before a default takes place to deleverage (to comply with minimum capital requirements) or to get funding liquidity. Furthermore, it is not quite clear why assets that are illiquid by definition should be marked-to-market in the balance sheets of the surviving banks.

[11] The lag of one period in the definition of x_{t-1} is necessary to avoid circularity problems.

[12] For an alternative, see Section 6.2. Furthermore, dependencies between the returns $r_{1,t}, \ldots, r_{N,t}$ and the random variables $Z_{1,t}, ..., Z_{N,t}$ that drive the losses in the banks' non-bank loan portfolios could be modeled. However, in the following, independence is assumed (for an extension, see Section 6.2).

market depth and, hence, a non-perfect liquidity. Using this mechanism, a second transmission channel for systemic risk is introduced: When many banks have cash needs and must sell liquidity buffer assets (fire sales), the funding liquidity risk of all banks in the network increases afterwards. As mark-to-market value depreciations and appreciations of the liquidity buffer assets of bank i are assumed to influence not only the funding liquidity position of a bank, but also its revenues and, hence, its equity value $E_{i,t}$, this second channel also affects the solvency risk of the banks in the network. Finally, as for the non-bank loans, it is assumed that the liquidity buffer assets of bank i generate a constant cash inflow and revenue of $e_i^L \cdot A_{i,t-1}^L$ in each period $\left(t-1, t\right]$.

With respect to the banks' liability side, assumptions have to be made concerning the evolution of the volume $L_{i,t}^D$ of the non-bank deposits. Assuming for simplicity that the steady increase of non-bank loans is completely refinanced by non-bank deposits and assuming that some kind of market discipline by depositors exists, the following representation for the volume $L_{i,t}^D$ of the non-bank deposits of bank i at time t is used:

$$L_{i,t}^D = L_{i,t-1}^D \cdot \left(\frac{etar_{i,t-1}}{etar_{i,t-2}} \right)^{\frac{1}{q}} + \left(g_i - 1\right) \cdot A_{i,t-1}^{NB} \tag{10}$$

with $q \in \mathbb{N}$ and the equity-to-assets ratio ($etar_{i,t-1}$) of bank i at time $t-1$ defined as

$$etar_{i,t-1} = 1 - \frac{L_{i,t-1}^D + L_{i,t-1}^{IB}}{A_{i,t-1}^{NB} + A_{i,t-1}^{IB} + A_{i,t-1}^L}. \tag{11}$$

The specification (10) implies that the volume of the non-bank deposits of a bank depends on the solvency of a bank measured by its equity-to-assets ratio which is assumed to be observable by the depositors. When the equity-to-assets ratio is larger (smaller) than its value in the period before, the volume $L_{i,t}^D$ of the non-bank deposits of a bank increases (decreases) (beside the refinancing effect for the growing volume of non-bank loans). The volume of the liquidity buffer assets $A_{i,t}^L$ of bank i increases (decreases) by the same amount $L_{i,t-1}^D \cdot \left(\left(etar_{i,t-1} / etar_{i,t-2} \right)^{1/q} - 1 \right)$. The negative value of the sum of these liquidity changes

$-\sum_{i=1}^{N} L_{i,t-1}^{D} \cdot \left(\left(etar_{i,t-1} / etar_{i,t-2} \right)^{1/q} - 1 \right)$ is one summand in the calculation of Δ_{t-1}^{L} in the next period (see (9)). Again, a time lag specification is necessary to avoid circularity problems. This kind of market discipline by non-bank depositors, even in the presence of a full deposit insurance, has been found for example by Domikowsky et al. (2015) based on a comprehensive panel of German banks. However, as expected, they find that this market discipline effect is stronger for uninsured interbank deposits.[13] Similar to the asset side, it is assumed that the non-bank deposits of bank i generate a constant cash outflow (costs) of $c_i^D \cdot L_{i,t-1}^{D}$ in each period $\left(t-1, t\right]$ for interest payments to the depositors.

The modelling of the interbank liabilities $L_{i,t}^{IB}$ and the interbank loans $A_{i,t}^{IB}$ ($i \in \{1, \ldots, N\}$) has to be done simultaneously because these volumes are interconnected in the network. Interconnection mechanisms that lead to a third transmission channel for systemic risk are described in the following. The volume of the interbank loans $A_{i,t}^{IB}$ and the interbank liabilities $L_{i,t}^{IB}$ of a bank i remain unchanged unless one of the rules described in the following is applied. Furthermore, similar to the other assets and liabilities, it is assumed that the interbank liabilities $L_{i,t}^{IB}$ (interbank loans $A_{i,t}^{IB}$) of bank i generate a constant cash outflow (inflow) and costs (revenues) of $c_i^{IB} \cdot L_{i,t-1}^{IB}$ ($e_i^{IB} \cdot L_{i,t-1}^{IB}$) in each period $\left(t-1, t\right]$ for paid (received) interest.

When at some time t a bank i defaults due to insolvency or illiquidity, it leaves the system.[14] As a consequence, it is assumed that a defaulted bank i calls all its granted interbank loans in the next period (see Hurd et al. (2014, p. 7)) from which results:

$$L_{ji,t+1}^{IB} = 0 \quad \forall \; j \neq i . \tag{12}$$

[13] One reason for a market discipline effect by non-bank depositors (despite a potential full deposit insurance) might be their distrust into the ability of the deposit insurance to cover all claims. Therefore, an extension of the above representation for $L_{i,t}^{D}$ could be to introduce a system-wide bank default indicator. The higher the total number of defaults in the banking system, the larger the distrust into the ability of the deposit insurance to pay and, hence, the larger the market discipline effect should be. Further refinements could consist in introducing an interest rate dependency for the volume of non-bank deposits or an independent additive stochastic component $\varepsilon_{i,t}^{D}$ that models funding liquidity effects for bank i due to random fluctuations of the volume of non-bank deposits (for such an extension, see Section 6.3).

[14] It is assumed that a bank is not able to raise new external equity.

The volume of liquidity buffer assets $A^{L}_{j,t+1}$ of all banks $j \neq i$ is assumed to be reduced by the same amount. The sum of these reductions $\sum_{j=1, j \neq i}^{N} L^{IB}_{ji,t+1}$ is a further summand in the calculation of Δ^{L}_{t+1} in the next period (see (9)). Furthermore, all claims $A^{IB}_{ji,t+1}$ of the other banks $j \neq i$ with respect to bank i are assumed to get worthless in the next period and the equity of banks $j \neq i$ is reduced by this amount (see Hurd et al. (2014, p. 7)):

$$A^{IB}_{ji,t+1} = 0 \quad \forall\ j \neq i , \tag{13}$$

$$E_{j,t+1} = E_{j,t} - A^{IB}_{ji,t} \quad \forall\ j \neq i . \tag{14}$$

Of course, a non-zero recovery rate on the interbank loans could also be assumed and endogenously modeled.[15] Caused by the reduction in equity value, not only the solvency but also the funding liquidity position of all banks $j \neq i$ could be harmed (due to an increased outflow of non-bank deposits (see (10)) and due to a potential credit rationing on the interbank market (see the overnext rule in the following)). Additionally, the call of the interbank loans previously granted by the defaulted bank i leads to a deterioration of the funding liquidity position of all banks $j \neq i$. Thus, the likelihood to default itself increases.[16]

Furthermore, assumptions have to be made concerning the actions a single bank takes when it faces (temporary) funding liquidity problems ($A^{L}_{i,t} \leq 0$) and what the other banks $j \neq i$ do when the solvency position of a bank i deteriorates. In the first case, it is assumed that, in the next period, bank i evenly reduces its interbank loans with respect to all other banks by a

[15] For example, in case of insolvency as default reason, it could be assumed that a defaulted bank i calls in all its interbank loans $A^{IB}_{ij,t+1}$ and sells all its liquidity buffer assets $A^{L}_{i,t+1}$ (without liquidation costs) and its non-bank loans $A^{NB}_{i,t+1}$ (with liquidation costs ω). This money is used to pay back at first the loans $L^{D}_{i,t+1}$ granted by non-bank depositors and then the remaining money is evenly distributed among bank i 's financial creditors $j \neq i$ to partly satisfy their claims $A^{IB}_{ji,t+1}$. Of course, for this kind of endogenous recovery rate of interbank loans, sequential defaults of banks have to be assumed. When banks can simultaneously default, a circularity problem would arise because the amount of money that the defaulted bank would get from its called interbank loans (and, hence, the recovery rate) would depend on whether some of the other banks default (what in turn would depend on the recovery rate). To solve this kind of problem, a settlement mechanism as described by Eisenberg and Noe (2001) would be necessary (see Frey and Hledik (2014, p. 8)).

[16] As a further degree of sophistication, a mark-to-market valuation of interbank loans $A^{IB}_{ji,t}$ at time t (e. g., depending on the equity-to-assets ratio $etar_{i,t-1}$ of bank i in the previous period) could be assumed. Doing this, solvency deteriorations of a single bank i would lead via the interbank market to solvency deteriorations of its creditor banks $j \neq i$ even before bank i defaults (see, e. g., Fink et al. (2014) or Glasserman and Young (2015)).

fraction λ so that its volume of liquidity buffer assets increases by an amount of $\lambda \cdot A_{i,t}^{IB}$ in $t+1$ (see Gai et al. (2011, p. 460), Hurd et al. (2014, p. 7)).[17] Conversely, the volume of liquidity buffer assets of all other banks $j \neq i$ decreases by an amount of $\lambda \cdot L_{ji,t}^{IB}$. The term $\sum_{j=1, j\neq i}^{N} \lambda \cdot L_{ji,t}^{IB}$ is also considered in the calculation of Δ_{t+1}^{L}. The reduction of interbank loans of bank i can cause funding liquidity problems for some bank $j \neq i$ causing the same actions in later periods (and so on). In the second case that the solvency position of a bank i deteriorates, an interbank credit rationing mechanism is introduced (similar to the modelling of non-bank deposits; see (10) and (11)), which would correspond to market discipline exerted by financial depositors. If the equity-to-assets ratio $etar_{i,t}$ of a solvent bank i reaches a lower boundary $etar_{Min}^{IB}$ at time t,[18] all other banks $j \neq i$ are assumed to reduce in the next period $t+1$ their interbank loans $A_{ji,t+1}^{IB}$ with respect to bank i by a fraction $\lambda *$. This leads to an increase of their liquidity buffer assets $A_{j,t+1}^{L}$ by the same amount and to a decrease of the interbank liabilities $L_{i,t+1}^{IB}$ and of the liquidity buffer assets $A_{i,t+1}^{L}$ of bank i by the sum of all reductions $\sum_{j=1, j\neq i}^{N} \lambda * \cdot A_{ji,t+1}^{IB} = \sum_{j=1, j\neq i}^{N} \lambda * \cdot L_{ij,t+1}^{IB}$. Of course, this can cause funding liquidity problems of bank i with the consequences as described before. The term $\sum_{j=1, j\neq i}^{N} \lambda * \cdot L_{ij,t}^{IB}$ is considered in the calculation of Δ_{t+1}^{L} (see (9)). Summing up, a reduction of the interbank liabilities of a bank j can be caused by a default or funding liquidity problems of other banks $i \neq j$ as well as by solvency problems of the bank j itself.

When there are many periods without large losses in the loan portfolios of a bank and with low cash outflows, the volume of the liquidity buffer assets $A_{i,t}^{L}$ of a bank i as well as its equity value $E_{i,t}$ might tend to swell up to unrealistic high levels. Thus, simple behavioral rules of the bank are needed:[19]

1. If at some time t the ratio of liquidity buffer assets to total assets is larger than a fraction $\beta_{\max}$, the bank has several possibilities to reduce the amount of liquidity buffer assets. First, it can invest liquidity buffer assets in non-bank loans or interbank loans

[17] Obviously, this implies that $A_{i,t}^{L}$ can remain negative for some time.
[18] Other indicators that might trigger an interbank credit rationing could be an inadequate level of liquidity buffer assets or huge losses for non-bank loans (see Domikowsky et al. (2015)).
[19] For similar rules ensuring a fixed Tier 1 capital ratio, see Aikman et al. (2011).

or in both of them (of course, assumed that there is enough demand for corporate and bank loans to carry out these transactions). Second, it can reduce its interbank liabilities or deposits or both of them by selling its liquidity buffer assets. The second strategy of deleveraging could be beneficial when the equity-to-assets ratio is low. However, I assume that basically, banks are not interested in reducing their balance sheet total (unless it is necessary, e. g., to fulfill minimum capital requirements) and, hence, follow the first strategy. It is assumed that the volume of liquidity buffer assets is reduced by such an amount Δ_1 that the ratio of liquidity buffer assets to total assets exactly equals $\beta_{\max}$. The non-bank loans are increased by $w_1 \cdot \Delta_1$ and the interbank loans are increased by $(1-w_1)\cdot\Delta_1$ with $w_1 \in [0,1]$:[20]

$$
\begin{aligned}
&\frac{A_{i,t}^{L}}{A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}} > \beta_{\max} \\
\Rightarrow\quad &\frac{A_{i,t}^{L} - \Delta_1}{A_{i,t}^{NB} + w_1 \cdot \Delta_1 + A_{i,t}^{IB} + (1-w_1)\cdot\Delta_1 + A_{i,t}^{L} - \Delta_1} = \beta_{\max} \\
\Leftrightarrow\quad &\Delta_1 = \frac{A_{i,t}^{L}}{\beta_{\max}\cdot(A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L})}.
\end{aligned}
\tag{15}
$$

The increase $(1-w_1)\cdot\Delta_1$ of interbank loans of bank i is allotted among those banks $j \neq i$ that are connected with bank i via its asset side (and have survived until time $t-1$) according bank j's share in bank i's total interbank loan volume $A_{i,t}^{IB}$.[21] For simplicity, it is assumed that banks do not take any pro-active measures (e. g., by reducing their interbank loans or not rolling over maturing non-bank loans) when the ratio of liquidity buffer assets to total assets is below some fraction $\beta_{\min}$. Only when the volume of liquidity buffer assets has become negative, the volume of interbank loans is reduced.

[20] Of course, an increase in the volume of the interbank loans of a single bank corresponds to an increase of the volume of the interbank liabilities and of the liquidity buffer assets of some other banks.

[21] If no bank $j \neq i$ with which bank i is connected via its asset side has survived until time $t-1$, the whole amount Δ_1 is invested in non-bank loans.

2. If at some time t the equity-to-assets ratio $etar_{i,t}$ is larger than some upper boundary $\eta_{\max}$, it is assumed that the bank takes actions to reduce its equity-to-assets ratio. Basically, a bank i can increase its interbank liabilities or its deposits or both of them and invest the new debt in a combination of the three asset classes non-bank loans, interbank loans and liquidity buffer assets. I assume that the bank increases its interbank liabilities by $w_{2,1} \cdot \Delta_2$ and its deposits by $(1-w_{2,1}) \cdot \Delta_2$ with $w_{2,1} \in [0,1]$. An increase in the volume of the interbank liabilities of a single bank i corresponds to an increase of the volume of the interbank loans and to a decrease of the volume of the liquidity buffer assets of some other banks $j \neq i$. It is assumed that the increase of the interbank liabilities $w_{2,1} \cdot \Delta_2$ of bank i is allotted among those banks $j \neq i$ that are connected with bank i via its liability side (and have survived until time $t-1$) according to bank j's share in the whole amount of liquidity buffer assets in this group of banks.[22] An amount of $w_{2,2} \cdot \Delta_2$ of this new debt Δ_2 is invested in non-bank loans and an amount of $(1-w_{2,2}) \cdot \Delta_2$ is invested in interbank loans with $w_{2,2} \in [0,1]$. It is assumed that the increase of the interbank loans $(1-w_{2,2}) \cdot \Delta_2$ of bank i is allotted among those banks $j \neq i$ that are connected with bank i via its asset side (and have survived until time $t-1$) according to bank j's share in bank i's total interbank loan volume $A_{i,t}^{IB}$.[23] The amount of new debt Δ_2 is chosen in such a way that the equity-to-assets ratio equals $\eta_{\max}$:

$$
\begin{aligned}
& etar_{i,t} = 1 - \frac{L_{i,t}^{D} + L_{i,t}^{IB}}{A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}} > \eta_{\max} \\
\Rightarrow \quad & 1 - \frac{L_{i,t}^{D} + (1-w_{2,1}) \cdot \Delta_2 + L_{i,t}^{IB} + w_{2,1} \cdot \Delta_2}{A_{i,t}^{NB} + w_{2,2} \cdot \Delta_2 + A_{i,t}^{IB} + (1-w_{2,2}) \cdot \Delta_2 + A_{i,t}^{L}} = \eta_{\max} \\
\Leftrightarrow \quad & \Delta_2 = \frac{(1-\eta_{\max}) \cdot (A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}) - L_{i,t}^{D} - L_{i,t}^{IB}}{\eta_{\max}}. \qquad (16)
\end{aligned}
$$

[22] If $w_{2,1} \cdot \Delta_2$ is larger than the whole amount of liquidity buffer assets within the group of banks $j \neq i$ that are connected with bank i via its liability side and have survived until time $t-1$, the maximum possible amount of money is borrowed from the interbank market and the remaining amount (to reach in total a new additional amount of debt Δ_2) is borrowed from depositors.

[23] If no bank $j \neq i$ with which bank i is connected via its asset side has survived until time $t-1$, the whole new debt Δ_2 is invested in non-bank loans.

3. If at some time t the equity-to-assets ratio $etar_{i,t}$ is smaller than some lower boundary $\eta_{\min}$, it is assumed that bank i takes actions to increase its equity-to-assets ratio (by deleveraging). This behavior corresponds to the fulfillment of a regulatory capital requirement.[24] In detail, it is assumed that bank i decreases its non-bank loans by $w_{3,1} \cdot \Delta_3$ and its interbank loans by $(1 - w_{3,1}) \cdot \Delta_3$ with $w_{3,1} \in [0,1]$. It is assumed that the decrease of the interbank loans $(1 - w_{3,1}) \cdot \Delta_3$ of bank i is allotted among those banks $j \neq i$ that are connected with bank i via its asset side (and have survived until time $t-1$) according to bank j's share in bank i's total interbank loan volume $A_{i,t}^{IB}$.[25] The liquidity Δ_3 that bank i gets from calling parts of its non-bank and interbank loans is used to reduce its interbank liabilities by $w_{3,2} \cdot \Delta_3$ and its non-bank deposits by $(1 - w_{3,2}) \cdot \Delta_3$. It is assumed that the decrease of the interbank liabilities $w_{3,2} \cdot \Delta_3$ of bank i is allotted among those banks $j \neq i$ that are connected with bank i via its liability side (and have survived until time $t-1$) according to bank j's share in bank i's total interbank liability volume $L_{i,t}^{IB}$.[26] The reduction of debt Δ_3 is chosen in such a way that the equity-to-assets ratio equals $\eta_{\min}$:

$$etar_{i,t} = 1 - \frac{L_{i,t}^{D} + L_{i,t}^{IB}}{A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}} < \eta_{\min}$$

$$\Rightarrow \quad 1 - \frac{L_{i,t}^{D} - (1 - w_{3,2}) \cdot \Delta_3 + L_{i,t}^{IB} - w_{3,2} \cdot \Delta_3}{A_{i,t}^{NB} - w_{3,1} \cdot \Delta_3 + A_{i,t}^{IB} - (1 - w_{3,1}) \cdot \Delta_3 + A_{i,t}^{L}} = \eta_{\min}$$

$$\Leftrightarrow \quad \Delta_3 = -\frac{(1 - \eta_{\min}) \cdot (A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}) - L_{i,t}^{D} - L_{i,t}^{IB}}{\eta_{\min}}. \tag{17}$$

With respect to bank i's profit and loss account, bank i generates revenues by received interest payments $e_i^{NB}, e_i^{IB}, e_i^{L}$ and by mark-to-market profits of its liquidity buffer assets, and it has costs c_i^{D}, c_i^{IB} due to interest payments on its non-bank deposits and interbank liabilities, due to

---

[24] As the assets are not risk-weighted, this resembles more the fulfillment of a leverage ratio rule. In contrast to reality, it is not assumed that a bank is closed by the regulatory authorities when $etar_{i,t} < \eta_{\min}$ holds, but only the default criteria (5) and (6) are applied.

[25] If the sum of the interbank and non-bank loans of bank i is smaller than Δ_3, then, additionally, liquidity buffer assets are sold to entities outside the banking system. If the volume of non-bank loans of bank i is smaller than $w_{3,1} \cdot \Delta_3$, the volume of interbank loans is more strongly reduced. Analogously, if the volume of interbank loans of bank i is smaller than $(1 - w_{3,1}) \cdot \Delta_3$, the volume of non-bank loans is more strongly reduced.

[26] If the volume of non-bank deposits of bank i is smaller than $(1 - w_{3,2}) \cdot \Delta_3$, the volume of interbank liabilities is more strongly reduced. Analogously, if the volume of interbank liabilities of bank i is smaller than $w_{3,2} \cdot \Delta_3$, the volume of non-bank deposits is more strongly reduced.

mark-to-market losses of its liquidity buffer assets and due to credit losses of its non-bank and interbank loans. With respect to bank i's cash flow statement, it follows that bank i increases its pool of liquidity buffer assets by receiving interest payments $e_i^{NB}, e_i^{IB}, e_i^L$, by a rise in market value of its liquidity buffer assets and by new non-bank deposits. Its pool of liquidity buffer assets is diminished by its own interest payments c_i^D, c_i^{IB}, by a market value reduction of the liquidity buffer assets and by a decrease of its non-bank deposits and interbank liabilities.

3 Systemic Risk Measures

Within the above defined banking network model, the following popular systemic risk measures (SRM) are computed. All of these measures are exposure SRMs (as opposed to contribution SRMs) which shall indicate how strong a financial institution would be affected by a financial distress on the system level. Thus, a comparison of their ranking consistency is meaningful.

1. *Marginal Expected Shortfall* (MES)

The MES was originally proposed by Acharya et al. (2010) and extensively estimated in various empirical studies mentioned above. It is defined as

$$MES_{\alpha,t}^i = E_{t-1}\left[R_{i,t} \middle| R_{m,t} < q_\alpha^{[t-D,t-1]}\left(R_m\right)\right] \tag{18}$$

where $R_{i,t}$ is the daily equity return of bank i at time t, $R_{m,t}$ is the daily value-weighted index of the equity returns of all (surviving) banks at time t ($R_{m,t} = \sum_{i=1, i\neq default\ in\ t}^{N} w_{i,t} \cdot R_{i,t}$ with $w_{i,t}$ being the relative market capitalization of bank i at time t) and $q_\alpha^{[t-D,t-1]}\left(R_m\right)$ is the α-quantile of the empirical marginal cumulative density function of the bank index R_m (based on all realizations $r_{m,t-D},...,r_{m,t-1}$ of R_m in the time period $\left[t-D,t-1\right]$). The $MES_{\alpha,t}^i$ of bank i at time t to a risk level of α is estimated in the following by (see Acharya et al. (2010, p. 17)):[27]

[27] The MES (as other SRMs) can also be estimated in a more sophisticated way by a dynamic multivariate time series approach that accounts for time-varying return volatilities and correlations (see, for example, Brownlees

$$MES_{\alpha,t}^{i} \approx -\frac{\sum_{s \in \{t-250,\ldots t-1\}} r_{i,s} \cdot 1_{\left\{r_{m,s} < q_{\alpha}^{[t-250,\ldots,t-1]}(R_m)\right\}}}{\sum_{s \in \{t-250,\ldots t-1\}} 1_{\left\{r_{m,s} < q_{\alpha}^{[t-250,\ldots,t-1]}(R_m)\right\}}} \tag{19}$$

Thus, the average equity return of bank i in the α % worst days of the banking system as a whole in the past 250 days time window is computed. As this average equity return is typically negative, it is multiplied by -1 to get positive numbers. A frequent choice for the risk level is $\alpha = 5\%$. This choice, however, seems (at least partly) be driven by the issue of data availability (see Löffler and Raupach (2013)). Based on power law considerations, Acharya et al. (2010) argue that $\alpha = 5\%$ indeed does not capture the tail of a true financial crisis, but that $MES_{5\%,t}^{i}$ is linked to the systemic expected shortfall of bank i.[28]

As Benoit et al. (2013) argue that the additional information contents of (among others) the MES is limited compared with classical market risk measures, the betas of each bank i are also computed:

$$\beta_t^i = \frac{Cov_{t-1}\left(R_{i,t}, R_{m,t}\right)}{Var_{t-1}\left(R_{m,t}\right)}. \tag{20}$$

Analogously to the estimation of the MES, β_t^i is proxied by the sample estimators for the covariance between the bankindividual daily equity return R_i and the market-wide daily index return R_m and for the variance of R_i, based on a rolling 250 days time window of the last observed equity returns.

2. *SRISK-Index*

The SRISK-index proposed by Brownlees and Engle (2016) and Acharya et al. (2012) is the expected capital shortfall of a bank i conditional on a system crisis. The capital shortfall is

and Engle (2016)). For an analysis of model and estimation risk when computing SRMs, see Danielsson et al. (2015, 2016).

[28] See Proposition 2 in Acharya et al. (2010, p. 16).

understood as the capital reserves that a bank has to hold due to regulatory or prudential requirements minus its equity value. This SRM can be interpreted as an extension of the MES taking into account both the volume of the bank liabilities and the bank size (measured by the bank's market capitalization). SRISK is defined as (see Acharya et al. (2012, p. 61)):

$$SRISK_t^i = k \cdot D_{i,t} - (1-k) \cdot \left(1 - LRMES_t^i\right) \cdot W_{i,t} \tag{21}$$

where $LRMES_t^i$ is the long-run MES of bank i at time t. The term 'long-run' means that instead of daily equity returns, equity returns over some longer time horizon (e. g., 6 months) are employed in (18). As a crisis scenario in (18), Acharya et al. (2012) propose to consider situations in which the market index drops by more than 40 percent over the next 6 months. They argue that $LRMES_t^i$ can be approximated by $1-\exp\left(-18 \cdot MES_{2\%,t}^i\right)$. This approximation is used in (21). Furthermore, k is the required prudential or regulatory capital ratio (chosen as 3% in the following because the assets are not risk-weighted), $D_{i,t}$ is the book value of total liabilities of bank i at time t ($= L_{i,t}^D + L_{i,t}^{IB}$), and $W_{i,t}$ is the equity value of bank i at time t ($= E_{i,t}$).

3. *Tail Dependencies*

As a further systemic risk measure, the lower tail dependence between the equity return of bank i and the return of the bank market index is considered:

$$LTD_t^{i,m} = \lim_{u \searrow 0} P_{t-1}\left(R_{i,t} \le F_{i,[t-D,t-1]}^{-1}(u) \middle| R_{m,t} \le F_{m,[t-D,t-1]}^{-1}(u)\right) \tag{22}$$

where $F_{i,[t-D,t-1]}^{-1}(\cdot)$ ($F_{m,[t-D,t-1]}^{-1}(\cdot)$) is the inverse of the empirical cumulative density function of the equity return R_i of bank i (of the return of the bank market index R_m) based on the realizations of the returns within the time period $[t-D, t-1]$. The lower tail dependence of equity returns is used as systemic risk measure for example by Weiß et al. (2014a, 2014b). They argue that, while the MES measures a bank's contribution to moderately bad tail events (at least, for the choice $\alpha = 5\%$), the LTD measures the bank's and the market's joint risk of a crash. In the following, $LTD_t^{i,m}$ is estimated as follows:[29]

$$LTD_t^{i,m} \approx \frac{1}{k} \cdot \sum_{s \in \{t-250,\ldots t-1\}} 1_{\left\{Rank_{i,s}^t \leq k \text{ and } Rank_{m,s}^t \leq k\right\}} \tag{23}$$

where $Rank_{i,s}^t$ and $Rank_{m,s}^t$ ($s \in \{t-250, t-1\}$) denote the rank of the equity return observations $r_{i,s}$ and $r_{m,s}$ in the sample of the last 250 return realizations at time t.[30] The parameter $k \in \{1,\ldots,250\}$ is set to $\left\lfloor \sqrt{250} \right\rfloor = 15$ as discussed in Dobrić and Schmid (2005).

Alternatively to Weiß et al. (2014a, 2014b), Trapp and Wewel (2013) parametrically estimate the upper tail dependencies between pairs of returns of bank-specific credit default swap (CDS) spreads and interpret these values as systemic risk measure. To check whether the usage of CDS or equity return data has an influence on the ranking consistency within the modeled banking network, I compute the one-year risk-neutralized default probability of bank i at time t in a Merton-style credit risk pricing model and use this as a proxy for the CDS premium:[31]

$$PD_t^i = \Phi\left(\frac{1}{\sigma_{t-1,AR_i}} \cdot \left(\ln\left(\frac{L_{i,t}^{IB} + L_{i,t}^{D}}{A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}}\right) - \left(i - 0.5 \cdot \sigma_{t-1,AR_i}^2\right)\right)\right) \tag{24}$$

where σ_{t-1,AR_i} is the sample estimator for the standard deviation of the daily asset return $AR_{i,t} = \ln\left(\left(A_{i,t}^{NB} + A_{i,t}^{IB} + A_{i,t}^{L}\right) / \left(A_{i,t-1}^{NB} + A_{i,t-1}^{IB} + A_{i,t-1}^{L}\right)\right)$ of bank i at time t, based on a rolling 250 days time window of the last observed asset returns,[32] which is scaled by $\sqrt{250}$.[33] The risk-free interest rate i in (24) is chosen as the average interbank lending rate in the banking net-

[29] See Weiß et al. (2014b, p. 179) who refer to Schmidt and Stadtmüller (2006).
[30] Lower equity returns correspond to lower ranks (rank 1: lowest equity return, rank 250: highest equity return).
[31] See Merton (1974).
[32] An alternative to the usage of historical asset return volatilities would be to compute implied asset return volatilities, based on the well-known fact that in the Merton-model, the equity value equals the value of a European call option with the bank assets as underlying and the nominal value of debt as exercise price.
[33] To account for a potential autocorrelation of the asset returns when computing the asset return volatilities, the following AR(1) scale factor $\left(250 + 2\rho\left[249\left(1-\rho\right) - \rho\left(1-\rho^{249}\right)\right] / \left(1-\rho\right)^2\right)^{0.5}$ with ρ being the correlation between two adjacent asset returns has also been tested (see Alexander (2008, p. 93)). However, the conclusions with respect to the ranking consistency of the SRMs (see Section 5) do not change.

work. As default barrier, the current amount of liabilities $L_{i,t}^{IB} + L_{i,t}^{D}$ of bank i at time t is employed because the future amount of liabilities $L_{i,t+250}^{IB} + L_{i,t+250}^{D}$ (which actually should be inserted in (24)) is unknown and evolves stochastically. Based on PD_t^i in (24), PD-log returns $r_{i,t}^{PD} = \ln\left(PD_t^i / PD_{t-1}^i\right)$ are calculated. From the bankindividual one-year risk-neutralized default probabilities in (24) and the respective log returns $r_{i,t}^{PD}$, a daily value-weighted market index $r_{m,t}^{PD}$ of all (surviving) banks at time t is computed where the weights correspond to the relative market capitalization of bank i at time t. Then, the upper tail dependence $UTD_t^{i,m}$ between $r_{i,t}^{PD}$ and $r_{m,t}^{PD}$ is estimated as follows:

$$UTD_t^{i,m} \approx \frac{1}{k} \cdot \sum_{s \in \{t-250,\dots t-1\}} 1_{\left\{Rank_{PD,i,s}^t > 250-k \text{ and } Rank_{PD,m,s}^t > 250-k\right\}} \tag{25}$$

where $Rank_{PD,i,s}^t$ and $Rank_{PD,m,s}^t$ ($s \in \{t-250, t-1\}$) denote the rank of $r_{i,s}^{PD}$ and $r_{m,s}^{PD}$, respectively, in the sample of the last 250 observations at time t and, analogously to the computation of the LTD, $k = 15$ is chosen.[34]

4 Balance Sheet Composition, Parameterization and Network Construction

All banks in the network are assumed to have the same basic balance sheet structure as displayed in Figure 1. However, for testing the ranking consistency of SRMs, various models that differ with respect to the degree of heterogeneity of the banks' balance sheet items and the network topology are considered. First, as a base model (model 1), complete homogeneity with respect to the volumes of the banks' balance sheet items and their parameters is assumed. The parameterization of the banking network in this base model and in the following model variations can be seen in Tables 1 and 2. Furthermore, a completely symmetric network topology is assumed, i.e. all banks are connected with all other banks via the interbank loan market. For each bank i, the initial volume $A_{i,1}^{IB}$ of the interbank loans is evenly distributed among the remaining $N-1$ banks in the network.[35] Second (model 2), heterogeneity with respect to the volumes of the banks' balance sheet items is assumed and, third (model 3), addi-

[34] Lower PD-log returns correspond to lower ranks (rank 1: lowest PD-log return, rank 250: highest PD-log return).

[35] In the following, it is assumed that all interbank loans (and, hence, interbank liabilities) have a normalized size of one.

tionally, heterogeneity with respect to the parameters describing the banks' balance sheet items is introduced. For the latter modification, the parameters of each bank are independently sampled from a uniform distribution on the intervals indicated in Table 2. The former modification implies that the initial equity-to-assets ratio $etar_{i,1} = E_{i,1} \big/ \left(A_{i,1}^{NB} + A_{i,1}^{IB} + A_{i,1}^{L} \right)$, the initial ratio of interbank loans to total assets[36] $\kappa_i = A_{i,1}^{IB} \big/ \left(A_{i,1}^{NB} + A_{i,1}^{IB} + A_{i,1}^{L} \right)$, and the initial ratio of liquidity buffer assets to total assets $lr_i = A_{i,1}^{L} \big/ \left(A_{i,1}^{NB} + A_{i,1}^{IB} + A_{i,1}^{L} \right)$ differ between the N banks in the system. These ratios are also independently sampled from a uniform distribution on the indicated intervals.

- insert Tables 1 and 2 about here -

Next, additionally, the assumption that all banks are connected with all other banks via the market for interbank loans is abandoned.[37] Instead, on one hand, a homogeneous (Erdös-Rényi) random graph network structure is generated (model 4). In this case, each bank $i \in \{1, \dots, N\}$ is connected with some other bank $j \neq i$ via its asset side with probability p_{ER}, i.e. with this probability bank i is creditor of bank $j \neq i$. The information on all interbank connections within the system are gathered in the adjacency matrix $A = \left(adja(i,j) \right)_{i,j \in \{1,\dots,N\}}$ with

$$adja(i,j) = \begin{cases} 1 & \text{if bank } i \text{ is creditor of bank } j \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

The total number of interbank connections on the asset side of bank i is called $\text{outdegree}(i) = \sum_{j=1}^{N} adja(i,j)$. It is assumed that the initial volume of interbank loans $A_{i,1}^{IB}$ of each bank i is evenly distributed among all $\text{outdegree}(i)$ many banks with which bank i is connected via its asset side. The total number of interbank connections on the liability side of bank i which results from the interbank connections on the asset side of all other banks $j \neq i$ is called $\text{indegree}(i) = \sum_{j=1}^{N} adja(j,i)$.

[36] Elliott et al. (2014) and Frey and Hledik (2014) call this ratio the level of 'integration' of a bank into the network.
[37] For the two considered alternatives, I follow Frey and Hledik (2014).

On the other hand, an inhomogeneous (core-periphery) random graph network structure is generated (model 5).[38] In this case, each bank $i \in \{1,\ldots,N\}$ belongs with probability p_{Core} to the core of the banking system and with probability $1-p_{Core}$ to the periphery. A core bank is assumed to be connected via its asset side with some other core bank with probability p_{CC} and with some periphery bank with probability p_{CP}. A periphery bank is assumed to be connected via its asset side with some other periphery bank with probability p_{PP} and with some core bank with probability $p_{PC} = p_{CP}$. All other network structures can be seen as special cases of this inhomogeneous (core-periphery) random graph network structure. The Erdös-Rényi random graph corresponds to the setting $p_{Core} = 1$, $p_{CC} = p_{ER}$ and $p_{PP} = p_{CP} = p_{PC} = 0$. The model in which all banks are connected with all other banks results from the setting $p_{Core} = p_{CC} = 1$ and $p_{PP} = p_{CP} = p_{PC} = 0$. Obviously, the assumption of an inhomogeneous (core-periphery) random graph network structure implies that the total asset sizes of the banks in the system are not uniformly distributed any more.

One of the characterising features of a given banking network is the expected number C of connections of a randomly chosen bank in the system which is called connectivity or average graph degree. In the Erdös-Rényi random graph, this number is $C = p_{ER} \cdot (N-1)$ and in the core-periphery random graph, it is:[39]

$$C = (N-1)\cdot\left[p_{Core}^2 \cdot p_{CC} + p_{Core}\cdot(1-p_{Core})\cdot(p_{CP}+p_{PC}) + (1-p_{Core})^2 \cdot p_{PP} \right]. \quad (27)$$

For the construction of the banks' initial balance sheets, I basically apply the methodology of Frey and Hledik (2014) which is extended by the additional balance sheet category 'liquidity buffer assets'.[40] It is assumed that all interbank loans (and, hence, interbank liabilities) have a normalized size of one. From this results $A_{i,1}^{IB} = \text{outdegree}(i)$ and $L_{i,1}^{IB} = \text{indegree}(i)$ for all

[38] The core periphery network model is competing with scale-free models with power law distributed degrees. In practice, it seems to be difficult to decide which kind of model fits better for a specific interbank market. On one hand, estimating power law distributions for the degrees suffers from limited financial network sizes. On the other hand, real interbank markets hardly seem to fulfil all three conditions that theoretically characterise a core periphery model (see the discussion in Craig and von Peter and in't Veld and van Lelyveld (2014)).
[39] See Frey and Hledik (2014, p. 11).
[40] For an alternative construction method, see Section 6.4.

banks $i \in \{1,\ldots,N\}$. Hence, the volumes of the initial interbank loans and liabilities are given by the simulated network structure. Next, I randomly generate the initial equity-to-assets ratios $etar_{i,1}$, the initial ratios of interbank loans to total assets κ_i and the initial ratios of liquidity buffer assets to total assets lr_i. These ratios are uniformly distributed within the intervals indicated in Table 2. Thus, the following relations should hold for each bank $i \in \{1,\ldots,N\}$:

$$\frac{E_{i,1}}{A_{i,1}^{NB}+A_{i,1}^{IB}+A_{i,1}^{L}}=\frac{E_{i,1}}{A_{i,1}^{Total}}=etar_{i,1}\Leftrightarrow E_{i,1}=etar_{i,1}\cdot A_{i,1}^{Total}, \tag{28}$$

$$\frac{A_{i,1}^{IB}}{A_{i,1}^{NB}+A_{i,1}^{IB}+A_{i,1}^{L}}=\frac{A_{i,1}^{IB}}{A_{i,1}^{Total}}=\kappa_i\Leftrightarrow A_{i,1}^{Total}=\frac{A_{i,1}^{IB}}{\kappa_i}, \tag{29}$$

$$\frac{A_{i,1}^{L}}{A_{i,1}^{NB}+A_{i,1}^{IB}+A_{i,1}^{L}}=\frac{A_{i,1}^{L}}{A_{i,1}^{Total}}=lr_i\Leftrightarrow A_{i,1}^{L}=lr_i\cdot A_{i,1}^{Total}, \tag{30}$$

$$A_{i,1}^{NB}=A_{i,1}^{Total}-A_{i,1}^{IB}-A_{i,1}^{L}, \tag{31}$$

$$L_{i,1}^{D}=A_{i,1}^{Total}-E_{i,1}-L_{i,1}^{IB}, \tag{32}$$

where $A_{i,1}^{Total}$ denotes the total sum of assets of bank i at time 1. Furthemore, of course, the initial volume of all balance sheet items should be non-negative. Combining (29) and (30) yields:

$$A_{i,1}^{L}=A_{i,1}^{IB}\cdot\frac{lr_i}{\kappa_i}. \tag{33}$$

However, if $A_{i,1}^{IB}$ is much smaller than $L_{i,1}^{IB}$, it might not be possible that the ratios (29) and (30), respectively, and $L_{i,1}^{D}=A_{i,1}^{Total}-E_{i,1}-L_{i,1}^{IB}\geq 0$ simultaneously hold. Ensuring non-negativity of $L_{i,1}^{D}$ is equivalent to:

$$L_{i,1}^{D}=A_{i,1}^{Total}-E_{i,1}-L_{i,1}^{IB}=A_{i,1}^{Total}-etar_{i,1}\cdot A_{i,1}^{Total}-L_{i,1}^{IB}=A_{i,1}^{Total}\cdot\left(1-etar_{i,1}\right)-L_{i,1}^{IB}\geq 0$$
$$\Leftrightarrow A_{i,1}^{Total}\geq\frac{L_{i,1}^{IB}}{1-etar_{i,1}}.$$

Thus, the total sum of assets $A_{i,1}^{Total}$ of bank i at time 1 is defined as:[41]

$$A_{i,1}^{Total} = Max\left\{\frac{A_{i,1}^{IB}}{\kappa_i};\frac{L_{i,1}^{IB}}{1-etar_{i,1}};1\right\}. \tag{34}$$

If the second value in the max-term is binding,[42] $L_{i,1}^{D}$ is equal to zero and the initial ratio of interbank loans to total assets and the initial ratio of liquidity buffer assets to total assets are smaller than κ_i and lr_i, respectively. If $\text{outdegree(i)} = \text{indegree(i)=0}$ implying that bank i is not connected to any other bank (neither via its asset side nor via its liability side), $A_{i,1}^{Total} = 1$ is set. To ensure $A_{i,1}^{NB} = A_{i,1}^{Total} - A_{i,1}^{IB} - A_{i,1}^{L} \geq 0$, the following condition must hold in case that the first value in the Max-term (34) is binding:

$$A_{i,1}^{NB} = A_{i,1}^{Total} - A_{i,1}^{IB} - A_{i,1}^{L} = \frac{A_{i,1}^{IB}}{\kappa_i} - A_{i,1}^{IB} - A_{i,1}^{IB}\cdot\frac{lr_i}{\kappa_i} = A_{i,1}^{IB}\cdot\left(\frac{1}{\kappa_i} - 1 - \frac{lr_i}{\kappa_i}\right) = A_{i,1}^{IB}\cdot\left(\frac{1-\kappa_i-lr_i}{\kappa_i}\right) \geq 0$$

$$\Leftrightarrow \kappa_i + lr_i \leq 1.$$

In case that the second value in the Max-term (34) is binding, the condition $\kappa_i + lr_i \leq 1$ also ensures $A_{i,1}^{NB} = A_{i,1}^{Total} - A_{i,1}^{IB} - A_{i,1}^{L} \geq 0$:

$$\kappa_i + lr_i \leq 1 \Leftrightarrow \frac{A_{i,1}^{IB}}{\kappa_{i,1}} - A_{i,1}^{IB} - A_{i,1}^{L} \geq 0 \Rightarrow \frac{L_{i,1}^{IB}}{1-etar_{i,1}} - A_{i,1}^{IB} - A_{i,1}^{L} = A_{i,1}^{NB} \geq 0.$$

5 Results

Table 3 shows for various models the mean p.a. and standard deviation (Std) p.a. of the simulated bank equity log-returns. These correspond to the mean (standard deviation) of the daily bank equity log-returns over the full sample length T scaled by 250 ($\sqrt{250}$). The skewness and excess kurtosis refer to the respective values of the empirical distribution function of the daily bank equity log-returns over the full sample length T. The correlation corresponds to the pairwise correlations between the daily bank equity log-returns over the full sample length T. The mean, median, standard deviation, minimum and maximum of the respective values

[41] See Frey and Hledik (2014, p. 6).

[42] This should be the exception because on average for the employed parameters, $1/\kappa_i$ is by factor 3 larger than $1/(1-etar_{i,1})$.

over all N banks and all $N \cdot (N-1)/2$ possible combinations (in case of correlations), respectively, are exhibited. As can be seen, the range of simulated means and volatilities of bank equity log-returns does not appear to be unrealistic. The (simulated) empirical distributions of the daily bank equity log-returns are approximately symmetric, but, as the excess kurtosis is positive, it is leptokurtic and, hence, exhibits fat tails which is also in line with stylized facts for daily equity returns. Furthermore, Table 3 shows that the null hypothesis of normally distributed equity returns can be rejected for most banks by the Jarque-Bera and the Kolmogorov-Smirnov test on a 1% significance level.

- insert Table 3 about here -

To analyze the ranking consistency of the various SRMs, I compute for each day t and for each SRM $d \in \{1,...,5\}$ (see Section 3), the rank $Rank_{d,i}^t \in \{1,...,N_t\}$ of bank i within the group of N_t banks that have survived until time t.[43] Larger values of the respective SRM at time t correspond to a larger systemic risk ($Rank_d^t = 1$: bank with highest SRM d at time t, $Rank_d^t = N_t$: bank with smallest SRM d at time t). When there are banks with the same SRM value at some time t, average rank values are calculated.[44]

Afterwards, first, for each bank $i \in \{1,...,N\}$ and for each combination of two SRMs $d_1, d_2 \in \{1,...,5\}$, the Pearson correlation coefficient $Corr\left(Rank_{d_1,i}, Rank_{d_2,i}\right)$ of the bank's ranks over time t[45] is computed:[46]

$$Corr\left(Rank_{d_1,i}, Rank_{d_2,i}\right) = \frac{\sum_{t=252}^{T}\left(Rank_{d_1,i}^t - \frac{1}{T-251}\sum_{t=252}^{T} Rank_{d_1,i}^t\right)\cdot\left(Rank_{d_2,i}^t - \frac{1}{T-251}\sum_{t=252}^{T} Rank_{d_2,i}^t\right)}{\sqrt{\sum_{t=252}^{T}\left(Rank_{d_1,i}^t - \frac{1}{T-251}\sum_{t=252}^{T} Rank_{d_1,i}^t\right)^2}\cdot\sqrt{\sum_{t=252}^{T}\left(Rank_{d_2,i}^t - \frac{1}{T-251}\sum_{t=252}^{T} Rank_{d_2,i}^t\right)^2}}. \tag{35}$$

[43] The upper tail dependence $UTD_t^{i,m}$ between $r_{i,t}^{PD}$ and $r_{m,t}^{PD}$ (see (25)) can only be computed for $t \geq 502$ because for calculating PD_t^i, the volatility σ_{t-1,AR_i} of the daily asset returns is needed which is based on the last 250 observed asset returns. Hence, the first risk-neutral default probability PD_t^i can only be computed for $t = 252$. All other SRMs can be calculated for $t \geq 252$.

[44] Instead of computing the rank $Rank_{d,i}^t \in \{1,...,N_t\}$ of bank i at time t based on its SRM $d \in \{1,...,5\}$ at time t, alternatively, moving averages (over time) of the respective SRMs could be calculated and employed for determining $Rank_{d,i}^t$ (see Section 6.1).

[45] When a bank defaults, the rank correlations are only computed until the default time.

[46] In case that $UTD_t^{i,m}$ is involved, the time index t starts in 502.

Thus, for each of the 10 possible combinations of SRMs, I get N correlations, from which the mean, the standard deviation, the minimum, the maximum and the 25%-, 50%- and 75%-quantiles are calculated. For model 1, these figures are displayed in the upper part of Table 4. As the daily SRMs are computed based on rolling 250 days time windows, the bankindividual SRMs and, hence, the ranks are highly autocorrelated. To reduce this effect, the computation of $Corr\left(Rank_{d_1,i}, Rank_{d_2,i}\right)$ in (35) is repeated based on SRMs and ranks that are calculated every 250 days and, hence, from data out of non-overlapping time windows. However, the corresponding results are comparable with those for overlapping time windows and, hence, are not displayed in Table 4.

Second, for each combination of SRMs $d_1, d_2 \in \{1,...,5\}$ and for each time t, the cross-sectional Pearson correlation coefficients $Corr\left(Rank_{d_1}^t, Rank_{d_2}^t\right)$ of the ranks over the number N_t of banks that have survived until time t are computed:[47]

$$Corr\left(Rank_{d_1}^t, Rank_{d_2}^t\right) = \frac{\sum_{i=1}^{N_t}\left(Rank_{d_1,i}^t - \frac{1}{N_t}\sum_{i=1}^{N_t} Rank_{d_1,i}^t\right)\cdot\left(Rank_{d_2,i}^t - \frac{1}{N_t}\sum_{i=1}^{N_t} Rank_{d_2,i}^t\right)}{\sqrt{\sum_{i=1}^{N_t}\left(Rank_{d_1,i}^t - \frac{1}{N_t}\sum_{i=1}^{N_t} Rank_{d_1,i}^t\right)^2}\cdot\sqrt{\sum_{i=1}^{N_t}\left(Rank_{d_2,i}^t - \frac{1}{N_t}\sum_{i=1}^{N_t} Rank_{d_2,i}^t\right)^2}}. \quad (36)$$

Thus, for each of the 10 possible combinations of SRMs, I get $T-251$ correlations ($T-501$ correlations in case that $UTD_t^{i,m}$ is involved), from which again the mean, the standard deviation, the minimum, the maximum and the 25%-, 50%- and 75%-quantiles are calculated. The results are displayed in the lower part of Table 4. Analogously to above, these figures are also computed based on the sample of every 250th correlation coefficient $Corr\left(Rank_{d_1}^t, Rank_{d_2}^t\right)$. Again, the results are comparable.

- insert Table 4 about here -

[47] These correlation coefficients are essentially Spearman's rho values.

The largest mean rank correlation (both in time series and cross-sectional dimension) yields the pair of SRMs MES and LTDE which is in line with the empirical results of Jiang (2012).[48] For the pair MES and Beta, the mean rank correlations are also relatively high. This result is in line with the theoretical arguments and empirical results of Benoit et al. (2013) and Jiang (2012), too.[49] For the other pairs of SRMs, the mean rank correlations are in general much smaller. This result is basically also in line with the empirical findings of Benoit et al. (2013) who, based on a sample of US financial institutions over the period 2000 – 2010, find that different SRMs indentify different systemically important financial institutions.[50] Benoit et al. (2013) argue that SRMs, such as MES or SRISK, only reflect one dimension of systemic risk (market risk or bank characteristics like liabilities) and, hence, are unable to capture the "multifaceted nature of systemic risk", which could explain the observed ranking inconsistencies. Astonishing are the slightly negative mean rank correlations in the cross-sectional dimension for the pair SRISK and UTDPD. However, as argued later, the SRM SRISK is strongly influenced by the assumed bank behavior rules and particularily by the capital ratio k in the definition (21) of SRISK (see Table 7 in the following).[51] For the pair MES and SRISK, the model implied cross sectional mean rank correlation is also smaller than the empirical counterpart computed by Nucera et al. (2016, Table 4, p. 16) for a monthly sample of 113 European financial institutions in the time period 2002 to 2013.

Based on an Augmented Dickey-Fuller (ADF) test, Nucera et al. (2016) report that for their sample, the rejection rate (across financial institutions) of the null hypothesis of a unit root in the time series of rankings varies between 36% and 85% (depending on the considered SRM).

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[48] Jiang (2012, p. 31, second and third panel of the first row of figure 12) finds that in the cross-section, there is a positive correlation between MES and LTDE. However, in contrast to the results implied by the banking network, Jiang (2012) also finds this positive correlation between SRISK and LTDE.

[49] For example, Benoit et al. (2013, p. 19) state "that systemic risk rankings of financial institutions based on their MES tend to mirror rankings obtained by sorting firms on beta." Indeed, they show that under specific distributional assumptions, the cross-sectional rank correlation between MES and beta must be one. The fact that this cannot be observed in the employed model might be due to estimation error (see Danielsson et al. (2015, 2016)) or due to implied endogeneous equity return distributions that deviate from the bivariate GARCH process assumed in the theoretical part of Benoit et al. (2013).

[50] Benoit et al. (2013) compare MES, SRISK and ΔCoVaR. In the empirical part of their paper, Benoit et al. (2013) find, for example, that on almost half of the days not even a single of the 94 considered financial institutions is simultaneously identified as a TOP 10 systemically important financial institution by all three SRMs.

[51] As non-risk-weighted assets are used in (21), the default setting is $k = 0.03$ for the simulations, whereas in many other studies $k = 0.08$ is employed.

Hence, non-stationarity seems to be an issue for many rankings and the computation of rank correlations in the time series dimension is not meaningful. For the model-implied rankings produced by the simulations, the same is true. Carrying out an ADF-Test for 5 SRMs · 50 banks = 250 time series of rankings in model 1, the null hypothesis of a unit root is not rejected in 16% to 45% of the cases (depending on the number of lags and whether a trend is considered in the ADF test) for a significance level of 5% and in 10% to 32% of the cases for a significance level of 10% (without Tables). The non-rejection rates are particularly high for the SRMs MES, Beta and SRISK. That is why in the following, I focus on the analysis of the rank correlations in the cross-sectional dimension.

Table 5 shows the mean (over T) rank correlations (cross-sectional dimension) for the various models described in Section 4. As can be seen, in general, the degree of heterogeneity in banks' balance sheets as well as the network structure of the banking system do have a significant impact on the rank correlations for many pairs of SRMs. Again, negative mean rank correlations can be observed (in particular, when SRISK is involved). Whether the mean rank correlations in models 2 to 5 are significantly different from those in model 1, is tested in as follows. First, 30 simulation runs have been done for all models 1 to 5.[52] Then, significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in model 1 and in one of the other models are identical (significance level 5% for both tests).

- insert Table 5 about here -

To get a better feeling for the comparability of the SRMs' classification performance found, on the one hand, in the simulation-based network model presented above and, on the other hand, in empirical studies, the cross-sectional averages of the time series standard deviations of the banks' ranks (based various SRMs) are shown in Table 6. These results are roughly comparable with those ones of Nucera et al. (2016, Table 1, p. 13).[53] For example, they also

[52] When using 100 simulation runs, the results are qualitatively similar.
[53] However, it has to be taken into account that Nucera et al. (2016) scale down the bankindividual ranks to numbers between 0 and 1 (by dividing through the number of considered banks), compute the time series standard deviations of these numbers, average these standard deviations over all banks and multiply the result with

find that the rank stability based on SRISK is larger than that one based on MES. Furthermore, Table 6 shows the time series means of the similarity ratios (for the TOP 10% and TOP 20%) for each pair of SRMs. The intuition for analyzing similarity ratios as consistency measures is that when different SRMs do not perform well in consistently ranking financial institutions with low systemic risk, this might be negligible as long as they do a good job for those ones with large systemic risk. For computing the similarity ratios, for each time t and each pair of SRMs m and o, the percentage of all banks that simultaneously based on both SRMs m and o belong to the respective TOP category is calculated. The closer the displayed percentage numbers are to 10% and 20%, respectively, the more similar is the classification performance of the two SRMs m and o. Comparing the results with Jiang (2012, Table 9), the empirical and theoretical results are again roughly comparable. In both cases, the consistency of the SRMs as measured by the similarity ratios is rather low.[54] Furthermore, in both cases, the consistency is best for the pair MES and Beta.

- insert Table 6 about here -

Next, the sensitivity of the mean rank correlations (over T) with respect to the parameterization of the model (including behavioral rules and network characterstics) is analyzed. To be able to check the sensitivity of the SRMs' ranking consistency with respect to basic features of the banking system is the essential advantage of this simulation-based network analysis over a pure empirical approach. Within the latter approach, estimation risk makes it rather difficult to derive comparable results. However, of course, the price one has to pay for this is that model risk may influence the results.

To carry out the sensitivity analysis, the following simulation is done: Within the inhomogeneous (core-periphery) random graph network structure (model 5), almost all parameters (in-

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100. If the simulation-based results with respect to the cross-sectional averages of the time series standard deviations of the banks' ranks (taking values between 1 and 50) shown in Table 6 are divided by the number of considered banks and multiplied with 100, the simulation-based results would be larger than the empirical results of Nucera et al. (2016) by a factor of 1.5 to 2. One reason for the larger rank volatilities might be that in the model, instantaneous actions are carried out when some indicators at some date meet a specific condition. In reality, a bank's reaction might be not so prompt.

[54] In contrast to this paper, Jiang (2012) computes the similarity ratio for a specific pair of SRMs by relating the number of banks that simultaneously belong to the TOP 10 category based on both SRMs to the number of elements in the considered TOP category (i.e., 10). Thus, a similarity ratio of 1 in Jiang (2012) would be identical to a similarity ratio of 10% and 20%, respectively, in Table 6 of this paper.

cluding bank-related parameters, general parameters and network probabilities; see Tables 1 and 2) are randomly drawn from a uniform distribution on specified intervals for each simulation run. The realizations of these parameters are assumed to be identical for all banks in the respective simulation run. Contagious simulation runs (defined as those with more than 20% defaulting banks) were discarded. In total, 650 simulation runs were considered. Then, within a multiple OLS regression, the mean rank correlations for the various pairs of SRMs were explained by the realizations of the model parameters. To avoid problems with collinearity, the connectivity is not used as explaining variable, but only the single network probabilities. The variables $etar_{Min}^{IB}$ (driving the beginning of the interbank credit rationing mechanism when the credit quality of a bank detoriates) and $\lambda*$ (driving the intensity of the interbank credit rationing mechanism) are only used in interaction terms, together with the event $etar_{Min}^{IB} > \eta_{\min}$. This ensures that a variation of the parameters $etar_{Min}^{IB}$ and $\lambda*$ can develop its full effect. When $etar_{Min}^{IB}$ is smaller than the lower boundary $\eta_{\min}$ of the $etar$-rule (as in the original parameterization; see Table 1), the bank will always adjust its equity-to-assets ratio (as long as this is possible for the bank) and the interbank credit rationing mechanism will only take effect when it is no longer possible for the bank to comply with the minimum equity-to-assets ratio $\eta_{\min}$.

As Table 7 shows, the most frequent significant influence on the mean rank correlations[55] have the parameters PD (governing the mean default rate in the non-bank loan portfolio), the parameters μ, σ and ρ^{market} (related to the stochastic development of the mark-to-market values of the liquidity buffer assets and their stochastic dependence across banks), the parameter $\eta_{\max}$ (related to the behavioral rules of the banks) and the parameter p_{Core} (determining the probability with which a bank belongs to the core of the network). The sign of the regression coefficients of the various parameters depends on the considered pair of SRMs. Thus, a variation of one of these parameters usually has no unambiguous influence on the ranking consistency of SRMs. Furthermore, a medium significant effect on the mean rank correlations also results from the parameters LGD (the loss given default of the non-bank loans), the initial ratio of interbank loans to total assets κ as well as the parameters $\beta_{\max}$ and $\eta_{\min}$ and the

[55] Measured by the number of pairs of SRMs for which the respective parameter has a significant (up to a significance level of 5%) impact on the mean rank correlation.

interaction term $etar_{Min}^{IB} \cdot 1_{\{etar_{Min}^{IB} > \eta_{\min}\}}$ (all three are related to the behavioral rules of the banks). The fact that many parameters related to the assumed behavioral rules of the banks are significant shows that changes in the business strategy of banks might have a major impact on the ranking consistency of SRMs. However, this also shows that the behavioral assumptions of Section 2 (reflecting the banks' business strategies) and the parameters chosen for these behavioral rules (see Tables 1 and 2) can be relevant for the results and that, thus, model risk is at work. Furthermore, as can be seen in Table 7, the value k for the required prudential or regulatory capital ratio in the definition (21) of SRISK is highly significant for the mean rank correlations of all pairs of SRMs in which SRISK is involved. For all pairs, the influence is positive: Increasing the value of k leads to higher mean rank correlations.[56] This shows that seemingly only minor modifications of the definition of a SRM might have a major impact on the ranking consistency of the SRMs. As Table 7 shows, changing the other parameters only has a minor effect on the mean rank correlations.[57] A significant influence can only be found for a few pairs of SRMs. It is remarkable that even a variation of the correlation parameter ρ^{bank}, which determines the stochastic dependence between the default rates in the non-bank loan portfolios across banks, has hardly any significant effect on the mean ranking correlations.

- insert Table 7 about here -

6 Robustness Checks

In this section, the sensitivity of the results with respect to various modelling assumptions is tested.

[56] This might also explain why strikingly many negative mean rank correlations can be observed in the various models when the SRM SRISK is involved (see Table 5). Compared to many empirical studies, where usually $k = 0.08$ is employed, I have chosen $k = 0.03$ which economically seems to be more plausible as the assets are not risk-weighted.

[57] Based on the DebtRank methodology of Battiston et al. (2012c), Roukny et al. (2013) argue that an interplay exists between the relevance of the structure of the financial network for the stability of the system and the degree of market illiquidity. They report that only when the market is illiquid, the network structure does matter for the stability of the system. Thus, liquidity issues might also influence the ranking consistency of SRMs. However, in the model employed in this paper, a variation of the liquidity related parameters τ and lr hardly shows any significant impact on the ranking consistency of the SRMs (see Table 7). Repeating the computations of Table 5 for models 4a, 5a and 5b (implying different network connectivities) and reduced boundaries $[0.05; 0.1]$ for the initial ratio lr of liquidity buffer assets to total assets (instead of $[0.15; 0.25]$ as before; see Table 2) also has hardly any impact on the rank correlations of the SRMs.

6.1 Moving Averages of SRMs

Instead of computing the rank $Rank_{d,i}^{t} \in \{1,...,N_t\}$ of bank i at time t within the group of N_t surviving banks based on its SRM $d \in \{1,...,5\}$ at time t, alternatively, moving averages (over the last 100 observations at each time t) of the respective SRMs are calculated and employed for determining $Rank_{d,i}^{t}$. Doing this, fluctuations in the SRMs and, hence, the ranks should be smoothed over time. As Table 8 shows, this indeed has in most cases a significant effect on the cross sectional averages of the time series standard deviations of ranks. However, comparing the respective numbers in Table 6 and Table 8, the absolute differences are rather small. For the mean rank correlations and the similarity ratios, only scattered significant effects result and again the absolute effect is rather small.

- insert Table 8 about here -

6.2 Additional Dependencies and Fat-Tailed Risk Factors

Up to now, it has been assumed that the random variables $Z_{1,t},\ldots,Z_{N,t} \sim N(0,1)$ driving the default rates in the non-bank loan portfolios (see (8)) are correlated with each other at each time t, but are uncorrelated with the normally distributed log-returns $r_{1,t},\ldots,r_{N,t}$ by which stochastic price fluctuations of the liquidity buffer assets (lba) are modelled (see (9)) and which are also correlated with each other at each time t. In this subsection, first, a constant positive correlation $\rho_{Z,lba}$ between all random variables $Z_{1,t},\ldots,Z_{N,t}$ and all log-returns $r_{1,t},\ldots,r_{N,t}$ is introduced. Thus, decreasing Z-values (and, hence, increasing default rates within the non-bank loan portfolios) are assumed to tend to go along with decreasing returns on the liquidity buffer assets. Second, additionally, $Z_{1,t},\ldots,Z_{N,t}$ and $r_{1,t},\ldots,r_{N,t}$ are assumed to be multivariate t-distributed with υ degrees of freedom. Switching from a multivariate normal to a multivariate t-distribution (with $\upsilon < \infty$) causes fatter tails of the marginal distributions of the default rates and the returns of the liquidity buffer assets. Furthermore, tail dependencies between these random variables are introduced by this modified modelling assumption.[58] As Table 9

[58] The first considered case (multivariate normal distribution) corresponds to a multivariate t-distribution with degree of freedom $\upsilon = \infty$. For empirical evidence that a t-copula (implying tail dependencies) might be more appropriate than a Gaussian copula for modelling the stochastic dependencies between the returns of various asset classes, see, for example, Grundke and Polle (2012) and the papers cited therein.

shows, these distributional modifications only have a minor to medium significant effect on the mean rank correlations in the various models. Thus, model risk with respect to the distributional assumptions seems not to be prominent.

- insert Table 9 about here -

6.3 Additional Stochastic Fluctuations of the Deposit Volume

According to (10), fluctuations in the volume of the non-bank deposits are mainly caused by changes in a bank's equity-to-assets ratio. Stochastic fluctuations of this volume that are not related to the bank's own credit quality are not considered. In this subsection, this assumption is mitigated. Instead of (10), the following representation for the volume of the non-bank deposits $L_{i,t}^{D}$ of bank i at time t is employed:

$$L_{i,t}^{D} = L_{i,t-1}^{D} \cdot Max\left\{0; \left(\frac{etar_{i,t-1}}{etar_{i,t-2}}\right)^{\frac{1}{q}} + \frac{\varepsilon_{i,t}}{4 \cdot \sqrt{250}}\right\} + \left(g_i - 1\right) \cdot A_{i,t-1}^{NB} \tag{37}$$

with $q \in \mathbb{N}$ and i.i.d. $\varepsilon_{i,t} \sim N(0,1)$, which are assumed to be independent from all other random variables of the model. Thus, changes in the volume of the non-bank deposits that are caused by market discipline exerted by the depositors are overlaid by purely random changes. The usage of the Max-term in (37) is sufficient to ensure that the deposit volume cannot become negative. As Table 10 shows, the introduction of additional stochastic fluctuations in the non-bank deposit volume has a medium significant effect on the mean rank correlations in various models.

- insert Table 10 about here -

6.4 Alternative Balance Sheet Construction

One problem of the methodology to construct the initial bank balance sheets described in Section 4 is that it does not ensure a sufficient name diversification within the group of interbank loans granted by a bank. For example, when $\text{outdegree}(i) = 1$ holds, bank i has lent all its interbank credit exposure to one single debtor. Thus, to mimic regulatory large credit exposure constraints in the following, the initial individual interbank loan size is limited to 30% of a bank's initial equity value:

$$\frac{A_{i,1}^{IB}}{\text{outdegree}(i)} = 1 \leq 0.3 \cdot E_{i,1} . \tag{38}$$

Furthermore, to ensure a sufficient diversification of funding sources (non-bank deposits versus interbank liabilities), a minimum level of integration into the network with respect to the liability side of a bank is required:

$$\frac{L_{i,1}^{IB}}{A_{i,1}^{Total}} \leq \kappa_i \Leftrightarrow \frac{L_{i,1}^{IB}}{\kappa_i} \leq A_{i,1}^{Total} . \tag{39}$$

Additionally, as before (see (28) and (30)), specific initial equity-to-assets ratios and ratios of liquidity buffer assets to total assets are required:

$$\frac{E_{i,1}}{A_{i,1}^{Total}} = etar_{i,1} \Leftrightarrow E_{i,1} = etar_{i,1} \cdot A_{i,1}^{Total} , \tag{40}$$

$$\frac{A_{i,1}^{L}}{A_{i,1}^{Total}} = lr_i \Leftrightarrow A_{i,1}^{L} = lr_i \cdot A_{i,1}^{Total} .\text{[59]} \tag{41}$$

Combining (38) with (40) yields:

$$\frac{10}{3 \cdot etar_{i,1}} \leq A_{i,1}^{Total} . \tag{42}$$

Furthermore, as before, to ensure $L_{i,1}^{D} = A_{i,1}^{Total} - E_{i,1} - L_{i,1}^{IB} \geq 0$,

$$\frac{L_{i,1}^{IB}}{1 - etar_{i,1}} \leq A_{i,1}^{Total} \tag{43}$$

must hold. Finally, to ensure $A_{i,1}^{NB} \geq 0$, the following condition must be met:

[59] In this subsection, using the required ratio lr_i, $A_{i,1}^{L}$ is derived from the initial volume of total assets (instead of using (33)). This has two advantages: First, the required ratio lr_i is indeed always fulfilled, and, second, the initial volume of the liquidity buffer assets $A_{i,1}^{L}$ is not equal to zero for $A_{i,1}^{IB} = 0$ ($L_{i,1}^{IB} = 0$).

$$A_{i,1}^{NB} = A_{i,1}^{Total} - A_{i,1}^{L} - A_{i,1}^{IB} = A_{i,1}^{Total} - lr_i \cdot A_{i,1}^{Total} - A_{i,1}^{IB} = A_{i,1}^{Total} \cdot (1 - lr_i) - A_{i,1}^{IB} \geq 0$$

$$\Leftrightarrow \frac{A_{i,1}^{IB}}{1 - lr_i} \leq A_{i,1}^{Total}. \tag{44}$$

Combining (39) and (42) to (44), the total sum of assets $A_{i,1}^{Total}$ of bank i at time t is defined as:

$$A_{i,1}^{Total} = Max\left\{\frac{L_{i,1}^{IB}}{\kappa_i}; \frac{10}{3 \cdot etar_{i,1}}; \frac{L_{i,1}^{IB}}{1 - etar_{i,1}}; \frac{A_{i,1}^{IB}}{1 - lr_i}\right\}. \tag{45}$$

As for the typical parameterization $1 - etar_{i,1} > \kappa_i$ and, hence, $L_{i,1}^{IB} / \kappa_i > L_{i,1}^{IB} / (1 - etar_{i,1})$ holds, the third value in the Max-term usually will not be binding which implies $L_{i,1}^{D} > 0$. The parameters κ_i, $etar_{i,1}$ and lr_i ($i \in \{1, \ldots, N\}$) are chosen as displayed in Tables 1 and 2 for the respective models. As Table 11 shows, the consequences of this alternative procedure for generating the banks' initial balance sheets are model-dependent. While for models 1 and 4a, there is no significant effect on the mean rank correlations, it is the direct opposite for model 5a. This might be interpreted as a hint that model risk with respect to the initial balance sheet construction is at work.

- insert Table 11 about here -

7 Policy Implications

What can we learn from the results? First of all, they show that market-based measures of systemic risk have to be used with care when judging the various facets of systemic risk of a financial institution. In the presented study, it has been shown that SRMs which measure the exposure to systemic risk can imply very different statements with respect to this facet of systemic risk. Basically, this low ranking consistency of SRMs found within the employed theoretical banking network model is in line with results of corresponding empirical analyses (see Benoit et al. (2013) and Nucera et al. (2016); for controversial interpretations, see Lin et al. (2016)). Moreover, in contrast to the empirical analyses, the usage of a theoretical banking network model offered the advantage to analyse the influence that specific characteristics of banks or the banking network might have on the ranking consistency of SRMs. The 'ideal' result would have been that constellations could have been identified in which the ranking consistency of all SRMs is rather high. In this case, regulators and supervisors would have been relatively safe when judging the systemic risk of a financial institution based on one of these SRMs. Unfortunately, this 'ideal' result has not been found. The ranking consistency in fact significantly varied when changing characteristic features, but forecasting how strong this effect is and in which direction it goes seems to be rather difficult because the effects can be different for different pairs of SRMs.

What are the reasons for the observed low consistency between different SRMs? One reason might be model and estimation risk as pointed out by Danielsson et al. (2015, 2016). In this case, using aggegrates of different SRMs (such as the principal components-based methodology proposed by Nucera et al. (2016)) could help to average out these risks. Nucera et al. (2016) show that their methodology leads to rankings that are less volatile than most rankings based on single SRMs and to less turnover among the top ranked financial institutions. Another reason might be that it is by construction that each SRM leads to another judgement of the systemic risk of a financial institution, i.e., even with an infinite length of the data sample and without model risk the usage of different SRMs might implies different judgements. For example, Nucera et al. (2016) find that purely market-based SRMs (e.g., MES) and SRMs that additionally use book values (e.g., SRISK) substantially deviated in the period leading up to the financial crisis 2007 – 2009. In this case, it might be less obvious that computing aggegrates of various SRMs is helpful for assessing the systemic risk of a financial institution. Instead, it would be interesting to know which SRMs are indeed most closely related to the systemic riskiness of financial institutions and the likelihood of a systemic crisis and, hence, could reliably serve (possibly in an aggregated way) as early warning indicators for supervisors and regulators. The empirical results on this topic are sparse, partially mixed and seem to depend on the considered kind of crisis (see Brownlees et al. (2015) and Zhang et al. (2016)). Thus, it would be necessary to shed further light on this question. Using the proposed banking network model (or adequate extensions), this would be possible because the existing empirical results could be complemented by theoretically derived results.

8 Conclusions

In a banking network model that, among others, accounts for bank insolvencies as well as illiquidities, stochastic dependencies of non-bank loans as well as of liquidity buffer assets across various banks, bank rating-dependent volumes of deposits and interbank liabilities and the funding liquidity reducing effect of fire sales of other banks, the ranking consistency of various popular systemic risk measures (SRM) has been analyzed. It could be shown that, in general, the ranking consistency (measured by the rank correlation) is rather low. Furthermore, the ranking consistency can significantly vary, for example for an increasing correlation between the returns of the liquidity buffer assets across banks, for an increasing degree of heterogeneity in the banks' balance sheets or with a changing network structure of the banking system. However, forecasting which effect a specific change in parameters, bank behavior or network characteristics has on the ranking consistency of SRMs in general seems to be rather difficult because the sign of the effect can be different for different pairs of SRMs.

In future research, first, the employed banking network model could be refined. For example, behavioral rules of the banks to meet liquidity requirements (such as the liquidity coverage ratio) could be implemented or the rules for meeting minimum capital requirements could be modified. The analysis has shown that the assumptions with respect to these behavioral rules can have a significant impact on the results. Second, the results derived in the theoretic banking network model which basically are prone to model risk should be supplemented by empirical findings. Doing this, also the influence of factors such as book-to-market ratios of bank equity or the degree of risk aversion of investors, which are not reproduced in the employed banking network model, on the ranking consisteny of SRMs could be analyzed.[60] Third, as mentioned in Section 7, the important question whether the SRMs proposed in the literature indeed can indicate the systemic risk of financial institutions and the likelihood of a systemic crisis could be analysed in the proposed banking network.

[60] For example, Döring et al. (2015) find that, beside the loan-to-deposit ratio, the book-to-market ratio of bank equity is a fundamental driver of systemic risk. Thus, it is imaginable that the book-to-market ratio could also have a significant influence on the ranking consisteny of SRMs.

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Tables

Table 1: Parameterization (Model 1)

Parameter	Value
Connectivity (C):	49
General parameters:	
Initial number of banks (N)	50
Length of the simulated time series (T)	5000
Liquidity rule parameter (τ)	0.02
Deposit rule parameter (q)	2
Interbank rule parameter ($etar_{Min}^{IB}$)	0.04
Interbank rule parameter (λ)	0.025
Interbank rule parameter ($\lambda *$)	0.025
Parameter for liquidity buffer assets reinvestment rule ($\beta_{\max}$)	0.3
Parameter for liquidity buffer assets reinvestment rule (w_1)	0.5
Equity-to-assets ratio reinvestment rule parameter ($\eta_{\max}$)	0.13
Equity-to-assets ratio reinvestment rule parameter ($\eta_{\min}$)	0.06
Equity-to-assets ratio reinvestment rule parameter ($w_{2.1}$)	0.5
Equity-to-assets ratio reinvestment rule parameter ($w_{2.2}$)	0.5
Equity-to-assets ratio reinvestment rule parameter ($w_{3.1}$)	0.5
Equity-to-assets ratio reinvestment rule parameter ($w_{3.2}$)	0.5
Initial bank balance sheet structure:	
Equity-to-assets ratio ($etar_1$)	0.085
Ratio of interbank loans to total assets (κ)	0.35
Ratio of liquidity buffer assets to total assets (lr)	0.2
Costs and revenues:	
Daily interest on non-bank loans (e^{NB})	0.065/250
Daily interest on interbank loans (e^{IB})	0.02/250
Daily interest on liquidity buffer assets (e^{L})	0.03/250
Daily interest on deposits (c^{D})	0.01/250
Daily interest on interbank liabilities (c^{IB})	0.02/250
Other bank-related parameters:	
One-year default probability of the banks' non-bank obligors (PD)	0.085
Asset return correlation of the banks' non-bank obligors (ρ)	0.35
Parameter determining the stochastic dependence between the bankindividual default rates in the non-bank loan portfolio (ρ^{bank})	0.35
One plus daily growth rate of the non-bank loan portfolio (g)	1+0.055/250
Loss given default for non-bank loans (LGD)	0.35
Mean of daily returns of the liquidity buffer assets (μ)	0.055/250
Standard deviation of daily returns of the liquidity buffer assets (σ)	$0.125/\sqrt{250}$
Parameter determining the stochastic dependence between the bankindividual daily returns of the liquidity buffer assets (ρ^{market})	0.2

This table shows the parameterization of the banking network model in the base case setting (model 1). In this case, it is assumed that all banks are homogeneous with respect to the parameters exhibited in the table. All banks are connected with all other banks ($p_{Core} = p_{CC} = 1$ and $p_{PP} = p_{CP} = p_{PC} = 0$).

Table 2: Parameterizations (Models 2 to 5)

Parameter	**Value**
Model 2 ($C = 49$):	
Equity-to-assets ratio ($etar_{i,1}$)	[0.07;0.10]
Ratio of interbank loans to total assets (κ_i)	[0.10;0.60]
Ratio of liquidity buffer assets to total assets (lr_i)	[0.15;0.25]
Model 3 ($C = 49$):	
One-year default probability of the banks' non-bank obligors (PD_i)	[0.01;0.15]
Asset return correlation of the banks' non-bank obligors (ρ_i)	[0.10;0.60]
Parameter determining the stochastic dependence between the bankindividual default rates in the non-bank loan portfolio (ρ_i^{bank})	[0.10;0.60]
One plus daily growth rate of the non-bank loan portfolio (g_i)	[1+0.01/250;1+0.1/250]
Loss given default for non-bank loans (LGD_i)	[0.10;0.60]
Mean of daily returns of the liquidity buffer assets (μ_i)	[0.01/250;0.10/250]
Standard deviation of daily returns of the liquidity buffer assets (σ_i)	[0.05/$\sqrt{250}$;0.20/$\sqrt{250}$]
Parameter determining the stochastic dependence between the bankindividual daily returns of the liquidity buffer assets (ρ_i^{market})	[0.10;0.30]
Model 4a (Erdös-Rényi random graph) ($C = 24.5$):	$p_{ER} = 0.5$
Model 4b ($C = 12.25$):	$p_{ER} = 0.25$
Model 4c ($C = 4.90$):	$p_{ER} = 0.1$
Model 5a (Core-periphery graph) ($C = 8.82$):	$p_{Core} = 0.1$, $p_{CC} = 0.9$ $p_{CP} = p_{PC} = 0.5$, $p_{PP} = 0.1$
Model 5b ($C = 4.63$):	$p_{Core} = 0.1$, $p_{CC} = 0.9$ $p_{CP} = p_{PC} = 0.25$, $p_{PP} = 0.05$

This table shows the parameterizations of the banking network model in models 2 to 5 as described in Section 4. For increasing model numbers, the modifications are cumulative. All parameters that are not mentioned in this table are chosen as exhibited in Table 1. When intervals are displayed, the corresponding bankindividual parameters are independently sampled from a uniform distribution on the indicated intervals. In models 2 and 3, all banks are connected with all other banks ($p_{Core} = p_{CC} = 1$ and $p_{PP} = p_{CP} = p_{PC} = 0$). C: Connectivity.

Table 3: Descriptive Statistics for Bank Equity Returns

Model 1

Equity log-returns	**Mean (over N)**	**Median (over N)**	**Std (over N)**	**Min (over N)**	**Max (over N)**
Mean (over T) p.a.	20.78%	21.11%	5.08%	7.31%	29.81%
Std (over T) p.a.	27.17%	26.39%	2.19%	24.31%	33.29%
Skewness (over T) (daily)	0.002	0.01	0.06	-0.19	0.18
Excess kurtosis (over T) (daily)	0.74	0.71	0.405	0.10	2.10
Correlation (over T) (daily)	0.1990	0.1990	0.0143	0.1539	0.2443
H_0 Normality rejected by	1%	5%	10%	*significance level*	
Jarque-Bera test	96%	98%	100%		
Kolmogorow-Smirnov test	62%	84%	94%		

Model 4a

Equity log-returns	**Mean (over N)**	**Median (over N)**	**Std (over N)**	**Min (over N)**	**Max (over N)**
Mean (over T) p.a.	17.18%	17.79%	9.05%	-19.25%	39.04%
Std (over T) p.a.	22.97%	20.17%	11.43%	7.46%	51.30%
Skewness (over T) (daily)	-0.02	-0.01	0.10	-0.26	0.26
Excess kurtosis (over T) (daily)	2.34	2.27	1.41	0.34	6.51
Correlation (over T) (daily)	0.1767	0.1732	0.0471	0.0568	0.2955
H_0 Normality rejected by	1%	5%	10%	*significance level*	
Jarque-Bera test	100%	100%	100%		
Kolmogorow-Smirnov test	94%	98%	100%		

Model 5a

Equity log-returns	**Mean (over N)**	**Median (over N)**	**Std (over N)**	**Min (over N)**	**Max (over N)**
Mean (over T) p.a.	18.51%	17.94%	9.80%	-7.08%	42.15%
Std (over T) p.a.	23.94%	21.07%	13.66%	5.09%	59.20%
Skewness (over T) (daily)	0.07	0.003	0.34	-0.44	1.64
Excess kurtosis (over T) (daily)	6.54	3.11	9.96	0.13	56.71
Correlation (over T) (daily)	0.1563	0.1554	0.0449	0.0301	0.3281
H_0 Normality rejected by	1%	5%	10%	*significance level*	
Jarque-Bera test	100%	100%	100%		
Kolmogorow-Smirnov test	98%	98%	98%		

Table 3 [continued]

The table above shows the descriptive statistics for bank equity returns for various models. The mean p.a. and standard deviation (Std) p.a. of the equity log-returns correspond to the mean (standard deviation) of the daily equity log-returns over the full sample length T scaled by 250 ($\sqrt{250}$). The skewness and excess kurtosis refer to the respective values of the empirical distribution function of the daily equity log-returns over the full sample length T. The correlation corresponds to the pairwise correlations between the daily equity log-returns over the full sample length T. In the second to fourth column the mean, minimum and maximum of the respective values over all N banks and all $N \cdot (N-1)/2$ possible combinations (in case of correlations), respectively, are exhibited. Furthermore, the table shows the percentage of banks for which the Jarque-Bera test and the Kolmogorow-Smirnov test reject the null hypothesis of normally distributed equity returns.

Table 4: Rank Correlations (Model 1)

Rank correlations (time series dimension)	Mean (over N)	Std (over N)	Min (over N)	25%-quantil	50%-quantil	75%-quantil	Max (over N)
Beta-MES	0.475	0.153	0.091	0.369	0.479	0.588	0.763
SRISK-MES	0.397	0.183	-0.102	0.277	0.408	0.533	0.720
SRISK-Beta	0.274	0.232	-0.299	0.103	0.280	0.441	0.725
LTDE-MES	0.549	0.121	0.222	0.468	0.559	0.636	0.768
LTDE-Beta	0.186	0.178	-0.238	0.054	0.188	0.307	0.559
LTDE-SRISK	0.135	0.187	-0.301	0.000	0.143	0.262	0.515
UTDPD-MES	0.224	0.150	-0.123	0.113	0.222	0.332	0.547
UTDPD-Beta	0.143	0.169	-0.245	0.016	0.142	0.259	0.486
UTDPD-SRISK	0.083	0.176	-0.309	-0.047	0.075	0.215	0.448
UTDPD-LTDE	0.250	0.144	-0.095	0.150	0.254	0.355	0.545

Rank correlations (cross-sectional dimension)	Mean (over T)	Std (over T)	Min (over T)	25%-quantil	50%-quantil	75%-quantil	Max (over T)
Beta-MES	0.503	0.115	0.116	0.426	0.508	0.585	0.783
SRISK-MES	0.294	0.200	-0.192	0.144	0.282	0.446	0.744
SRISK-Beta	0.235	0.237	-0.279	0.046	0.201	0.427	0.743
LTDE-MES	0.544	0.105	0.180	0.477	0.552	0.618	0.807
LTDE-Beta	0.180	0.143	-0.255	0.083	0.186	0.281	0.577
LTDE-SRISK	0.002	0.148	-0.400	-0.102	0.000	0.105	0.418
UTDPD-MES	0.223	0.155	-0.254	0.116	0.227	0.332	0.633
UTDPD-Beta	0.138	0.153	-0.329	0.034	0.139	0.245	0.556
UTDPD-SRISK	-0.048	0.151	-0.464	-0.150	-0.052	0.056	0.382
UTDPD-LTDE	0.267	0.157	-0.223	0.160	0.274	0.378	0.682

The table above shows the rank correlations for the base model 1. All values are means over 30 simulation runs. The results for the rank correlations correspond to equations (35) and (36) for overlapping time windows. The results for non-overlapping time windows are comparable.

Table 5: Mean Rank Correlations (Models 2 to 5)

Mean rank correlations (over T) (cross-sectional dimension)	Model 2	Model 3	Model 4a	Model 4b	Model 4c	Model 5a	Model 5b
Beta-MES	0.569$^{*\circ}$	0.861$^{*\circ}$	0.872$^{*\circ}$	0.907$^{*\circ}$	0.917$^{*\circ}$	0.907$^{*\circ}$	0.913$^{*\circ}$
SRISK-MES	0.320$^{*\circ}$	0.344$^{*\circ}$	0.290	0.292	0.329$^{*\circ}$	0.323	0.288
SRISK-Beta	0.336$^{*\circ}$	0.322$^{*\circ}$	0.259	0.256	0.288$^{*\circ}$	0.288*	0.237
LTDE-MES	0.506$^{*\circ}$	0.384$^{*\circ}$	0.378$^{*\circ}$	0.389$^{*\circ}$	0.428$^{*\circ}$	0.394$^{*\circ}$	0.437$^{*\circ}$
LTDE-Beta	0.153$^{*\circ}$	0.189	0.190	0.240$^{*\circ}$	0.308$^{*\circ}$	0.248$^{*\circ}$	0.323$^{*\circ}$
LTDE-SRISK	-0.047$^{*\circ}$	-0.083$^{*\circ}$	-0.091$^{*\circ}$	-0.079$^{*\circ}$	-0.055$^{*\circ}$	-0.070$^{*\circ}$	-0.075$^{*\circ}$
UTDPD-MES	0.207	0.029$^{*\circ}$	0.025$^{*\circ}$	0.097$^{*\circ}$	0.183$^{*\circ}$	0.110$^{*\circ}$	0.210
UTDPD-Beta	0.110$^{*\circ}$	-0.015$^{*\circ}$	-0.012$^{*\circ}$	0.073$^{*\circ}$	0.167°	0.086$^{*\circ}$	0.202$^{*\circ}$
UTDPD-SRISK	-0.102$^{*\circ}$	-0.173$^{*\circ}$	-0.155$^{*\circ}$	-0.146$^{*\circ}$	-0.127$^{*\circ}$	-0.156$^{*\circ}$	-0.170$^{*\circ}$
UTDPD-LTDE	0.283*	0.236$^{*\circ}$	0.208$^{*\circ}$	0.204$^{*\circ}$	0.214$^{*\circ}$	0.194$^{*\circ}$	0.236$^{*\circ}$

The table above shows the mean rank correlations (over T) for models 2 to 5. All values are means over 30 simulation runs. The results for the rank correlations correspond to equation (36) for overlapping time windows. The results for non-overlapping time windows are comparable. Significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in model 1 and in one of the other models are identical. The symbol * marks a rejection of the null hypothesis of identical means based on the Welch two sample t-test and the symbol $^{\circ}$ marks a rejection based on the Mann-Whitney-U test (significance level 5% for both tests).

Table 6: Time Series Standard Deviations of Ranks and Similarity Ratios

Time series standard deviations of ranks	Model 1	Model 2	Model 3	Model 4			Model 5	
				4a	4b	4c	5a	5b
MES	13.89	13.52$^{*\circ}$	8.03$^{*\circ}$	8.50$^{*\circ}$	8.59$^{*\circ}$	8.75$^{*\circ}$	8.76$^{*\circ}$	8.34$^{*\circ}$
Beta	13.70	12.83$^{*\circ}$	5.20$^{*\circ}$	6.34$^{*\circ}$	7.23$^{*\circ}$	7.68$^{*\circ}$	7.39$^{*\circ}$	7.25$^{*\circ}$
SRISK	8.03	6.16$^{*\circ}$	5.10$^{*\circ}$	5.29$^{*\circ}$	5.57$^{*\circ}$	5.69$^{*\circ}$	5.65$^{*\circ}$	5.68$^{*\circ}$
LTDE	13.65	13.62	12.84$^{*\circ}$	12.85$^{*\circ}$	12.81$^{*\circ}$	12.71$^{*\circ}$	12.87$^{*\circ}$	11.99$^{*\circ}$
UTDPD	13.62	13.55$^{*\circ}$	12.92$^{*\circ}$	12.89$^{*\circ}$	12.73$^{*\circ}$	12.52$^{*\circ}$	12.66$^{*\circ}$	11.58$^{*\circ}$

Similarity Ratios TOP	10	20	10	20	10	20	10	20	10	20	10	20	10	20	10	20
Beta-MES	2.9	8.3	3.3$^{*\circ}$	9.0$^{*\circ}$	5.6$^{*\circ}$	13.9$^{*\circ}$	5.9$^{*\circ}$	14.3$^{*\circ}$	6.4$^{*\circ}$	15.3$^{*\circ}$	6.3$^{*\circ}$	15.7$^{*\circ}$	6.5$^{*\circ}$	15.6$^{*\circ}$	6.3$^{*\circ}$	15.9$^{*\circ}$
SRISK-MES	1.7	5.9	1.3$^{*\circ}$	5.3$^{*\circ}$	1.4	5.5	1.5°	5.5	1.6	5.6	2.0	6.2	1.8	5.9	1.7	5.8
SRISK-Beta	1.2	4.9	1.1$^{*\circ}$	4.9	1.4	5.2	1.4	5.2	1.3	5.1	1.3	5.3	1.6	5.5*	1.2	5.0
LTDE-MES	3.3	9.6	3.2	9.3$^{*\circ}$	2.9$^{*\circ}$	7.7$^{*\circ}$	2.8$^{*\circ}$	7.5$^{*\circ}$	2.7$^{*\circ}$	7.8$^{*\circ}$	2.9$^{*\circ}$	8.3$^{*\circ}$	2.7$^{*\circ}$	7.7$^{*\circ}$	3.0$^{*\circ}$	8.4$^{*\circ}$
LTDE-Beta	1.6	5.8	1.6	5.6$^{*\circ}$	1.7	5.4$^{*\circ}$	1.6	5.3$^{*\circ}$	1.8$^{*\circ}$	6.0	2.4$^{*\circ}$	7.2$^{*\circ}$	1.9$^{*\circ}$	6.1°	2.6$^{*\circ}$	7.3$^{*\circ}$
LTDE-SRISK	0.9	4.0	0.7$^{*\circ}$	3.5$^{*\circ}$	0.6$^{*\circ}$	3.1$^{*\circ}$	0.6$^{*\circ}$	3.1$^{*\circ}$	0.7$^{*\circ}$	3.3$^{*\circ}$	0.8	3.5$^{*\circ}$	0.7$^{*\circ}$	3.3$^{*\circ}$	0.7$^{*\circ}$	3.3$^{*\circ}$
UTDPD-MES	1.7	5.6	1.7	5.6	1.2$^{*\circ}$	4.5$^{*\circ}$	1.6	5.2$^{*\circ}$	2.4$^{*\circ}$	7.6$^{*\circ}$	2.1*	9.5$^{*\circ}$	2.7$^{*\circ}$	8.4$^{*\circ}$	2.5$^{*\circ}$	10.4$^{*\circ}$
UTDPD-Beta	1.5	5.0	1.5	4.9$^{*\circ}$	1.2$^{*\circ}$	4.1$^{*\circ}$	1.7	5.0	2.5$^{*\circ}$	7.5$^{*\circ}$	2.1$^{*\circ}$	9.4$^{*\circ}$	2.8$^{*\circ}$	8.3$^{*\circ}$	2.6$^{*\circ}$	10.4$^{*\circ}$
UTDPD-SRISK	0.8	3.3	0.6$^{*\circ}$	2.9$^{*\circ}$	0.4$^{*\circ}$	2.5$^{*\circ}$	0.4$^{*\circ}$	2.6$^{*\circ}$	0.5$^{*\circ}$	3.1°	0.7°	4.4$^{*\circ}$	0.7°	3.6	0.6$^{*\circ}$	4.0$^{*\circ}$
UTDPD-LTDE	1.8	6.1	1.9	6.2	1.6$^{*\circ}$	5.8$^{*\circ}$	1.5$^{*\circ}$	5.6$^{*\circ}$	1.5$^{*\circ}$	6.0	1.2$^{*\circ}$	6.6$^{*\circ}$	1.5$^{*\circ}$	6.0	1.4$^{*\circ}$	6.9$^{*\circ}$

The table above shows in the upper half the cross sectional averages of the time series standard deviations of ranks for various SRMs and models. In the lower half of the table, the time series averages of the similarity ratios for various pairs of SRMs for the TOP 10% and 20% are displayed (numbers in percent). All values are means over 30 simulation runs. Significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in model 1 and in one of the other models are identical. The symbol * marks a rejection of the null hypothesis of identical means based on the Welch two sample t-test and the symbol ◦ marks a rejection based on the Mann-Whitney-U test (significance level 5% for both tests).

Table 7: Sensitivity Analysis (Cross-Sectional Dimension)

Parameters	Beta-MES	SRISK-MES	SRISK-Beta	LTDE-MES	LTDE-Beta	LTDE-SRISK	UTDPD-MES	UTDPD-Beta	UTDPD-SRISK	UTDPD-LTDE
PD	-0.570***	0.397***	0.281**	0.245***	-0.162**	0.350***	-0.0107	-0.368***	0.0722	0.736***
	(-14.39)	(4.26)	(2.66)	(6.03)	(-3.20)	(6.89)	(-0.15)	(-4.99)	(1.17)	(14.64)
ρ	-0.00963	-0.00921	-0.0101	0.0362**	0.0262	0.00996	0.0221	0.0182	0.00755	0.0295*
	(-0.86)	(-0.35)	(-0.34)	(3.15)	(1.83)	(0.69)	(1.08)	(0.87)	(0.43)	(2.08)
ρ^{bank}	-0.0199	-0.0254	-0.00402	0.00384	0.00264	-0.0151	-0.0207	-0.0138	-0.0404*	-0.0167
	(-1.78)	(-0.97)	(-0.14)	(0.34)	(0.18)	(-1.05)	(-1.01)	(-0.66)	(-2.33)	(-1.18)
g	-62.30***	-0.824	-17.23	43.61**	5.418	34.53	21.66	6.731	2.014	53.34**
	(-4.00)	(-0.02)	(-0.42)	(2.73)	(0.27)	(1.73)	(0.76)	(0.23)	(0.08)	(2.70)
LGD	-0.103***	0.0222	0.00939	0.0643***	0.00811	0.0863***	0.0515*	-0.00988	0.0510**	0.174***
	(-8.89)	(0.82)	(0.31)	(5.43)	(0.55)	(5.83)	(2.44)	(-0.46)	(2.85)	(11.89)
μ	67.74***	649.5***	-717.0***	99.41***	163.7***	-68.53***	118.0***	210.1***	6.475	-152.6***
	(4.37)	(-17.80)	(-17.35)	(6.25)	(8.24)	(-3.45)	(4.16)	(7.27)	(0.27)	(-7.75)
σ	13.80***	22.94***	19.05***	-6.151***	3.361***	12.35***	-17.61***	-22.61***	-3.660***	4.994***
	(23.40)	(16.53)	(12.12)	(-10.16)	(4.45)	(16.32)	(-16.33)	(-20.56)	(-4.00)	(6.67)
ρ^{market}	0.619***	0.621***	0.669***	-0.361***	-0.177***	0.259***	0.103	0.0745	0.312***	0.126***
	(21.22)	(9.05)	(8.61)	(-12.06)	(-4.75)	(6.93)	(1.92)	(1.37)	(6.89)	(3.39)
τ	-0.334*	0.148	0.0696	0.211	0.0667	0.339	-0.269	-0.0966	0.387	-0.288
	(-2.31)	(0.43)	(0.18)	(1.42)	(0.36)	(1.83)	(-1.02)	(-0.36)	(1.72)	(-1.57)
q	0.00896**	-0.00333	0.00137	0.000231	0.00606	-0.000934	0.00327	0.0140**	0.00475	-0.0168***
	(3.23)	(-0.51)	(0.19)	(0.08)	(1.71)	(-0.26)	(0.64)	(2.71)	(1.10)	(-4.78)
$etar^{IB}_{Min} \cdot 1_{\{etar^{IB} > n\}}$	-0.388*	1.325***	-1.581***	0.680***	0.483*	0.130	0.171	0.187	0.395	-0.0687
	(-2.45)	(-3.56)	(-3.75)	(4.19)	(2.38)	(0.64)	(0.59)	(0.63)	(1.61)	(-0.34)
λ	0.171	-0.401	-0.718*	-0.177	-0.0869	0.0551	0.182	0.190	0.275	0.159
	(1.40)	(-1.40)	(-2.22)	(-1.42)	(-0.56)	(0.35)	(0.82)	(0.84)	(1.46)	(1.03)
$\lambda * \cdot 1_{\{etar^{IB} > n\}}$	0.559*	0.460	0.220	-0.166	0.301	-0.0126	0.795	1.027	-0.673	0.102
	(1.97)	(0.69)	(0.29)	(-0.57)	(0.83)	(-0.03)	(1.53)	(1.94)	(-1.52)	(0.28)
k	-0.0375	3.802***	2.967***	0.0941	0.222	3.395***	0.374	0.423	2.444***	0.0850
	(-0.31)	(13.56)	(9.34)	(0.77)	(1.46)	(22.21)	(1.72)	(1.90)	(13.21)	(0.56)
$\beta_{\max}$	0.259***	0.247***	0.196*	-0.186***	-0.0431	0.103**	-0.166**	-0.192***	-0.0877	-0.0435
	(8.95)	(3.63)	(2.54)	(-6.25)	(-1.16)	(2.78)	(-3.13)	(-3.55)	(-1.95)	(-1.18)

Table 7 [continued]

Parameters	Beta-MES	SRISK-MES	SRISK-Beta	LTDE-MES	LTDE-Beta	LTDE-SRISK	UTDPD-MES	UTDPD-Beta	UTDPD-SRISK	UTDPD-LTDE
$\eta_{\max}$	1.562***	2.112***	-1.600***	-0.213*	-1.342***	-2.587***	2.860***	2.431***	0.0560	1.810***
	(-16.46)	(-9.46)	(-6.33)	(-2.19)	(-11.04)	(-21.25)	(16.48)	(13.74)	(0.38)	(15.01)
$\eta_{\min}$	-0.0963	-1.131**	-1.477**	1.025***	1.092***	0.387	-0.379	-0.191	-0.992***	-0.352
	(-0.55)	(-2.75)	(-3.17)	(5.71)	(4.87)	(1.73)	(-1.18)	(-0.59)	(-3.66)	(-1.58)
$etar_1$	0.146	0.0621	0.0465	-0.270	-0.417*	0.157	-0.234	0.211	-0.188	-0.938***
	(1.02)	(0.18)	(0.12)	(-1.84)	(-2.28)	(0.85)	(-0.90)	(0.79)	(-0.85)	(-5.17)
κ	0.0345**	0.0243	0.0358	0.0409***	-0.0276	-0.0387**	-0.0490*	-0.0489*	-0.0317	-0.0293*
	(3.02)	(0.91)	(1.18)	(-3.49)	(-1.89)	(-2.64)	(-2.35)	(-2.30)	(-1.79)	(-2.02)
lr	0.225***	-0.191	-0.140	-0.0958	0.0179	-0.0623	0.235*	0.174	-0.0157	0.0906
	(3.97)	(-1.43)	(-0.93)	(-1.65)	(0.25)	(-0.86)	(2.27)	(1.65)	(-0.18)	(1.26)
p_{Core}	-0.249***	0.175*	0.230*	-0.107**	-0.337***	-0.141**	-0.388***	-0.521***	-0.220***	0.0423
	(-6.68)	(2.00)	(2.32)	(-2.79)	(-7.05)	(-2.95)	(-5.69)	(-7.50)	(-3.81)	(0.89)
p_{CC}	0.0121	0.112**	0.104**	-0.00876	0.00375	0.0429*	-0.0148	-0.0307	-0.0158	0.0105
	(0.84)	(3.30)	(2.71)	(-0.59)	(0.20)	(2.33)	(-0.56)	(-1.14)	(-0.71)	(0.58)
p_{CP}	0.0783***	0.0160	0.00945	0.00243	-0.0443**	-0.0154	-0.0333	-0.0517*	0.0259	0.0221
	(-7.00)	(0.61)	(0.32)	(0.21)	(-3.09)	(-1.07)	(-1.63)	(-2.48)	(1.49)	(1.55)
p_{PP}	-0.322***	0.00784	-0.0535	0.0525	-0.235***	0.0887	-0.362***	-0.401***	-0.0740	-0.0686
	(-8.41)	(0.09)	(-0.53)	(1.34)	(-4.79)	(1.81)	(-5.17)	(-5.62)	(-1.25)	(-1.41)
const	63.09***	1.063	17.50	-43.09**	-5.064	-34.60	-21.72	-6.724	-2.166	-53.45**
	(4.05)	(0.03)	(0.42)	(-2.70)	(-0.25)	(-1.73)	(-0.76)	(-0.23)	(-0.09)	(-2.70)
N	650	650	650	650	650	650	650	650	650	650
R^2	0.751	0.623	0.543	0.433	0.414	0.698	0.541	0.585	0.358	0.603

The above table shows the results of a multiple OLS regression, where the mean rank correlations for the various pairs of SRMs were explained by the realizations of the model parameters. For this, within the inhomogeneous (core-periphery) random graph network structure (model 5), the exhibited parameters are randomly drawn from a uniform distribution on specified intervals for each simulation run. The realizations of these parameters are assumed to be identical for all banks in the respective simulation run. Contagious simulation runs (defined as those with more than 20% defaulting banks) were discarded. In total, 650 simulation runs were considered. The maximum VIF is 3.31. t-statistics in parentheses; significances: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Moving Averages of SRMs

Cross sectional averages of the time series standard deviations of ranks	Model 1	Model 4a	Model 5a
MES	13.8$^{*\circ}$	7.8$^{*\circ}$	8.0$^{*\circ}$
Beta	13.6$^{*\circ}$	5.9$^{*\circ}$	7.0$^{*\circ}$
SRISK	7.6$^{*\circ}$	4.7$^{*\circ}$	5.2$^{*\circ}$
LTDE	13.9$^{*\circ}$	13.0$^{*\circ}$	12.8
UTDPD	13.8$^{*\circ}$	12.9	12.6

Mean rank correlations (over T) (cross-sectional dimension)	Model 1	Model 4a	Model 5a	Similarity Ratios TOP	Model 1			Model 4a			Model 5a		
					10	20	40	10	20	40	10	20	40
Beta-MES	0.54$^{*\circ}$	0.90$^{*\circ}$	0.93$^{*\circ}$	**Beta-MES**	3.0	8.7$^{*\circ}$	24.7$^{*\circ}$	6.3$^{*\circ}$	14.9$^{*\circ}$	33.6$^{*\circ}$	6.8	16.1$^{*\circ}$	35.5$^{*\circ}$
SRISK-MES	0.32$^{*\circ}$	0.33	0.32	**SRISK-MES**	1.7	6.0	20.7*	1.4	5.2	19.9	2.1	5.9	19.8
SRISK-Beta	0.28$^{*\circ}$	0.30	0.29	**SRISK-Beta**	1.2	5.1	19.5	1.2	4.9	19.4	1.7	5.4	19.4
LTDE-MES	0.56$^{*\circ}$	0.37	0.41	**LTDE-MES**	3.7$^{*\circ}$	9.8$^{*\circ}$	25.7	2.9	7.7	21.9	2.9	8.1	22.9*
LTDE-Beta	0.18	0.19	0.28*	**LTDE-Beta**	1.7$^{*\circ}$	5.8	19.1	1.7	5.6	18.9	2.3$^{*\circ}$	6.7$^{*\circ}$	20.8$^{*\circ}$
LTDE-SRISK	-0.01	-0.09	-0.08	**LTDE-SRISK**	0.9	3.9°	15.9	0.6	3.1	14.7	0.7	3.3	15.0
UTDPD-MES	0.25$^{*\circ}$	0.01	0.10	**UTDPD-MES**	1.9$^{*\circ}$	6.2$^{*\circ}$	20.1$^{*\circ}$	1.8	5.5	16.6	2.8	8.8	19.0
UTDPD-Beta	0.15	-0.03	0.08	**UTDPD-Beta**	1.5	5.4$^{*\circ}$	18.6	2.0	5.3	15.9	2.8	8.6	18.7
UTDPD-SRISK	-0.06	-0.17	-0.17	**UTDPD-SRISK**	0.8	3.5	14.9$^{*\circ}$	0.4	2.5	13.6	0.8	3.8	14.0
UTDPD-LTDE	0.31$^{*\circ}$	0.23$^{*\circ}$	0.21	**UTDPD-LTDE**	2.2$^{*\circ}$	6.7$^{*\circ}$	21.0	1.9$^{*\circ}$	6.1$^{*\circ}$	19.7	1.6	6.6$^{*\circ}$	19.7

The table above shows the mean rank correlations (over T) for various models when moving averages (over the last 100 observations at each time t) of the respective SRMs are calculated and employed for determining the banks' ranks. The results for the rank correlations correspond to equation (36) for overlapping time windows. Furthermore, the cross sectional averages of the time series standard deviations of ranks for moving averages of various SRMs are displayed. Additionally, the time series averages of the similarity ratios for various pairs of moving averages of SRMs for the TOP 10%, 20% and 40% are exhibited (numbers in percent). All values are means over 30 simulation runs. Significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in the respective models with and without using moving averages of SRMs are identical. The symbol * marks a rejection of the null hypothesis of identical means based on the Welch two sample t-test and the symbol $\circ$ marks a rejection based on the Mann-Whitney-U test (significance level 5% for both tests).

Table 9: Additional Dependencies and Fat-Tailed Risk Factors

Mean rank correlations (over T) (cross-sectional dimension)	$\rho_{Z,lba} = 0.1, \upsilon = \infty$			$\rho_{Z,lba} = 0.1, \upsilon = 13$			$\rho_{Z,lba} = 0.1, \upsilon = 8$		
	Model 1	**Model 4a**	**Model 5a**	**Model 1**	**Model 4a**	**Model 5a**	**Model 1**	**Model 4a**	**Model 5a**
Beta-MES	0.51°	0.87	0.91	0.53*°	0.89*°	0.91	0.54*°	0.90*°	0.92*°
SRISK-MES	0.31	0.31	0.33	0.33*°	0.31	0.32	0.33*°	0.34	0.35
SRISK-Beta	0.26°	0.28	0.30	0.27*°	0.28	0.29	0.28*°	0.30	0.32
LTDE-MES	0.54	0.37	0.36*°	0.54	0.38	0.37*°	0.54	0.38	0.37°
LTDE-Beta	0.18	0.19	0.22*°	0.17	0.21	0.23	0.18	0.22	0.24
LTDE-SRISK	0.01	-0.08	-0.07	0.01	-0.08	-0.10	0.02°	-0.05*°	-0.06
UTDPD-MES	0.23	0.02	0.13	0.24*	0.06	0.10	0.25*°	0.05	0.14
UTDPD-Beta	0.15	-0.02	0.11	0.14	0.02	0.08	0.14	0.02	0.12
UTDPD-SRISK	-0.04	-0.16	-0.15	-0.02*°	-0.14	-0.17	-0.03*°	-0.14	-0.15
UTDPD-LTDE	0.27	0.22	0.17*°	0.29*°	0.23*°	0.19	0.29*°	0.25*°	0.20

The table above shows the mean rank correlations (over T) for various models when the random variables $Z_{1,t},\ldots,Z_{N,t}$ driving the default rates in the non-bank loan portfolios and the liquidity buffer asset returns $r_{1,t},\ldots,r_{N,t}$ are not only correlated among themselves, but are also correlated with each other with correlation parameter $\rho_{Z,lba}$, and, additionally, are multivariate t-distributed with υ degrees of freedom. The results for the rank correlations correspond to equation (36) for overlapping time windows. All values are means over 30 simulation runs. Significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in the respective models with and without the original distributional assumptions are identical. The symbol * marks a rejection of the null hypothesis of identical means based on the Welch two sample t-test and the symbol ° marks a rejection based on the Mann-Whitney-U test (significance level 5% for both tests).

Table 10: Additional Stochastic Fluctuations of the Deposit Volume

Mean rank correlations (over T) (cross-sectional dimension)	Model 1	Model 4a	Model 5a
Beta-MES	0.83*°	0.89*°	0.90
SRISK-MES	0.29	0.34	0.34
SRISK-Beta	0.24	0.31	0.30
LTDE-MES	0.41*°	0.40	0.41
LTDE-Beta	0.17	0.23*°	0.25
LTDE-SRISK	0.02*°	-0.04*°	-0.05
UTDPD-MES	0.30*°	0.30*°	0.26*°
UTDPD-Beta	0.22*°	0.27*°	0.24*°
UTDPD-SRISK	0.01*°	0.00*°	-0.06*°
UTDPD-LTDE	0.29*°	0.28*°	0.22*°

The table above shows the mean rank correlations (over T) for various models when a bank's credit quality (proxied by its equity-to-assets ratio) and, additionally, a bankindividual independent stochastic factor drive the volume of the bank's non-bank deposits (see (37)). The results for the rank correlations correspond to equation (36) for overlapping time windows. All values are means over 30 simulation runs. Significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in the respective models with and without additional stochastic factor are identical. The symbol * marks a rejection of the null hypothesis of identical means based on the Welch two sample t-test and the symbol ° marks a rejection based on the Mann-Whitney-U test (significance level 5% for both tests).

Table 11: Alternative Balance Sheet Construction

Mean rank correlations (over T) (cross-sectional dimension)	Model 1	Model 4a	Model 5a
Beta-MES	0.51	0.87	0.91°
SRISK-MES	0.31	0.30	0.23*°
SRISK-Beta	0.25	0.27	0.17*°
LTDE-MES	0.54	0.37	0.44*°
LTDE-Beta	0.19	0.19	0.31*°
LTDE-SRISK	0.01	-0.08	-0.05°
UTDPD-MES	0.23	0.04	0.21*°
UTDPD-Beta	0.14	0.01	0.20*°
UTDPD-SRISK	-0.04	-0.17	-0.14
UTDPD-LTDE	0.27	0.20	0.22*°

The table above shows the mean rank correlations (over T) for various models when the alternative methodology for constructing the banks' initial balance sheets described in Section 6.4 is applied. The results for the rank correlations correspond to equation (36) for overlapping time windows. The parameters κ_i, $etar_{i,1}$ and lr_i ($i \in \{1,\ldots,N\}$) are chosen as displayed in Tables 1 and 2 for the respective models. All values are means over 30 simulation runs. Significance statements are based on the Welch two sample t-test and the Mann-Whitney-U test. For both tests, the null hypthesis is that the means over all 30 simulation runs in the respective models with and without the original methodology for constructing the banks' initial balance sheets are identical. The symbol * marks a rejection of the null hypothesis of identical means based on the Welch two sample t-test and the symbol ° marks a rejection based on the Mann-Whitney-U test (significance level 5% for both tests).

Figure

Figure 1: Stylized Balance Sheets of the Banks and Relationships in a 2-Bank-Network