Systemic Risk in an Interconnected Banking System with Endogenous Asset Markets*

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Abstract

We analyze the emergence of systemic risk in a network model of interconnected bank balance sheets. The model incorporates multiple sources of systemic risk, including size of financial institutions, direct exposure from interbank lendings, and asset fire sales. We suggest a new macroprudential risk management approach building on a system wide value at risk (SVaR). Under the SVaR metric, the contribution of individual banks to systemic risk is well defined and can be approximated by a Shapley value-type measure. We show that, in a SVaR regime, a fair systemic risk charge which is proportional to a bank's individual contribution to systemic risk diverges from the optimal macroprudential capitalization of the banks from a planner's perspective. The results have implications for the design of macroprudential capital surcharges.

Keywords: Systemic risk, systemic risk charge, macroprudential supervision, Shapley value, financial network
JEL Classification: C15, G01, G21, G28

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1 Introduction

Since the outbreak of the global financial crisis in 2007, and the dramatic effects of the Lehman collapse in 2008, systemic risk has become a matter of great concern for policy makers and central bankers. However, macroprudential monitoring is still at a very early stage and there is no generally accepted metric capturing the state of systemic risk. Not surprisingly, there is also no general agreement on an adequate policy response. This paper studies the consistency of two macroprudential policy instruments, namely systemic capital requirements and systemic risk charges, in the framework of a network model.

Systemic risk can be characterized as a negative pecuniary externality exerted by financial institutions.[1] Financial institutions may be induced to increase their contribution to systemic risk and their status as a too-big-to-fail or too-interconnected-to-fail institution will put them under the government safety net, thereby delinking bank funding costs from their own asset risk. This has two important consequences. First, regulatory intervention such as, for example, a risk charge, might be used to incentivize financial institutions to internalize their negative externality.[2] Second, systemic banking risk may not be easily inferred directly from debt instruments, like bonds or CDS, because their market prices may be distorted by government guarantees.[3]

We therefore use a structural model portraying a network of interrelated bank balance sheets with endogenous asset markets. This set up in which we extend the model of Cifuentes et al. (2005) for two way interactions between banks allows for measuring systemic risk as well as individual banks' contribution to it. In our setting, systemic risk is driven essentially by three channels: the size of banks, the direct exposures among these institutions, and the asset market-driven correlations. We then suggest a simple method to investigate the relation between systemic risk, capital requirements, and systemic risk charges. The new method applies value at risk, the quantile of a loss distribution, to a system of interconnected financial institutions. The resulting system value at risk (SVaR) metric defines the institutions' optimal macroprudential capitalizations and a risk charge which is proportional to each institution's contribution to overall systemic risk. We then apply our framework to the question how an optimal risk charge should be designed. Recently, it has been argued that required bank capital should be closely related to banks' systemic risk contribution.[4] In the context of our model we

[1] See, for example, Benigno (2013).

[2] Financial stability features characteristics similar to a public good without clearly defined property rights. In this respect government intervention can help achieve better outcomes in terms of welfare or utility. See Snidal (1979).

[3] See, for example, Acharya et al. (2013) and Tsesmelidakis and Schweikhard (2012).

[4] See, for example, Acharya et al. (2009).

show that the optimal bank capitalization will in general diverge from the same bank's contribution to systemic risk. Thus, our findings indicate that the design of a systemic risk charge and the design of macroprudential capital standards should be treated as two separate problems rather than one and the same. In our analyses we also find that direct interconnections between banks are a dominant driver of systemic risk in our model, corroborating the findings in Drehmann and Tarashev (2011) show that systemic importance depends materially on a bank's role in the interbank network. Furthermore, in line with the results in Shin (2008) we find that the fire sale channel is an important amplifier of exogenous shocks providing evidence that marking-to-market accounting in times of financial turmoil may amplify distress in the financial system.

More generally, our paper is related to three strands of the literature. Firstly, it is related to the literature on financial contagion in which the transmission of shocks across financial systems is investigated. Second, it can be associated with the field of literature measuring financial institutions' negative externality on the financial system which arises in the form of systemic risk. Third, it relates to the literature about macroprudential regulation.

The literature on financial contagion is vast.[5] Influential early analyses were carried out in the seminal works by Allen and Gale (2000) and Diamond and Dybvig (1983). The former investigate financial contagion as an equilibrium phenomenon in a theoretical banking model and show that complete claims structures between banks are more robust than incomplete structures. The latter develop a theoretical model featuring a market for bank deposits with the possibility of bank runs and find that deposit insurance can be beneficial for financial stability. Freixas et al. (2000) model systemic risk in an interbank market in which banks are connected via credit lines to cope with liquidity shocks. They find that though the interbank market allows to minimize the amount of resources held in liquid assets it can lead to contagion. More recently, with the aim to get a general overview on systemic risk from contagion, Haldane (2009) considers the financial network as a complex and adaptive system and applies several lessons from other disciplines such as ecology, epidemiology, biology, and engineering. In this respect, systemic risk in our model of interconnected financial institutions is also largely driven by contagion. Regarding the various approaches to assessing systemic risk in the contagion-related literature, one can distinguish between 'market-based' and 'network-based approaches'.[6] While the former use correlations and default probabilities that can be extracted from market prices of financial instruments, the latter explicitely model linkages between

[5]An earlier review of the literature on contagion is given by De Bandt and Hartmann (2000). For a more recent overview see Allen et al. (2009).

[6]See the background paper of Financial Stability Board et al. (2009) for a similar distinction.

financial institutions, mostly using balance sheet information.

In the market-based literature, systemic risk is mostly quantified using tail-measures ('reduced form approach'), for example, Acharya et al. (2011)'s marginal expected shortfall (MES), Adrian and Brunnermeier (2011)'s value at risk of the financial system conditional on institutions being under distress (CoVaR), and Brownlees and Engle (2012)'s systemic risk indices (aggregate SRISK), or using contingent claims analysis ('structural approach'), for example Jobst and Gray (2013)'s system contingent claims analysis (System CCA).[7] In the network-based literature, the measure for systemic fragility is usually the fraction of financial institutions in default, for example in Cifuentes et al. (2005) and Gai and Kapadia (2010).[8] The model used in our analysis is closely related to that of Cifuentes et al. (2005), extending it among other things to allow for two-way interactions among banks and using Shapley value analysis to investigate banks' expected contribution to systemic risk. Similar, to this strand of the literature, our metric for systemic risk is measured by the proportion of the financial system in default conditional on a shock.

The second strand our paper is related to is the literature assessing the systemic importance of financial institutions. In this field one can again distinguish between market-based and network-based approaches. The market-based approaches use financial institutions contribution or correlation with the tail distribution or contingent claims metrics to measure their impact on systemic stability.[9] In the network-based approaches, the Shapley value metric or variants of it are used to measure banks' contribution to systemic risk.[10] Drehmann and Tarashev (2011) who show that systemic importance depends strongly on bank relations in the interbank market and that different risk measures lead to substantial differences in assessments on contribu-

[7]An overview on these metrics is given in Hansen (2013). Early analyses of systemic risk include Bartram et al. (2007) and Lehar (2005). More recent noticeable market-based analyses include, but are not limited to, Acharya et al. (2012), Huang et al. (2009), Huang et al. (2012), López-Espinosa et al. (2013), Saldías (2013), and Suh (2012).

[8]An overview on methods to assess the danger of contagion in interbank markets is provided in Upper (2011). Other noticeable network-based analyses include, but are not limited to, Degryse and Nguyen (2007), Elsinger et al. (2006), Georg (2013), and Upper and Worms (2004).

[9]For example, Acharya et al. (2011) define an institution's contribution as is its propensity to be undercapitalized when the system as a whole is undercapitalized (system expected shortfall, SES), Adrian and Brunnermeier (2011) define an institution's contribution to systemic risk as the difference between CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution (ΔCoVaR), Brownlees and Engle (2012) define it as the expected capital shortage of a firm conditional on a substantial market decline (individual SRISK), and Jobst and Gray (2013) measure contribution of a firm by calculating the cross-partial derivative of the joint distribution of expected losses. A comparison of these measures is provided in Benoit et al. (ming). Further applications using market-based measures can be found in De Jonghe (2010), Giglio et al. (2012), Hautsch et al. (2012), Hovakimian et al. (2012), and Weiß et al. (ming).

[10]See Tarashev et al. (2010).

tions to systemic risk. Gauthier et al. (2012) use a network model to measure systemic risk and banks' contribution to it employing several risk allocation mechanisms. In our paper we extend the network-based approaches with distributional assumptions on the vector of shocks to the financial system which we combine with the Shapley value methodology to compute expected values for systemic risk as well as banks' contribution to it.

Finally, our paper is related to the literature dealing with macroprudential regulation. An early comparison of micro- and macroprudential dimensions in financial regulation is given in Borio (2003). The author argues that the macroprudential orientation of financial regulation needs to be strengthened to improve financial stability. A more recent approach is provided in Acharya (2009a) who shows that microprudential regulation can accentuate systemic risk via mitigating aggregate risk-shifting incentives. The author argues that prudential regulation therefore should operate at an individual as well as at a system level. Acharya et al. (2009) suggest that financial regulation should be focused on limiting systemic risk and that a firm's individual contribution to aggregate risk should determine the extent of regulatory constraints such as capital requirements. Gauthier et al. (2012) use a sample of Canadian banks to show that optimal macroprudential capital allocations can differ substantially from microprudential capital levels. Zhou (2013) examines the impact on systemic risk of imposing capital requirements and finds that a system under microprudential capital rules might feature higher systemic risk than an unregulated system. In our analyses, we focus on financial institutions' capital as one of the most important regulatory tools. In particular, we propose a novel macroprudential risk management approach which provides a unified framework to determine banks' optimal macroprudential capitalization to achieve a desired level of systemic stability and charge banks a fair risk tax corresponding to their contribution to systemic risk.

The remainder of the paper is organized as follows: Section 2 outlines our model and Section 3 shows how it can be used to analyze systemic risk as well as individual institutions' contribution to systemic risk along various dimensions. Using the outlined model, Section 4 develops and analyzes the SVaR as a new approach to macroprudential risk management. Section 5 concludes. Further details on our analyses can be found in an appendix at the end of the paper.

2 Model of an Interrelated Financial Network

The model outlined in this section consists of three banks[11] that adjust their portfolio to fulfill a capital requirement. Though it is highly stylized, it replicates several features observed during the recent financial crisis. In

[11] Here and in the following, banks and financial institutions are used interchangeably.

particular, it has three main risk channels which cause systemic risk: banks' size, interconnections in the form of interbank lendings, and fire sale spirals driven by a marking-to-market mechanism. The model is framed in terms of banks' balance sheets on which they hold deposits from the rest of the world, liquid assets (LA) as well as non-liquid assets (NLA), and are interconnected through borrowing from and lending to each other. Non-liquid assets, for example financial contracts in banks' loan book, are marked to market while liquid assets, for example cash instruments and highly liquid government bonds, are modeled with a constant value on banks' balance sheets. This stylized financial system is mapped into a financial system matrix of row-wise assets and column-wise liabilities as displayed on Figure 1. For example, the second row displays bank 1's assets, while its liabilities are captured in the second column.

	Bank 1	Bank 2	Bank 3	ROW	
				NLA	LA
Bank 1					
Bank 2					
Bank 3					
ROW					

Figure 1: Financial System Matrix
The financial system matrix gives a visual outline of the financial system. Banks' assets can be found in the respective rows and banks' liabilities in the respective columns. 'ROW', 'LA', and 'NLA' designate 'rest of the world', 'liquid assets', and 'non-liquid assets', respectively.

The capital requirement which banks have to fulfill, γ, is displayed in Equation (1):

$$\gamma = \frac{\sum_j a_j + p \cdot b_i + c_i - \sum_j l_j - d_i}{\sum_j a_j + p \cdot b_i}, \tag{1}$$

where $i, j \in (1, 2, 3), i \neq j$, are indices for the three banks in the system, a_j are interbank lendings, p is the market price of the non-liquid asset, b_i are non-liquid assets, c_i are liquid assets, l_j are interbank borrowings, and d_i are deposits. Note that liquid assets do not show up in the denominator of Equation (1) because they are deemed a safe investment position for which banks do not have to hold capital.[12]

In our framework, a specific financial system is determined by (i) the network of exposures among banks, that is, a so-called adjacency matrix

[12] See Cifuentes et al. (2005) for a similar theoretical set up.

filled with ones for all entries where a lending-borrowing relationship exists, and zeros otherwise; (ii) banks' ratio of interbank lending to other assets (that is, non-liquid and liquid asset holdings), $0 \leq \alpha \leq 1$, with α the overall proportion lent to other banks, and $1-\alpha$ the proportion invested in other assets; (iii) the ratio of investment in non-liquid to liquid assets, β, $0 \leq \beta \leq 1$, where β is the fraction invested in non-liquid assets and $1-\beta$ is the fraction invested in liquid assets; (iv) the capital requirement, γ; and (v) an initial endowment of capital, A, that is allocated to banks' assets according to α and β. Note that in a system of three banks which can borrow from and lend to each other, there are 2^6 different adjacency matrices. A set of parameters α, β, A, and γ thus results in 64 different financial system matrices.

To fix ideas, consider how a specific financial system matrix is set up for a given adjacency matrix and given values for α, β, A, and γ. First, all banks' lendings and borrowings in the financial system matrix are determined. Each bank engaged in interbank lending provides the fraction αA to the interbank market. For bank i, the specific amounts lent to each of its counterparties l_j are determined by $l_j = \frac{\alpha A_i}{\#_i}$, with # the number of counterparties a bank lends to as indicated in the adjacency matrix. Next, assuming that banks invest all borrowed funds into liquid and non-liquid assets, the overall amounts bank i holds in non-liquid and liquid assets then are $((1-\alpha)\cdot A + \sum_j l_j)\beta$ and $((1-\alpha)\cdot A + \sum_j l_j)(1-\beta)$, respectively. The entry for the i'th bank in the last row of the financial system matrix, that is, its deposits, is residual in the sense that the capital requirement is just met, using Equation (2).

$$\begin{aligned} d_i =& A_i \cdot \alpha + \left((1-\alpha)\cdot A_i + \sum_j l_j \right) [\beta p + 1 - \beta] - \sum_j l_j \\ & - \gamma \left[A_i \cdot \alpha + (1-\alpha) A_i \cdot \beta \cdot p + \sum_j l_j \cdot \beta \cdot p \right]. \end{aligned} \tag{2}$$

As an example, Figure 2 illustrates the symmetric case in which all banks have identical initial capital, A, borrow from and lend to each other, and have identical portfolio allocations, α and β. In the example on Figure 2 each bank's balance sheet is displayed in Table 1. As can be seen at the bottom of the table, in the consolidated asset and liability sum, the parameter A enters as multiplicator, thus merely scaling banks' balance sheets.

In our model, a bank has two ways to improve its capital ratio in case it does not fulfill the regulatory requirement (given in Equation (1)). First, it can net interbank exposure with its counterparties, and, second, if that is not sufficient to achieve the desired capital ratio, it can sell non-liquid assets on the market, effectively reducing its loan book.[13] As will become clear

[13]Theoretically, banks also have the option to raise new equity. In Section 4 of our

	Bank 1	Bank 2	Bank 3	ROW	
				NLA	LA
Bank 1		$\frac{A\alpha}{2}$	$\frac{A\alpha}{2}$	Aβp	A(1-β)
Bank 2	$\frac{A\alpha}{2}$		$\frac{A\alpha}{2}$	Aβp	A(1-β)
Bank 3	$\frac{A\alpha}{2}$	$\frac{A\alpha}{2}$		Aβp	A(1-β)
ROW	d	d	d		

Figure 2: Symmetric Financial System Matrix
Banks' assets are in the respective rows and banks' liabilities in the respective columns. In the symmetric financial system all banks have the same amount of assets and liabilities. Furthermore, each bank has the same amount of borrowings and lendings. 'ROW', 'NLA', and 'LA' designate 'rest of the world', 'non-liquid assets', and 'liquid assets', respectively. Parameters A and β are banks' initial assets and the proportion banks invest in non-liquid assets, respectively. Parameter α is the fraction assigned by banks to interbank lending, p is the market price of the non-liquid asset, and d are deposits.

Assets	Liabilities
LA: $A(1-\beta)$	Deposits: $A(\beta(p-1)-\gamma(\alpha+\beta p)+1)$
NLA: $A\beta p$	Interbank borrowings: $A\alpha$
Interbank lendings: $A\alpha$	Equity: $A(\gamma(\alpha+\beta p))$
$\sum = A(\alpha+\beta(p-1)+1)$	$\sum = A(\alpha+\beta(p-1)+1)$

Table 1: Banks' Balance Sheets in the Symmetric Case
In the symmetric financial system all banks have the same amount of assets and liabilities outlined on the balance sheet. 'NLA' and 'LA' designate 'non-liquid assets' and 'liquid assets', respectively. Parameters A and β are banks' initial assets and the proportion banks invest in non-liquid assets, respectively. Parameter α is the fraction assigned by banks to interbank lending, γ is banks' capital ratio requirement, and p is the market price of non-liquid assets.

in the following, in both cases the denominator in Equation (1) decreases relative to the numerator. Note that banks which cannot meet the capital requirement ratio default.

First, consider the effect of netting counterparty exposure on the interbank market. Equation (3) displays the capital ratio of bank i after netting (part of) its exposures with other banks, j, by θ units:

$$\gamma_i = \frac{(\sum_j a_j - \theta) + p \cdot b_i + c_i - (\sum_j l_j - \theta) - d_i}{(\sum_j a_j - \theta) + p \cdot b_i}. \tag{3}$$

Netting reduces the denominator by θ units while the numerator remains

analysis, we investigate mandatory capital injections from the supervisory agent as a means to stabilize the financial system. However, we rule out the possibility of raising new equity on capital markets, since raising equity during financial turmoil is very costly or might even be impossible if capital markets are shut. Furthermore, it is a lengthy process, difficult to implement by means of emergency measures. For a similar argument see Cifuentes et al. (2005).

unchanged. Note that in the model, banks may net any cross-exposure – which means that two banks have borrowed from and lent to each other at the same time– as long as their equity value is non-negative, that is $ev_i = \sum_j a_j + p \cdot b_i + c_i - \sum_j l_j - d_i \geq 0$.[14] Solving Equation (3) for the amount of bank i's desired netting to achieve the capital requirement ratio yields Equation (4):

$$\theta_i^d = -\mathbf{1}_{[ev_i \geq 0]} \frac{(1-\gamma)(\sum_j a_j + p \cdot b_i) + c_i - \sum_j l_j - d_i}{\gamma}, \tag{4}$$

where $\mathbf{1}$ is an indicator function. The amount of netting the j'th bank is willing to accept with bank i is displayed in Equation (5)

$$\theta_j^s = \mathbf{1}_{[ev_j \geq 0]} min(a_i, l_i). \tag{5}$$

Note that the minimum operator is used since only cross-exposures can be netted. The resulting amount netted between bank i and bank j is given by Equation (6):

$$\theta_{ji} = min(\theta_j^s, \theta_i^d). \tag{6}$$

Second, consider the effect of selling non-liquid assets to improve a bank's capital ratio. Equation (7) shows the capital ratio bank i expects to obtain if it engages in selling s_i units of its non-liquid assets in exchange for $p \cdot s_i$ units of liquid assets.

$$\gamma^* = \frac{\sum_j a_j + p(b_i - s_i) + c_i + p \cdot s_i - \sum_j l_j - d_i}{\sum_j a_j + p(b_i - s_i)}. \tag{7}$$

Asset sales by bank i have further repercussions on all banks with positive exposure[15] in that very asset, because asset sales have an impact on its secondary market price. In our model, market prices of non-liquid assets, p, are a function of supply and demand on the market. If banks engage in liquidating (part of) their non-liquid assets, several effects on banks' balance sheets have to be considered: the seller obtains a liquid asset, and hence improves her capital ratio. However, at the same time an increased supply of non-liquid assets to the market decreases the market price of the asset, lowering the market value of the bank's remaining portfolio holdings of the same asset. Furthermore, the price effect also influences other banks' balance sheets since the market value of their non-liquid assets is reduced as well.[16]

[14] In case a debtor bank has negative equity it might be paid back its loans from banks with positive equity without having to pay back its debt due to seniority of interbank loans over equity. Therefore, banks with negative equity value do not net interbank exposures.

[15] We restrict b_i to be non-negative, assuming that bank asset holdings refer to cash flow streams outside the financial sector. Put differently, bonds issued by banks are included in l_j.

[16] See, for example, Kryshnamurthy (2010), Shin (2008), and Shin and Adrian (2010) for a more detailed outline of this amplification mechanism of financial shocks.

In our model, the market price of the non-liquid asset is found via a tâtonnement process between supply and demand.[17] The supply of non-liquid assets is given by banks' sales decision. Solving Equation (7) for the amount of non-liquid assets sold by bank i to fulfill the capital requirement leads to Equation (8):

$$s_i = min\left(b_i, \frac{-(1-\gamma)(p \cdot b_i + \sum a_i) - c_i + \sum l_i + d_i}{\gamma p}\right), \tag{8}$$

where the minimum operator is used to prevent short sales of assets. Since each s_i is decreasing in p, the aggregate sales function of all banks, $S(p)$, is also decreasing in p.

The inverse demand function is assumed to follow Equation (9)

$$p = exp(-\xi \sum_i s_i), \tag{9}$$

where ξ is a positive constant to scale the price responsiveness with respect to non-liquid assets sold.

Three regularity conditions ensure that an equilibrium market price for non-liquid assets always exists.[18] First, the initial price of the non-liquid asset, that is, prior to any shock when all banks fulfill the regulatory capital requirement ratio and aggregate supply of non-liquid assets is zero, is normed to 1. At that stage, $S^{init}(1) = 0$ and, from Equation (9), $D(1) = 0$. Hence, $S^{init}(1) = D(1)$, demand and supply curve intersect. Second, a shock, provided it is large enough to trigger asset sales in the market, shifts the supply curve S upwards, that is, there are no positive shocks to banks' assets which might result in a downward shift of the supply curve. This effectively rules out asset price bubbles which could result in an explosive path of the market price. Third, the supply curve becomes horizontal from some point onwards, since the amount of non-liquid assets banks can sell is limited (see Equation (8)). Therefore, when banks have sold their complete stock of non-liquid assets, $S(sup(0)) \prec D(sup(0))$, that is, the supply curve lies below the demand curve.

[17] In the following we draw upon Cifuentes et al. (2005).

[18] Our model does not account for the possibility of asset market freezes. For example, Leitner (2011) outlines that during the recent financial crisis the market for mortgage backed securities did not function properly because the buying side was missing. Trading on markets might also come to a halt because of circuit breakers in case of strong market volatility. In our network model such a market freeze might be implemented via only allowing asset sales until prices have declined by $x\%$. The overall effect on systemic fragility is likely to be ambiguous. On the one hand undercapitalized banks would lack a means of recapitalization and eventually default. On the other hand, evaluating the portfolio at the last prevailing market price (or instead using marking to model techniques as was done during the recent financial crisis) puts a halt to fire sale spirals, shutting down this channel of shock amplification. While it would be interesting to pursue an investigation of market freezes in our network model, implementing this analysis is beyond the scope of this paper.

If a shock to banks is not large enough to trigger asset sales, the initial market equilibrium price persists. However, if the shock is large enough, by regularity conditions two and three, there exists an intersection of supply and demand curve which is achieved by the tâtonnement process described in the following.

A shock to bank i shifts the supply curve upwards, resulting in $0 \prec s_i = S(1)$, that is, bank i starts selling non-liquid assets to fulfill its capital ratio. However, for $S(1)$ the bid price, obtained by Equation (9), equals only $p(S(1))^{bid}$, while the offer price is 1. The resulting market price is $p(S(1))^{mid} = \frac{p(S(1))^{bid}+p(S(1))^{offer}}{2}$, the mid price between bid and offer prices which is obtained by bank i for selling $S(1)$ on the market. Since the market price (mid price) thus decreases and banks have to mark their non-liquid assets to market, additional non-liquid asset sales may result to fulfill the capital requirement. The stepwise adjustment process continues until the demand and supply curves intersect at p^*. The tâtonnement-process is displayed on Figure 3.

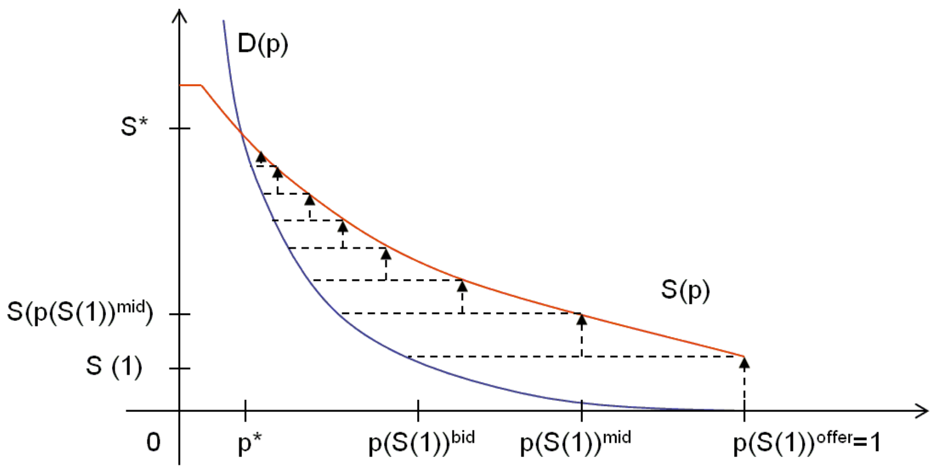

Figure 3: Tâtonnement Process in the Model
The market price of the non-liquid asset is determined by the intersection of demand and supply curves and found via a tâtonnement process. The y-axis displays the quantity of non-liquid assets offered by banks on the market as a function of prices on the x-axis. The x-axis displays bid, mid, and offer prices which are indexed by bid, mid, and offer, respectively. The $D(\cdot)$-function is the demand curve which determines the bid-price for a given quantity of non-liquid assets on the market and the $S(\cdot)$-function is the supply curve which gives the offer price banks expect to obtain for selling a quantity of non-liquid assets on the market. The mid-price designates the market price for a given supply and demand of non-liquid assets.

The following sub-section outlines how systemic risk consecutive on a shock is measured in our model.

2.1 Shocks, Shock Transmission, and Metric for Systemic Risk

A specific financial system matrix, as outlined in the previous sub-section, consists of three potentially interconnected banks (cp. Figure 1). In the absence of an exogenous shock, this system is in equilibrium in the sense that all banks fulfill the regulatory capital requirement ratio. In the following we first outline how an exogenous shock puts the financial system matrix out of equilibrium, second, how the transmission of the shock results in a new equilibrium, and, third, how we measure systemic risk conditional on the exogenous shock.

An exogenous (common) shock to the banking system is modeled as a vector of percentage losses to banks (non-weighted) sum of assets, that is, each bank is exposed to a shock of variable magnitude. A shock always manifests as a loss of liquid assets. Such a loss in net-value might be triggered, for example, by an interest rate shock.[19] Since various shocks with different intensity can arise in the financial system, we consider a wide range of possible shock events, from mild to severe, denoted by m. Strongly adverse scenarios with high unexpected losses will be included among these scenarios, as such shocks are likely candidates to trigger systemic risk events, involving defaults of parts of the financial system. All shocks are modeled over a discrete grid, with ι the number of shocks which can hit an individual bank. ι ranges from 1% to ς%, with ς being the highest conceivable shock. Considering all permutations (with repetition) of shocks for the three banks therefore yields a total number of ι^3 shock vectors. Each shock vector (equivalent to one shock scenario) consists of 3 elements, that is, the loss associated with the shock for each institution in our model. For example, if each bank can be exposed to two different shocks only, say high and low, there are $m = 8$ possible shock scenarios for the 1 by 3 shock vector, with the first, second, and third element being the loss for banks one, two, and three, respectively. The probability of a shock realization is captured by a discretized multivariate normal distribution centered at values between 0 and ς.

The transmission of shocks is modeled with an iterative procedure similar to Cifuentes et al. (2005) extended for netting counterparty exposures.[20] After shock transmission, a new equilibrium of the system is established by

[19] Note that other shock manifestations are possible, for example a loss of non-liquid assets due to a credit shock, or deposit withdrawals due to bank-runs. These shocks would spur, in our model, a reduction of capital ratios and/or net values of banks, triggering further bank portfolio adjustments. Furthermore, in a dynamic setting, shocks from interbank market freezes could be modeled as creditor banks not prolonging credit lines. While it would be interesting to analyze the impact of different shock origins, extending our model in that direction is beyond the scope of this paper.

[20] For a general overview on simulation methods for shock transmission in interbank networks see Upper (2011).

means of the quadruple $(\boldsymbol{\theta}, \boldsymbol{x}, \boldsymbol{s}, p)$ which contains a vector of banks netting decisions $\boldsymbol{\theta}$, a vector of net values of all banks liabilities $\boldsymbol{x}$, a vector of sales of non-liquid assets $\boldsymbol{s}$, and the price of the non-liquid asset p such that

1. for all banks i, there is a clearing vector $\boldsymbol{x}$ which, given the equity value of banks, indicates the net value of interbank liabilities,[21]
2. for all banks i, $\sum_j \theta_{ji}$ is the smallest netting operation that ensures the desired capital ratio is fulfilled,
3. for all banks i, s_i is the smallest sale that ensures the desired capital ratio is fulfilled,
4. there exists a downward sloping inverse demand function $d^{-1}(\sum_i s_i)$ such that the market price of the non-liquid asset can be determined by the mid price between bid and offer prices.

If subsequent to a shock, a bank does not fulfill the regulatory capital requirement, it will first try to net its counterparty exposures. Banks put priority on reducing interbank lending because in the model netting has no negative repercussions via ensuing pressure on the market price of assets on the balance sheet as is the case for liquidating non-liquid assets. Next, if netting is not sufficient to meet the capital requirement, the bank will sell non-liquid assets, thereby indirectly transmitting the shock to the system via downward pressure on the market price of non-liquid assets. If after netting all possible counterparty exposure and selling all its non-liquid assets it still cannot fulfill the capital requirement, the bank defaults. In this event, creditors of the bank which is in default receive a claim on the market value of its existing assets. Each claim is assigned, respecting seniority between different types of creditors and proportionality among the same type of creditors. Respecting seniority means that first the deposit holders are paid out, then other banks and the residual goes to equity holders. Proportionality means that the given amount claimed by a group of creditors of same seniority is shared as a proportion to their nominal claim.

To fix ideas, consider the following sequential steps the iterative clearing algorithm takes after assigning the initial exogenous shock to banks. First, the clearing vector $\boldsymbol{x}$ and banks' capital ratios are computed. Second, given banks' capitalization, the netting vector $\boldsymbol{\theta}$ is computed and capital ratios are updated.[22] Third, given the updated capital ratios, banks which do not fulfill the capital requirement ratio sell non-liquid assets, $\boldsymbol{s}$, on the market. Given the aggregate sum of non-liquid asset sales, a new market price p

[21]For a detailed exposition of obtaining the clearing vector $\boldsymbol{x}$ using the Eisenberg and Noe (2001) algorithm, see Cifuentes et al. (2005).

[22]Note that netting does not change the clearing vector but can improve banks' capital ratio.

is computed. The algorithm iterates over steps 1 to 3 until equilibrium conditions 1-4 are fulfilled and the financial system matrix does not change anymore, having reached an equilibrium.

Finally, after having described how exogenous shocks manifest in our model and how they are transmitted via direct and indirect asset contagion, we next consider our metric for systemic risk. The Financial Stability Board, International Monetary Fund, and Bank for International Settlements define systemic risk as "disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy".[23] In line with this definition, we understand systemic risk as the partial or total financial system breakdown such that an adequate supply of credit and financial services is no longer guaranteed, causing negative real effects to the economy. Defining the financial system as the aggregate of all financial institutions, systemic risk conditional on a shock can be expressed as the proportion of the financial system that defaults as displayed in Equation (10)

$$\Phi_m = \frac{\sum_{def}(\sum_j a_{def,j} + p \cdot b_{def} + c_{def})}{\sum_i(\sum_j a_{i,j} + p \cdot b_i + c_i)}, \tag{10}$$

where $def \in i$ indexes banks that are in default after the initial exogenous shock has been transmitted. Note that the amounts of assets used to compute this measure for systemic risk are taken from the financial system set-up prior to the shock. The reason for this is that the dynamic absorption of the shock in the financial system changes the allocation of assets, potentially resulting in banks having no assets at all when they default.

Given this metric, systemic risk in our model is driven essentially via three channels: (i) size, (ii), exposure of the system to direct interconnections, that is, from interbank lending, and, (iii), fire sales. First, the size of an individual bank, measured by the sum of its assets, matters because it increases the numerator of Equation (10) in case it defaults. Second, shocks can spread directly through the financial system if banks with outstanding debt held by other banks default. The higher the level of direct interconnectedness, the higher the likelihood of a default of a large proportion of the financial system, assuming a large enough shock. Higher interconnectedness may therefore trigger cascades of defaults, raising the numerator of Equation (10). Third, similar to direct contagion from interbank lending, banks which hold significant amounts of non-liquid assets are also exposed to contagion and default cascades, driven by fire sale prices, which will also increase the numerator in Equation (10).

To obtain an overall measure of systemic risk conditional on the distribution of shocks considered, we compute a weighted sum of systemic risk.

[23]Financial Stability Board et al. (2009), p. 2.

Equation (11) defines our measure of systemic risk:

$$\Phi^* = \sum_{m=1}^{\iota^3} \Phi_m \cdot prob_m, \tag{11}$$

where Φ^* is overall (expected) systemic risk. ι designates the number of different shocks each bank can be exposed to with ι^3 designating all possible shock permutations in the 1 by 3 shock vector. Therefore, m, $m = 1...\iota^3$, indexes the number of possible shock scenarios. Finally, Φ_m is systemic risk conditional on shock scenario m and $prob_m$ is the probability of shock scenario m realizing.

The following sub-section outlines how we can analyze individual financial institutions' contribution to our measure of systemic risk.

2.2 Banks' Contribution to Systemic Risk

To investigate the systemic importance of a financial institution one can quantify its negative externality on the financial system. In our model we use the Shapley value to measure individual banks' contribution to systemic risk.[24] In game theory this value is used to find the fair allocation of gains obtained by cooperation among players. The Shapley value for player i is defined as

$$\phi_i(v) = \sum_{K \ni i; K \subset N} \frac{(k-1)!(n-k)!}{n!} \left[v(K) - v(K - \{i\}) \right], \tag{12}$$

where k is the number of players in coalition K, N is the set of all players n, v(K) is the value obtained by coalition K including player i and $v(K - \{i\})$ is the value of coalition K without player i. The Shapley value is thus the average contribution of a player to the gain of the coalition over all permutations in which players can form a coalition. The analogy between gains allocation in game theory and systemic risk contribution in financial economics is evident, as individual banks may influence the likelihood of a given financial system to experience multiple bank defaults through their portfolio structures and their direct interconnection exposure from interbank lending. Furthermore, the marginal effect of a bank on overall systemic risk cannot be estimated from bank-individual data alone. The interplay with other banks' balance sheets and their portfolio compositions is needed to assess the bank's impact on system stability.

The Shapley value has a number of well-known properties: the total gain of a coalition is distributed (pareto efficiency); players with equivalent marginal contributions obtain the same Shapley value (symmetry); individual contributions add up to the overall outcome (additivity); a player that

[24] See Shapley (1953).

has no marginal contribution to any coalition has a Shapley value of zero (zero player). Of course, systemic risk is a negative externality on the financial system.[25] Therefore, the Shapley value is used to compute the marginal contribution of any single bank to this overall negative externality on the financial system.

Using the Shapley value methodology and our previously outlined model, the contribution of each single bank to systemic risk in a specific financial system matrix conditional on a shock is determined in Equation (12) with $K = \{1, 2, 3\}$. In particular, $v(K)$ is the coalition K of 'all banks that can default and transmit shocks' and hence contribute to the measure for systemic risk, and $v(K - \{i\})$ is the coalition K without the i'th bank. Intuitively, the latter is a situation in which bank i cannot default and thus not transmit shocks to the financial system, for example, because it is bailed out by the fiscal authority. In the model this is done via temporarily providing an infinite amount of liquid assets to bank i. Such a 'safe' bank does not seek to net counterparty exposure or sell non-liquid assets on the markets because it always fulfills the capital requirement.[26] It thus behaves completely passive, not contributing to any direct or indirect shock transmission. Since it therefore does not impact on any of the three risk channels in the model, size, interbank lendings, and fire sales, it is effectively excluded from the coalition that can contribute to systemic risk. Note that our framework is similar to Drehmann and Tarashev (2011)'s generalized contribution approach in the sense that interbank lendings with banks excluded from a coalition are replaced with risk-free assets.[27]

Since our systemic risk measure, Equation (10), is expressed as a proportion, its value and the individual Shapley values are restricted to the interval 0 to 1. Similar to calculating systemic risk as a weighted sum of systemic risk from a set of shock scenarios, Equation (13) outlines bank i's contribution to systemic risk from a weighted sum of its Shapley values.

$$\phi_i^* = \sum_{m}^{\iota^3} \phi_{im} \cdot prob_m, \tag{13}$$

where ϕ_{im} is bank i's contribution to systemic risk, computed as outlined in Equation (12), under shock scenario m, ι is the number of possible shocks to a bank, and $prob_m$ is the probability that shock scenario m realizes. Note that due to the additivity property of the Shapley value, overall systemic risk can be computed as the sum of the banks' contributions to systemic risk, $\Phi^* = \sum_i^3 \phi_i^*$.

[25]Gul (1989) proves that Shapley values are a good approximation of agents' payoff in efficient equilibria also under non-cooperative games.

[26]Note that banks cannot use these funds to invest in other assets classes.

[27]Gauthier et al. (2012) alternatively replace interbank links with assets reflecting the market value of the loan. In their study, both approaches yield qualitatively same results.

The following sub-section outlines network metrics which can be used to obtain an indication on the constitution of the risk channels in our model for different financial system matrices.

2.3 Network Metrics

In the model, systemic risk is driven by the three risk channels size, direct interconnection through interbank market exposure, and fire sales through liquidation of non-liquid assets. To give some broad measures for these three risk channels (i) in a given financial system matrix as well as, (ii) for an individual bank in a given financial system matrix, we use two sets of metrics:[28] in the following, the former measures, related to the financial system as a whole, will be referred to as 'system metrics' and the latter measures, related to individual banks in a given financial system matrix, will be referred to as 'bank metrics'.

First, consider a measure to indicate differences in non-liquid asset holdings across different financial system matrices, as displayed in Equation (14):

$$C_h^{nla} = \sigma_h^{nla}, \tag{14}$$

where C denotes channel and σ_h^{nla} is the standard deviation of non-liquid asset holdings of banks in financial system matrix h, $h = 1, ..., 64$ (recall that in a system with three banks with bilateral lending, there are 64 possible adjacency matrices, resulting in 64 possible financial system matrices). Since the sum over all banks of non-liquid assets held in a financial system matrix is constant across all financial system matrices investigated for given model parameters, we use a measure of dispersion, the standard deviation, to investigate the heterogeneity of banks' non-liquid asset investments in the financial system. Higher values of our metric indicate a more heterogeneous financial system with respect to non-liquid asset holdings. More heterogeneity in non-liquid asset holdings means that part of the financial system, namely banks which hold relatively more non-liquid assets, are more susceptible to contagion via fire sales.

To measure homogeneity of banks' size in the financial system, the metric displayed in Equation (15) is used:

$$C_h^{size} = \sigma_h^{size}, \tag{15}$$

where σ_h^{size} is the standard deviation of banks' sizes, measured as the sum of their assets, in financial system h. Similar to the previous metric, the sum of banks' assets is constant across all financial system matrices, h, investigated for given model parameters. Higher values of our metric indicate a more heterogeneous system with respect to banks' sizes. More heterogeneity in

[28] The following measures are taken partly from Bonchev and Rouvray (2005) as well as Jackson (2008).

banks' sizes means that systemic risk is driven increasingly by the default of large banks.

To measure exposure through interconnectedness in the financial system, Equation (16) is used:

$$C_h^{intercon} = \frac{\sum_i \sum_j l^*_{i,j,h}}{N}, \tag{16}$$

where $N = 3$ is the number of banks, and $l^*_{i,j,h}$ is the net amount bank i has borrowed from bank $j \in i, i = 1, 2, 3$ and $i \neq j$. In the network literature this measure is referred to as 'average in-degree' and measures the average exposure of banks via interbank lendings in a given financial system matrix. Higher values of our metric indicate higher exposure through interconnectedness in the financial system.

Second, consider bank metrics which we use to indicate a bank's individual involvement in the three risk channels for a given financial system matrix. To measure bank i's non-liquid asset holdings relative to other banks, the measure displayed in Equation (17) is used:

$$CC_{i,h}^{nla} = \frac{b_{i,h}}{\sum_i b_{i,h}}, \tag{17}$$

where CC denotes 'contribution to channel' and $b_{i,h}$ are bank i's holdings of non-liquid assets in financial system matrix h. Higher values indicate more holdings of non-liquid assets of bank i relative to what is held by all banks in the system.

To measure bank i's size relative to the financial system we use the metric displayed in Equation (18):

$$CC_{i,h}^{size} = \frac{\sum_j a_{i,j} + p \cdot b_i + c_i}{\sum_i (\sum_j a_{i,j} + p \cdot b_i + c_i)} \tag{18}$$

where a, p, b, and c are bank lendings, the market price of non-liquid assets, non-liquid asset holdings, and liquid assets, respectively. Therefore, Equation (18) is the ratio of bank i's assets relative to system-wide assets in financial system h. Higher values of this metric indicate a bigger size of bank i relative to the financial system.

To measure bank i's degree of interconnectedness relative to the financial system interconnectedness, the measure displayed in Equation (19) is used:

$$CC_{i,h}^{intercon} = \frac{n \cdot \sum_j l_{i,j,h}}{\sum_i \sum_j l_{i,j,h}}, \tag{19}$$

which is the in-degree of bank i divided by the average in-degree in the financial system, both in financial system matrix h. Higher values of our metric indicate a higher interconnectedness of bank i relative to the average interconnectedness prevalent in the financial system matrix.

In the next section, we use our model and the network metrics to analyze the main determinants of systemic risk.

3 Systemic Risk and Its Determinants

In the following analyses, we investigate our model along three dimensions which have been identified during the recent financial crisis as key drivers of systemic risk, banks' size and interconnectedness as well as fire sales in the financial system.[29] Our investigations are carried out by means of comparative static analyses with respect to a baseline specification of the model. To shed some light on the role of bank equity and its role as a shock buffer, the effect of different levels of capital requirement on systemic risk is also investigated.

Though highly stylized, we calibrate our model such that financial system matrices under investigation are not too far off the mark from actual financial system key metrics. Therefore parameters in our baseline specification are set such that banks' initial balance sheet proportions roughly correspond to those actually found in banking systems. The factor α which indicates banks' ratio of funds provided on the interbank market to capital is set to 0.3. The resulting financial system matrices feature roughly the average exposure on the interbank market between German banks.[30] The factor β is set to 0.8 which is roughly the proportion of non-liquid assets to cash and cash equivalents for the Deutsche Bank in 2009.[31] Regarding bank equity capital, following the Basel Commitee on Banking Supervision (2006), the capital requirement ratio, γ, is set to 8%. The price sensitivity parameter for non-liquid assets, ξ, is fixed at a value of 0.03, implying a decrease of approximately 7% of asset prices if banks sell all their non-liquid holdings in a fire sale operation.[32] Banks are initially equipped with 1 unit of capital, parameter A. Since A is merely a scaling parameter (cp. Table 1 in Section 2), and all results will be investigated in light of a ratio, involving A in both nominator and denominator (cp. our metric for systemic risk in Equation (10)), choosing A to be 1 for all institutions is without loss of generality.

Shocks that affect individual banks are modeled as a loss of a bank's assets ranging from 1% to ς =9% of its balance sheet total, assuming discrete steps of ι = 2%.[33] The (discretized) multivariate normal shock distribu-

[29]Note that while we limit our focus on these three risk dimensions, there are further risk drivers not captured in our model. For example, Brunnermeier et al. (2012) argue that banks with higher non-interest income such as investment banking, have a higher contribution to systemic risk than traditional banking such as deposit taking and lending. Furthermore, funding fragility of banks can also impact negatively on financial stability. See, for example Martin et al. (ming) and Brunnermeier and Pedersen (2009).

[30]See Upper and Worms (2004) who find a ratio of interbank loans over capital of about 4.6 for German commercial banks.

[31]See Deutsche Bank AG (2010).

[32]In a comparative static analysis of the fire sales channel in the following section, it will become clear that our parameter choice for ξ results in a relatively high shock transmission through fire sales.

[33]The upper limit of a 9% loss of a bank's (unweighted) assets is chosen to expose all financial system matrices resulting from the baseline parameter setting and the 64 possible

tion is centered at a loss of 6% of banks' assets and the main diagonal of the variance-covariance matrix is uniformly set to 3, resulting in a pairwise correlation coefficient for shocks between different banks of $\frac{1}{6}$.[34]

Note that the distribution of shock scenarios influences the outcome of the simulation exercise. For example, choosing the parameters of the distribution such that small shocks are relatively likely will typically reduce the risk contribution of the interlinkage channel which becomes contagious if a bank defaults on an interbank credit. This property is due to the fact that banks only transmit shocks via the interconnection channel if a shock is large enough to reduce the sum of banks' assets below the sum of their liabilities, that is, their equity is exhausted. Conversely, if very large shocks have a high probability of occurrence, the size channel dominates banks' contribution to systemic risk. In the case of an extreme shock, when all banks lose their equity, and absent recapitalizations, the banking system will be in default. In this extreme case, there is no room –one may say: no need– for contagion via fire sales, or interconnections. In this respect, the variance and covariance of shocks matter as well. For example, to identify banks which contribute to systemic risk via the interlinkage channel it is necessary to model shock scenarios in which banks as creditors are subject to a relatively small shock. 'Small' implies it does not cause the bank to default initially, even if, at the same time, its counterparties (that is, the borrowing banks) are subject to a relatively large shock. However, if the latter default on their liabilities, creditor-banks are ultimately exposed to default risk. The distributional assumptions thus influence systemic risk directly as well as indirectly. Our parameter assumptions governing the distribution of shock scenarios have therefore been chosen such that shock scenarios cover a wide domain, allowing systemic risk to emerge via all risk-channels. Note that while simulation results are affected by distributional assumptions and interactions between the risk-channels, the main insights obtained from the outcomes of the following macroprudential analyses are qualitatively robust to changes in these underlying parameters.

In the next sub-section, the properties of our model are explored in greater detail. The objective is to identify the role of different channels of risk contagion in the emergence of systemic risk. Results will be presented in terms of systemic risk and bank 1's contribution to it. Focussing on bank

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adjacency matrices to the same shock distribution. In all financial systems investigated in the following analyses, banks hold at least 9% of their assets in the form of liquid assets. Since a shock manifests in a loss of liquid assets on a bank's balance sheet, this ensures that no shock scenario results in negative liquid asset holdings.

[34]Concerning mean and variance of the shock distribution, there is little empirical guidance as to how these parameters can be chosen. Moody's Investor Service (2005) estimates the asset correlations for major structural finance sectors to range between 2% and 18%. Given that the recent financial crisis has demonstrated that correlations in the financial sector can be even higher than was previously assumed, a value slightly above the upper range of the interval is chosen.

1 is without loss of generality because the interlinkage structures as seen from banks 2 and 3 are symmetric, and it therefore suffices to report results from the perspective of one bank only.[35]

3.1 Systemic Risk in the Baseline Specification

In the following we analyze systemic risk and banks' contribution to it in all possible financial system matrices in our baseline parameter specification. Furthermore we visualize the previously outlined system and bank metrics by means of so-called heatmaps. Each metric is computed for all 64 financial system matrices considered in this analysis. Subsequently, each value of the 6 (one for each metric) resulting 64 by 1 vectors will be transformed into a discrete value $\pi \in \{-1, 0, 1\}$, indicating a low (-1), normal (0), or high (1) value for the metric under investigation. A value is considered to be high (low) if it features a value of one standard deviation or more above (below) the vector's mean. Following this approach, low values are assigned minus ones, normal values are assigned zeros, and high values are assigned ones. A heatmap then displays the different metric states over the range of financial system matrices under investigation. Note that the metrics are reduced to three possible states, essentially to make the heatmaps more readable.

Figure 4 displays systemic risk in all financial system matrices investigated as well as the relative importance of the risk channels, both in the baseline parameter specification. The upper panel shows systemic risk (y-axis) which is computed following Equation (11). On the figure, the financial system matrices analyzed have been ordered from lowest to highest systemic risk (x-axis). In the data set, 0.873 (financial system matrix 32) is the lowest value, and .986 is the highest value (financial system matrix 61). Given the shock distribution these values indicate that in expectation 87.3% and 98.6% of the financial system default in the respective financial system matrix.[36]

If we want to understand more about the determining factors of systemic risk levels, we have to look at the lower panel of Figure 4 which adds information on the relative importance of the three system metrics for fire sales (fire sales), interconnectedness (intercon), and size (size) in each financial system matrix displayed on the x-axis. Red (overlayed with '-' symbol), white, and green (overlayed with 'plus' symbol) areas indicate below normal, normal, and above normal values of the network metrics in the given financial system

[35] For example, as can be seen in the Appendix, financial system matrix 19 from the perspective of bank 1 is the same as financial system matrix 25 from the perspective of bank 3.

[36] Systemic risk is set at high levels in our numerical analyses, by assuming the means of the multivariate normal shock distribution to be high (6%). Reducing the means leads to lower values of systemic risk. For example, taking the average over all 64 possible banking structures on Figure 4, mean systemic risk equals 0.93. Reducing the means of the multivariate shock distribution to 1 results in a mean systemic risk over all 64 possible banking structures (not displayed) of 0.07.

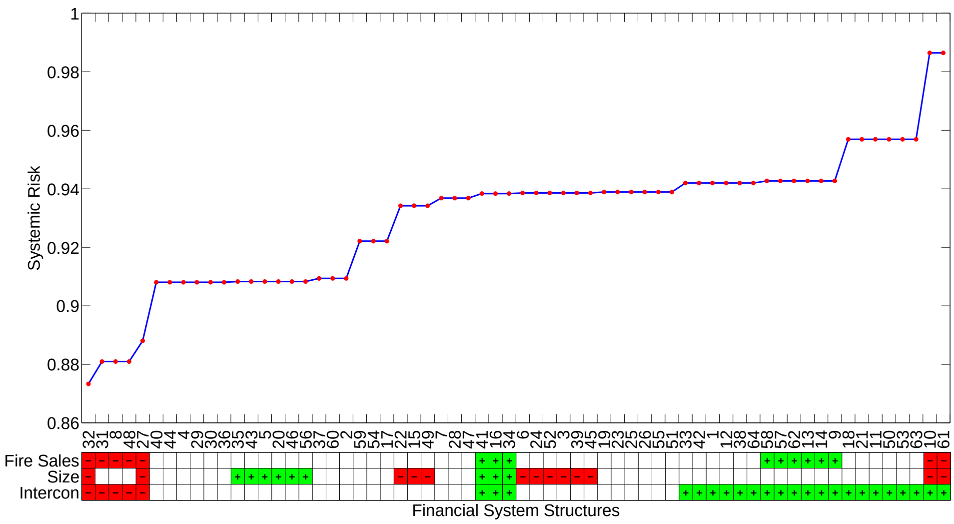

Figure 4: Systemic Risk and System Metrics
The upper panel displays systemic risk (y-axis) in each of the 64 possible financial system matrices (x-axis) which are outlined in the Appendix. The financial system matrices have been ordered according to systemic risk with the left-most matrix featuring the lowest systemic risk. The lower panel displays the system metrics for the fire sales, size and interconnection channels (y-axis) for each of the 64 possible financial system matrices (x-axis) which have been ordered as on the upper panel. Red (overlayed with a '-' symbol), white, and green (overlayed with a '+' symbol) indicate below, normal and above normal values of the system metric in a given financial system matrix.

matrices, respectively. Thus, the left-most financial system matrix in Figure 4 represents a financial architecture with banks featuring little heterogeneity in banks' sizes and amount of non-liquid asset investments, and being lowly interconnected. Not surprisingly, such a system will end up having a relatively low level of systemic risk. The five left-most financial system matrices which feature relatively low systemic risk are characterized by a relatively low heterogeneity in non-liquid asset holdings and a low interconnectedness.

In contrast, at the right-most end we find a number of financial system matrices that all score high on the interconnectedness scale. This is actually true for most financial system matrices in the upper half of the systemic risk range. More than two thirds of these excel in terms of the interconnection metric, making it the dominant determinant of systemic risk in our simulation exercise. Of course, the dominant role of exposure through interconnectedness, relative to heterogeneity in sizes and amounts invested in non-liquid assets, can be traced to some extent to the assumptions of the simulation exercise in our analysis, in particualr the magnitudes of shocks. In this case, we have allowed for a shock distribution including also shocks of a considerable magnitude which, in combination with a relatively high sensitivity to fire sales, allow for strong contagion effects via the direct interconnection channel.

Next we turn to investigating bank 1's contribution to systemic risk. Figure 5 displays bank 1's contribution to systemic risk (computed as outlined in Equation (13)) in all financial system matrices investigated as well as the respective bank metrics, both in the baseline parameter specification. The upper panel displays all 64 financial system matrices analyzed from the perspective of bank 1, ordered from low to high levels of contribution to systemic risk. In the data set, 0.241 is the lowest value (financial system matrix 31), and 0.370 is the highest value (financial system matrix 64). Given the distribution of shocks, these values indicate that bank 1 contributes 24.1 percentage points and 37 percentage points to systemic risk in the given financial system matrix, respectively.

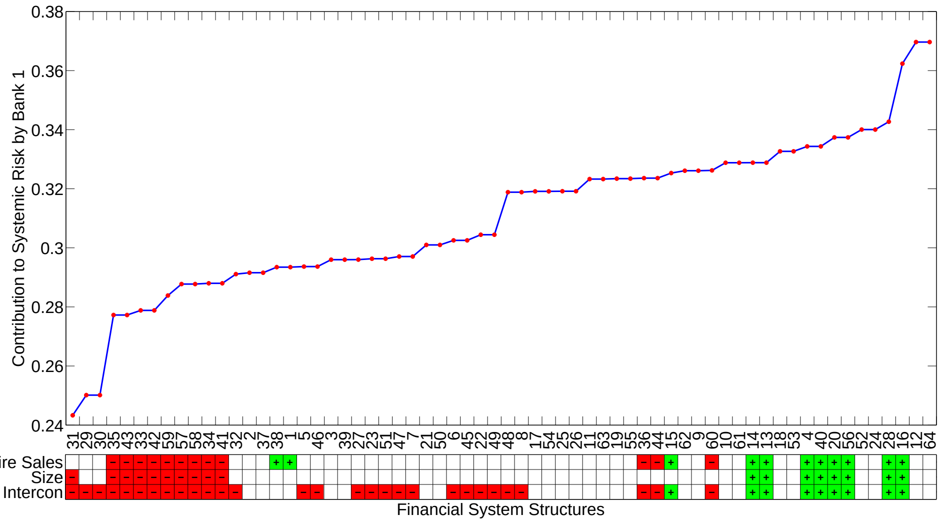

Figure 5: Contribution to Systemic Risk and Bank Metrics
The upper panel displays bank 1's contribution to systemic risk (y-axis) in each of the 64 possible financial system matrices (x-axis) which are outlined in the Appendix. The financial system matrices have been ordered according to their contribution to systemic risk with the left-most financial system matrix featuring the lowest contribution to systemic risk. The lower panel displays the bank metrics for the fire sales, size and interconnection channels (y-axis) for each of the 64 possible financial system matrices (x-axis) which have been ordered as on the upper panel. Red (overlayed with a '-' symbol), white, and green (overlayed with a '+' symbol) indicate below, normal and above normal values of the bank metric in a given financial system matrix.

If we want to understand more about the determining factors of bank 1's contribution to systemic risk, we have to look at the three bank metrics which indicate a bank's involvement in the three risk channels (size, interconnections, and fire sales) on the lower panel heatmap on Figure 5. For example, the left-most element, financial system matrix 31, is characterized by relatively small size as well as direct interconnection exposure from both relative to the financial system. Note that in the three left-most financial system matrices (29 to 31) bank 1 is not directly connected via interbank lending to banks 2 and 3.[37] Intuitively bank 1's strict separation from one channel of contagion lowers the amount of risk bank 1 can contribute to overall systemic risk.

By contrast, at the right-most end of Figure 5 we find two financial system matrices (12 and 64) which score high on contribution to systemic

[37]See the outline of financial system matrices in the Appendix.

risk while all three risk metrics indicate a normal level. A closer inspection of the financial system matrices in the Appendix, however, reveals that in these particular systems bank 1 can be a 'transmitter' of direct shocks from bank 3 to bank 2 (financial system matrix 12) or vice versa (financial system matrix 64). In the former case, bank 1 does not only expose bank 2 to contagion via the interbank lending channel when bank 1 individually defaults on its liability, but there is also the possibility that it directly transmits a large shock from bank 3 to bank 2 if bank 3 defaults on its liability and bank 1 has not enough equity to buffer this shock. Similar to the low end of contribution to systemic risk, this gives evidence that the interconnection channel and banks' position in the interbank market are key drivers of banks' contribution to systemic risk.

To isolate the effect of any particular risk channel (size, interbank lending, and fire sales), in the following analyses we will modify the simulations such that other channels are partially shut down. The next sub-section analyzes the effect of fire sales on systemic risk.

3.2 Effect of Fire Sales on Systemic Risk

The effect of the fire sale channel on systemic risk can be analyzed if the interconnection and size channels remain unchanged while the parameter governing price sensitivity to non-liquid asset sales, ξ, is modified. We expect the effects to be network-dependent, that is, different banking systems may produce distinct responses to a given shock. We thus investigate the simplest such financial system matrix, as laid out in the stand-alone banking system (financial system matrix 32 in the Appendix) where all banks have the same size and do not borrow from or lend to other banks. With respect to the outlined system metrics, this financial system features low interconnectedness as well as low heterogeneity in sizes and non-liquid asset holdings. In this experiment parameter ξ, is increased from 0 to 0.05. Figure 6 displays the effect on systemic risk (y-axis on lower panel) and bank 1's contribution to it (y-axis on upper panel) of such an increase in the price sensitivity to non-liquid asset sales.

Not surprisingly, the impact of the fire sale channel strongly depends upon the price sensitivity on secondary asset markets to asset supply.[38] High price sensitivities translate into increased systemic risk, and bank 1's contribution rises accordingly. For parameter values of 0.05 and above, even small shocks to asset values may translate into the default of the entire financial system. The analysis thus indicates that the fire sale channel can be an important amplifier of the initial shock to banks' assets.

[38]Note that the functions displayed on Figure 6 do not follow a smooth pattern due to the coarseness of the assumed shock grid, featuring a stepsize of 2% over the defined loss range. Over some regions of the parameter space of ξ, a sizeable increase in price elasticity is required to cause an increase in systemic risk.

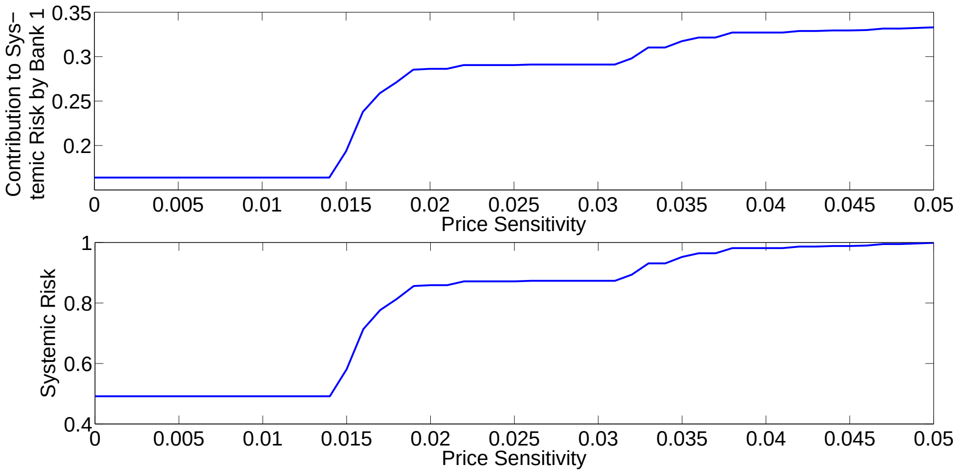

Figure 6: Effect of Fire Sales on Systemic Risk
The lower panel displays systemic risk and the upper panel bank 1's contribution to it, both on the y-axis along different levels of the non-liquid asset's price sensitivity to market sales in financial system matrix 32 (see the Appendix for an overview on all financial system matrices investigated) on the x-axis.

The next sub-section turns to the role of interbank lending in the emergence of systemic risk.

3.3 Effect of Interconnectedness on Systemic Risk

To focus on the pure effect of direct interlinkages between banks, we have to abstract from other risk determinants, like asset fire sales and bank size. Therefore, the parameter of price responsiveness, ξ, is now fixed temporarily at zero and all banks maintain the same amount of initial assets, $A = 1$. Figure 7 displays a boxplot of systemic risk (y-axis on lower panel) as well as bank 1's contribution to it (y-axis on upper panel), for different numbers of interbank links, in the 64 possible financial network matrices in our baseline scenario (x-axes). Note that two banks are considered as being directly interconnected as soon as there is a lending-borrowing relationship between them. For example, in the right-most element on the boxplot, all three banks are interconnected with each other, resulting in three interconnections.

Investigating the upper and lower quartiles (designated by the upper and lower lines closing the boxes), the whiskers which extend to the extreme data points (horizontal lines above and below the boxes), and outliers (plus symbol), shows that there is no clear monotonic relationship between the number of interbank links and the resulting systemic risk, nor the bank's systemic risk contribution, that is, a higher interconnectedness can lead to lower or higher systemic risk and banks' contribution to it. In the network literature this property is labeled 'robust-yet-fragile', meaning that a growing number of interbank linkages can render the network more robust vis-à-vis small

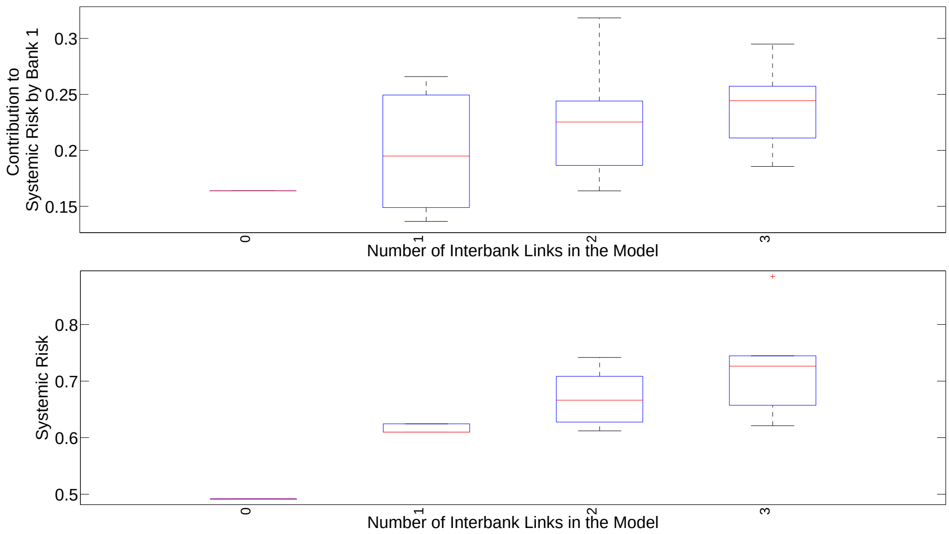

Figure 7: Effect of Interconnectedness on Systemic Risk
The lower panel displays systemic risk and the upper panel bank 1's contribution to it, both on the y-axis, along financial system matrices which have been ordered according to the number of directly connected banks in the model on the x-axis. The upper and lower lines closing the boxes designate the upper and lower quartiles, respectively. The whiskers show extreme data points, and outliers are designated by a plus symbol.

shocks, and at the same time more vulnerable to large shocks.[39] This result provides further evidence in favor of the findings in Gai and Kapadia (2010) and Upper (2011) who also show that highly interconnected systems are relatively stable in the face of small shocks however can be prone to high systemic risk when exposed to large shocks. However, focusing on the medians (horizontal lines in the boxes of Figure 7), the boxplots suggest that systemic risk, as well as a bank's contribution to it, tend to increase with the number of active links across banks.

In the next sub-section we analyze the effect of bank size on systemic risk.

3.4 Bank Size and Systemic Risk

To identify the effect of bank size on systemic risk the interlinkage and fire sale channels are kept static while the parameter impacting banks' size, A, is modified. Therefore, we again carry out our analysis using the stand-alone banking system (financial system matrix 32) already used in the analysis of the fire sale channel and set the price responsiveness of the non-liquid asset, ξ, to 0. Our analysis then consists of investigating the effect of increasing the

[39]Since in this case the shock vectors are the same, the 'robust-yet-fragile' property follows from a specific network property in our model, namely the possibility of cross-exposures, that is, two banks have lent to and borrowed from each other at the same time, akin to a mutual insurance. In the case of cross-exposure more links can stabilize the system because banks can improve their capital requirement ratio via netting their exposures in the face of shocks.

assets of bank 1 while banks 2 and 3 retain their initial asset holdings. Figure 8 shows systemic risk (y-axis on lower panel), and bank 1's contribution to it (y-axis on upper panel) when its initial assets are increased from 1 to 3 (x-axes) while holding the other two banks' initial assets constant at 1.

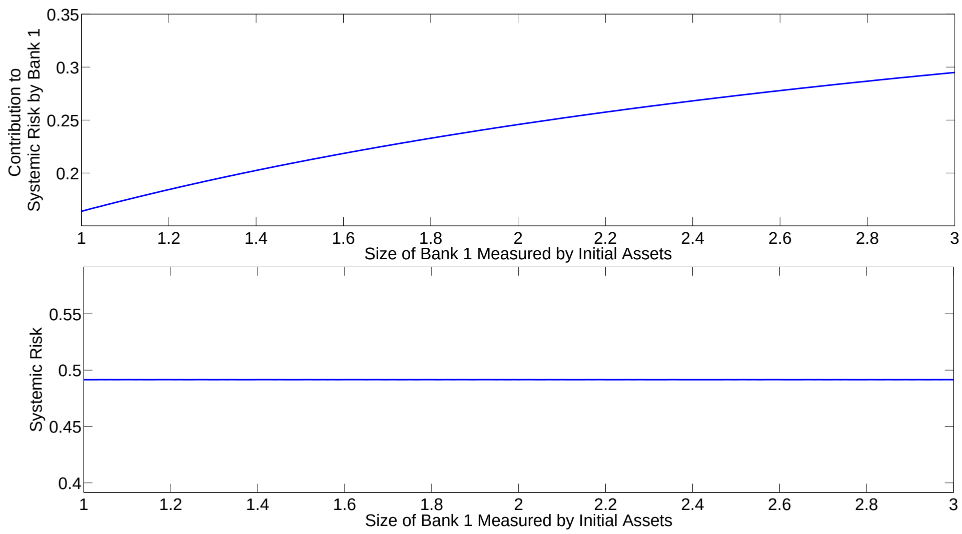

Figure 8: Effect of an Increase of Bank 1's Size on Systemic Risk
The lower panel displays systemic risk and the upper panel bank 1's contribution to it in financial system matrix 32, both on the y-axis, along increasing values of initial capitalization of bank 1 on the x-axis.

Controlling for the effect of the fire sale and interlinkage channels and increasing bank 1's size results in increasing its contribution to systemic risk (from 0.16 to 0.29). However, given the definition of systemic risk as well as the symmetry of the shock vectors and assigned probabilities which are used in the computation of systemic risk, the level of systemic risk does not change (constant at about 0.49). This result is driven by the fact that in the weighted sum of systemic risk over all shock scenarios, the changes in systemic risk resulting from increasing bank 1's size relatively to the other banks in the financial system exactly offset each other.

In the next sub-section we investigate the effect of the capital requirement ratio on systemic risk.

3.5 Capital Requirements and Systemic Risk

Increasing bank capital requirements has been one of the most common proposals since the outbreak of the financial crisis in the second half of 2007. Equity capital is widely seen as the main buffer against adverse shocks to bank balance sheets. Therefore, under the proposed Basel III framework, one of the main rule changes concerns a significant increase in the minimum capital requirement, in order to render the financial system more resilient.[40]

[40] Bank for International Settlements (2010).

In what follows, the role of system wide bank capital ratios for the emergence of systemic risk will be analyzed. To investigate the universal role of bank capital as a shock buffer, all financial system matrices analyzed in the baseline setting will be re-investigated in light of banks' required capital endowment. As in the previous analyses, all other parameters of the model remain unchanged from the baseline specification.

Figure 9 displays systemic risk (y-axis on lower panel) as well as bank 1's contribution (y-axis on upper panel) when the required equity ratio in the financial system is increased from 1% to 25% (x-axes). Financial system matrices have been ordered along the z-axis following the outcomes in the baseline scenario (same order as on Figures 4 and 5).

Overall, increasing the capital requirement ratio lowers systemic risk across the board, and in tendency also decreases banks' contribution to systemic risk. The analysis in this sub-section thus supports the claim that an increase of capital requirements leads to a less fragile financial system.

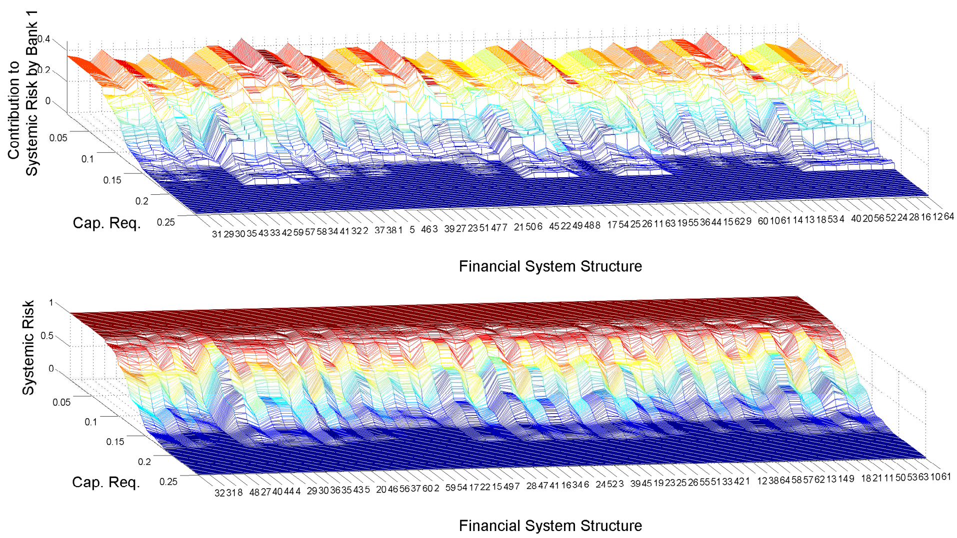

Figure 9: Effect of the Capital Requirement on Systemic Risk
The figure displays systemic risk (y-axis on lower panel) as well as bank 1's contribution to it (y-axis on upper panel) when the required equity ratio in the financial system is increased from 1% to 25% (x-axes, designated by Cap. Req.). Financial system matrices have been ordered along the z-axes following the outcomes in the baseline scenario as displayed on Figures 4 and 5.

In this section we investigated our model with respect to its systemic risk properties. Our main findings are outlined in the following. First, interconnectedness of financial institutions on the interbank market is key to understanding systemic risk in the model. All else equal, we find that in tendency lower interconnectedness can be associated with a lower level of systemic risk as well as banks' contribution to it. During the recent financial crisis this property was labelled 'too-interconnected-to-fail' which reflects the importance of this channel for systemic risk. Second, the fire sale channel is an important amplifier of shocks to the financial system. When the financial system becomes more sensitive to sales of non-liquid assets, systemic risk goes up significantly. In the recent financial crisis, this fire sale channel played a key role for shock transmission in the financial system.[41] Third, all else equal, banks contribution to systemic risk increases with their size. The larger a bank relative to its counterparties, the higher is its contribution to systemic risk. During the recent financial crisis this property was labelled 'too-big-to-fail'. Fourth, increasing the capital requirement ratio lowers systemic risk and in tendency banks' contribution to it. Overall, our model thus replicates some of the most important stylized facts observed during the recent financial crisis.

In the following section we will use our model to explore a novel macroprudential risk management approach, the System Value at Risk (SVaR).

4 Investigating a Systemic Risk Charge

Systemic risk threatens financial stability and therefore the proper functioning of financial markets, economies and ultimately societies. During the recent financial crisis numerous macroprudential risk management approaches to counter systemic risk have been proposed.[42] Most of these proposals consider two goals. The first is to ensure financial stability at system level, that is, to achieve a tolerable level of systemic risk. Usually it is inter alia argued to increase banks' capitalization to achieve this goal. In line with this, our previous analyses provide evidence that banks' capitalization is indeed an effective tool to reduce systemic risk and banks' contribution to it. The second goal is to charge those who cause systemic risk –financial institutions– the cost of stabilizing the financial system. However, as has also become clear in the previous sections, banks' negative externality on the financial system, that is, their contribution to systemic risk, depends on several dimensions, in particular the three risk channels banks' size, interconnectedness, and fire sales. Therefore, additional regulatory risk charges need to take into account the emergence of systemic risk through the interplay of these risk channels.

One approach to fulfill both goals in a separated way is to, on the one hand, charge banks a fair systemic risk levy which depends on their contribution to systemic risk. On the other hand, the proceeds from the levy are used to optimally inject additional capital into the financial system to make it more resilient. As a by-product to financing the cost of financial stabilization, a risk charge, akin to a Pigouvian tax, incentivizes financial institutions to reduce their contribution to systemic risk and thus to lower their negative externality on the financial system. Alternatively to separately covering the

[41] See, for example, Brunnermeier and Pedersen (2009).

[42] See, for example, Acharya (2009b), Acharya et al. (2009), Financial Stability Board, International Monetary Fund, and Bank for International Settlements (2011), International Monetary Fund (2011), and German Council of Economic Experts (2011).

two related goals, they can be pursued at the same time via requiring banks to build up (macroprudential) capital as a function of their contribution to systemic risk, thus ensuring in a single sweep financial stability and incentivizing banks to internalize their negative externality.[43] Both approaches –separating the two goals and pursuing them in one step– lead to the same outcomes in terms of financial stability and banks' incentives if banks contribution to systemic risk is a sufficient statistic to determine banks' optimal macroprudential capitalization. By optimal we mean 'achieving a desired level of systemic stability with the smallest amount of (macroprudential) capital necessary'.

In the following, we use our model to analyze these two approaches via introducing the SVaR concept.[44]

4.1 System Value at Risk as a Macroprudential Risk Management Approach

In the SVaR concept, a systemic risk fund which is financed by levying a fair risk charge from financial institutions is used to provide the necessary macroprudential capital for stabilizing the financial system. We use this framework to investigate whether banks' contribution to systemic risk is a sufficient statistic to determine the optimal macroprudential capital allocation in a financial system. We carry out this analysis in terms of the following hypothesis:

Hypothesis: There is always a correspondence between banks' contribution to systemic risk and their optimal macroprudential capitalization.

In a statistical sense, our hypothesis amounts to investigating the correlation between banks' contribution to systemic risk and their optimal macroprudential capitalization –with the extreme case of perfect correlation if there is a correspondence between the two measures.[45] In case such a correspondence exists, distinction between both outlined macroprudential goals is not necessary, because linking individual macroprudential capital requirements to banks' contribution to systemic risk will automatically result in

[43]See, for example, Acharya et al. (2009). The authors propose, that "[c]apital requirements could be set as a function of a financial firm's marginal expected shortfall" (p. 8) which is their measure for a bank's contribution to systemic risk. See also Acharya and Richardson (2009).

[44]Our SVaR approach features some of the characteristics of the value at risk (VaR) concept which is a well established measure in risk management used on the level of individual banks. The VaR indicates for a given portfolio the loss it will not exceed in a specified time horizon with a given probability. See, for example, Jorion (2006).

[45]In a weaker sense, correspondence can also be interpreted as positive correlation between banks' contribution to systemic risk and their optimal macroprudential capitalization. Intuitively, one would expect that an optimal macroprudential capitalization of the financial system results in banks which cause more systemic risk, that is, those which have a higher contribution to systemic risk, to be required to hold more macroprudential capital relative to those which cause less systemic risk.

the optimal macroprudential capital allocation of the financial system. Put differently, if our hypothesis is true, a bank's optimal macroprudential capitalization and its fair systemic risk charge coincide. In the following, we will first outline our macroprudential risk management approach in more detail and then use it to investigate our hypothesis.

In our SVaR concept, the supervisor first has to define a distribution of extreme shock scenarios deemed possible in the financial system. Second, the supervisor computes systemic risk, and individual institutions' contribution to systemic risk, conditional on the assumed shock distribution. Third, the supervisor chooses a critical SVaR level. The SVaR is defined as the proportion of the financial system in default which will not be exceeded with a given probability p_{SVaR}.[46] Fourth the supervisor injects the minimum additional capital buffer required at the level of individual banks to achieve this level of financial stability in the form of equity into the financial institutions. Banks are required to hold the equity capital in liquid assets in addition to any microprudential capital requirement. The sum of all macroprudential capital injections constitutes the necessary additional systemic capital which ensures that the first goal of our macroprudential risk management approach –financial stability at system level– is fulfilled.

As noted before, to fulfill the second goal –charging banks for their negative externality on the financial system– the fund is financed by levying financial institutions a fair risk charge, that is, a risk charge proportional to their contribution to systemic risk. Equation (20) displays such a fair systemic risk charge, H, for the i'th bank.

$$H_i = \Psi \cdot \frac{\phi_i^*}{\sum_j^3 \phi_j^*}, \tag{20}$$

where $i \in j,\ j = 1, 2, 3,\ \Psi$ is the optimal amount of capital for the systemic risk fund, and ϕ_i^* is the contribution to systemic risk by bank i as measured by the Shapley value (Equation (13)). Since all banks' contributions to systemic risk in the denominator sum up to overall systemic risk, each bank is charged to finance a proportion of the additional systemic capital equivalent to the proportion of its contribution to systemic risk.[47]

An important feature of the SVaR concept is that despite the presence of systemic stability, banks are still subject to bankruptcy risk –provided

[46] Note, that the objective need not be achieving a maxium level of stability, as it is well understood that, beyond a certain point, an increase in stability may decrease welfare. In our SVaR-approach, the policy maker has to select a tolerance level at which the failure of a particular fraction of the financial system is deemed admissible. For example, in terms of total assets, up to 25% of the financial system are accepted to default once every 33 years, that is, up to 25% of the financial institutions may lose their equity capital at the 97^{th} percentile of the consolidated loss distribution.

[47] Note that at this point it is assumed that banks can pay these charges from profits, for example, by deferring dividend payments. That is, there is no re-allocation of existing bank capital.

that individual sizes (as proportion of the financial system) do not exceed the critical value. To achieve this, the proportion of the financial system in default which is compatible with financial stability must be large enough to allow for the individual default of each bank in the financial system. The prevalence of individual default risk keeps moral hazard (stemming from the existence of the additional systemic capital) at bay.

To compute the optimal amount of additional capital needed for conforming with the SVaR rule we use the loss function given in Equation (21):

$$min_{\boldsymbol{\tau}}\ \epsilon = \sum_{i}^{3} \tau_i + \Theta \#_{\Phi > SVaR(\tau)}, \tag{21}$$

where ϵ is the loss to be minimized by the supervisor, τ_i is the additional amount of capital injected into financial institution i, $\#_{\Phi > SVaR(\tau)}$ the number of scenarios that exceed the critical proportion of systemic risk beyond $1 - p_{SVaR}$, and $\Theta > 0$ is a scaling parameter to make sure that the increase in the loss from any violation of the stipulated SVaR conditions is larger than the reduction in terms of the capital injection. In our exercises we set $\Theta = 1$. Since Equation (21) may not be continuous it requires a non-standard optimization technique. In our analyses we use generalized pattern search, a heuristic search algorithm which does not require functions to be differentiable or continuous.[48]

Note that the optimal allocation found via minimizing Equation (21) is not a function of our measure for banks' contribution to systemic risk, that is, the Shapley value.[49] In our approach, we determine, (i) the optimal amount of additional system capital and, (ii) its optimal allocation to achieve a desired level of systemic risk. It is possible that under this optimal allocation banks in the system feature different contributions to systemic risk. The reason for this is that in our model capital affects the channels which drive systemic risk to different extents. In the following analyses, we show that while additional capital can efficiently dampen banks' contribution to systemic risk arising from the interbank lending and fire sale channels, it is less efficient in dampening systemic risk arising from the size channel. However, if (i) the risk channels are dampened by additional

[48] See Audet and Dennis (2003).

[49] Under certain conditions the optimal allocation of a given amount of capital in a financial system can be determined via re-allocating capital among banks until all banks feature the same contribution to systemic risk. The argument for this approach is that as long as a bank features a higher contribution to systemic risk relative to another bank, one can lower systemic risk via re-allocating some capital from the bank with the lower contribution to the one with a higher contribution to systemic risk. Note that this approach leads to different optimal capital allocations for a given financial system, depending on the metric chosen to measure banks' contribution to systemic risk. While it would be interesting to compare both approaches in more detail, this analysis is beyond the scope of our paper. See, for example, Gauthier et al. (2012) for an analysis using the alternative approach. For a comparison of these alternative approaches see Tarashev et al. (2010).

capital to different extents and, (ii) banks cause systemic risk via different channels with different intensities, then systemic risk can best be lowered via injecting additional capital into banks which contribute strongly to systemic risk via the channels that are efficiently dampened by additional capital.[50] In our model exercises we generally don't find congruent contributions to systemic risk under the optimal macroprudential capital allocation fulfilling the SVaR.

Using our model and the outlined SVaR methodology, we next turn to investigating our hypothesis that there is always a correspondence between banks' contribution to systemic risk and their optimal macroprudential capitalization. To carry out this analysis, we choose a specific financial system matrix for which we change the size of bank 1 as in the analysis in Section 3.4 via increasing its initial assets (by 20% relative to the other two banks) and lower the required capital ratio for all banks by 20%. The two specific changes influence the financial system under investigation in the following direction: First, augmenting bank 1's initial assets by 20%, we increase its contribution to systemic risk (relative to the other two banks' contribution to systemic risk) via the size channel. Second, the lower required capitalization of banks in the financial system causes shock transmission via the interbank lending channel to become more severe. In terms of system metrics the financial system under investigation then has the following characteristics: it features low heterogeneity in non-liquid asset investments and banks sizes, and normal heterogeneity in interbank exposure (see bottom of the Appendix, financial system matrix 23*).[51] The SVaR in our exercise is defined as 'With 97% probability systemic risk is lower than 36%'. Note that the following results are qualitatively robust to changing the probability mass to values different from 0.97 as well as varying the proportion of

[50] To fix ideas, consider a financial system consisting of three banks, one big bank which only contributes to systemic risk via the size channel (it holds neither non-liquid assets nor has borrowed from other banks), and two small banks which contribute to systemic risk both by the size and fire sale channels (both banks have not borrowed from other banks). Furthermore these two banks are so small that even summing up their contributions to systemic risk results in less than the contribution to systemic risk of the single big bank. Hence, the big bank contributes most to systemic risk and its contribution is completely driven by the size channel which is not affected by additional capital. In this setting, systemic risk can be effectively lowered by injecting additional capital into the small banks, because contribution to systemic risk via the fire sale channel is dampened by additional capital. Note that shifting capital from the small banks to the big bank until all banks feature the same contribution to systemic risk results in an overall higher systemic risk because the contribution to systemic risk from the two small banks increases (less capital heightens the contribution to systemic risk via the fire sale channel) while the contribution to systemic risk from the big bank is unchanged (additional capital does not affect its contribution to systemic risk via the size channel).

[51] Note that the specific financial system matrix is chosen with the aim to show that there needs not be a correspondence between banks optimal macroprudential capitalization and their contribution to systemic risk. To reject our hypothesis it is sufficient to show at least one financial system matrix in which the claimed correspondence does not hold.

the system which is accepted to default. Also note that 36% is chosen as critical proportion in the specific SVaR exercise because the largest bank (bank 3) accounts for 36% of the financial system in terms of total assets. The chosen value thus ensures that the default of each individual bank is compatible with the SVaR.

Table 2 shows the results for our SVaR analysis, with the individual steps of our macroprudential risk management approach displayed sequentially. To facilitate interpretations, values are expressed as percentage of systemic risk (rows 1 to 3) or in percent of system equity (rows 5 to 11), defined as the sum of all banks' equity before the realization of any shock.

Contribution to Systemic Risk of Bank 1 (Percentage Points)	32.1
Contribution to Systemic Risk of Bank 2 (Percentage Points)	31.6
Contribution to Systemic Risk of Bank 3 (Percentage Points)	35.6
Systemic Risk	99.3
Capital Injected to Bank 1 (% of System Equity)	21.2
Capital Injected to Bank 2 (% of System Equity)	42.8
Capital Injected to Bank 3 (% of System Equity)	37.8
Minimum Capital Required for Systemic Risk Fund (% of System Equity)	101.8
Bank 1's Risk Charge (% of System Equity)	32.9
Bank 2's Risk Charge (% of System Equity)	32.4
Bank 3's Risk Charge (% of System Equity)	36.5

Table 2: Results of the Systemic Risk Fund Exercise
Results are obtained by carrying out the SVaR analysis in financial system matrix 23* (See the Appendix for an outline of financial system matrix 23*.)

Rows 1 to 3 display banks' contribution to systemic risk in the outlined financial system conditional on the defined shock distribution as measured by the Shapley value (computed following Equation (13)). Bank 3 contributes with 35.6 percentage points most to systemic risk, followed by banks 1 (32.1 percentage points) and 2 (31.6 percentage points), respectively. Looking into the Appendix, bottom right panel, it becomes clear why bank 3 has the highest contribution to systemic risk. It is the biggest bank in the system (covering a proportion of 36% of the financial system) and holds most non-liquid assets (covering a proportion of 37% of non-liquid assets held in the financial system). It thus contributes heavily via the size and fire sale channels. Note that Shapley values (rows 1 to 3) are based on the financial system without additional macroprudential capital injections. Since the capital injection is an additional layer of macroprudential regulation to be funded by those who cause the negative externality, individual contributions to systemic risk before the capital injection are the metric on which the risk charge is based. The 4$^{\text{th}}$ row displays overall systemic risk as computed following Equation (11). Without any macroprudential capital injections, the level of systemic risk amounts to 99.3%, that is, in expectation 99.3% of the financial system default conditional on the distribution of shocks. Rows 5 to 7 display the optimal macroprudential capital injections into the financial institutions to achieve the SVaR. These values are computed via minimizing Equation (21).[52] As can be seen in row 6, with an injection of 42.8% of system equity, bank 2 requires the highest macroprudential capital injection followed by banks 3 (37.8% of system equity) and 1 (21.2% of system equity), respectively. Row 8 shows the optimal amount of necessary additional capital (sum of rows 5 to 7). To obtain systemic stability, the system wide capitalization needs to be increased by 101.8%. Rows 9 to 11 display banks' fair systemic risk charge computed following Equation (20). Overall, rows 5 to 8 thus reflect achieving the first goal of our macroprudential risk management approach –ensuring that a viable part of the financial system remains solvent– and are obtained by optimally fulfilling the stipulated SVaR. The remainder rows in Table 2 cover achieving the second goal which is charging banks a fair risk levy proportional to their negative externality on the financial system.

Turning to the main question of this section, namely whether there is always a correspondence between a bank's contribution to systemic risk and its optimal macroprudential capital allocation, the results on Table 2 show that no such correspondence needs to exist. Although bank 2 contributes less to systemic risk than banks 1 and 3, it is optimal to inject more macroprudential capital into this bank. The correlation between the vectors of contribution to systemic risk (rows 1 to 3) and optimal macroprudential capital injections (rows 5 to 7) equals 0.20. We have shown one financial system matrix in which the correspondence does not hold and therefore reject our hypothesis that there is always a correspondence between a bank's contribution to systemic risk and its optimal macroprudential capitalization.

Our results can be explained when observing that capital enhancement operates differently on the three risk channels in our model. While the interbank lending and fire sale channels are directly affected by additional capital, the size channel is only indirectly affected. The interbank lending channel is directly affected because of seniority of interbank loans with respect to equity. The additional macroprudential capital a bank holds increases the equity buffer which prevents shocks from being transmitted to creditors and therefore lowers its contribution to systemic risk via the direct interbank lending channel. The fire sale channel is directly affected because additional

[52] As robustness check, the minimization routine for the problem at hand has been carried out 100 times using random starting values for the vector of capital injections. The minimization always results in the parameter values displayed in Table 2. Furthermore, using the simulated annealing algorithm as alternative (though computationally less efficient) optimization routine also leads to the same optimal parameter values. See Kirkpatrick et al. (1983) and Huang et al. (1986) for an outline of optimization by simulated annealing.

capital has to be held in liquid assets. Ceteris paribus, increasing a bank's holding of liquid assets, increases the positive effect of non-liquid asset sales on its equity ratio. This effect becomes clear by investigating the change in a bank's capital ratio when it engages in selling s units of non-liquid assets, that is, subtracting Equation (1) from Equation (7):

$$\Delta\gamma = (\sum a + pb + c - \sum l - d)(\frac{1}{\sum a + p(b-s)} - \frac{1}{\sum a + pb}) \qquad (22)$$

where indices have been omitted for simplicity. Differentiating Equation (22) by c shows a positive relation between liquid asset holdings and the effects of selling non-liquid assets.[53] Therefore, if a bank ceteris paribus holds more liquid assets because of a macroprudential capital injection, it needs to liquidate less non-liquid assets to achieve a desired improvement in its capital ratio, $\Delta\gamma$, which in turn dampens its contribution to systemic risk via the fire sale channel. The size channel is not directly affected because the additional capital is not included in computing banks' relative size within the financial system. Doing so could counterintuitively lead to increasing banks' contribution to systemic risk via the size channel if they are injected additional macroprudential capital. Furthermore, banks have to maintain the enhanced capital and are not allowed to run it down in the face of shocks.[54]

Noting the different impact of additional capital on risk channels and observing the constitution of financial system matrix 23* (see Appendix) helps explaining the outcome of our SVaR exercise. While banks 1 and 3 contribute mainly via the size and fire sale channels (direct exposures via interbank lending to them can be netted), bank 2 contributes via all three channels. In particular, bank 1 is exposed to bank 2 via the direct interbank lending channel. It is thus efficient in terms of lowering systemic risk to inject much additional capital into bank 2.[55] Intuitively, if the instrument chosen to achieve a desired level of systemic stability impacts the various risk channels driving banks' contribution to systemic risk differently, there

[53] The second term in Equation (22) is positive since $b \geq s \geq 0$ when banks engage in selling non-liquid assets.

[54] To fix ideas, consider a bank which contributes to systemic risk only because of its size, that is, it contributes neither by the fire sales nor the direct interconnection channels. If the capitalization of the bank is increased and has to be maintained, then the likelihood of default does not change provided the same shock distribution is applied.

Note that theoretically, a supervisor could announce a state of systemic emergency during which banks are allowed to run down their macroprudential capital. However, besides potentially causing more risk taking in the financial system during tranquil times it is not clear how the supervisor could identify such systemic shocks in real time.

[55] Note that from a certain amount of capital injected, the impact of additional capital on the direct interbank lending channel vanishes, namely when under no shock scenario the debtor banks' equity becomes negative anymore. The impact of additional capital is thus not only different between channels but it can also be also non-linear with respect to the same channel.

needs not be a correspondence between banks' contribution to systemic risk and their optimal macroprudential capitalization. In that case it is efficient to inject most additional capital into those banks that contribute heavily to systemic risk via channels that are strongly affected by additional equity capital.

To get an idea about the average correlation between optimal macroprudential capitalization and banks' contribution to systemic risk, we generate 1000 random financial systems. For each of these systems we randomly draw one of the 64 possible direct interlinkage structures using a uniform distribution. The remainder model parameters are also drawn from a uniform distribution, with each parameter distribution limited to +/-25% of the respective parameter value in the baseline specification.[56] In our simulation, the average correlation between banks contribution to systemic risk and their optimal macroprudential capitalization equals 0.08 with a standard deviation of 0.67. Given our simulation outcome and taking conventional statistical confidence levels, all correlations ranging from perfectly negative (-1) to perfectly positive (1) are possible.

Our analysis shows that linking a bank's macroprudential capital requirements directly to its contribution to systemic risk is not necessarily an optimal and consistent policy approach when taking a systemic risk management perspective. We have used one specific financial system in our modeling framework to describe why there needs not be a correspondence between banks' contribution to systemic risk and their optimal macroprudential capitalization. Furthermore, our random simulation exercise provides evidence that typically there is no such correspondence. While we have chosen to use a very stylized network model consisting of three banks only, this intuition also applies to more sophisticated contagion models with $N > 3$ banks.[57] Clearly, the SVaR concept could hardly be actually implemented without any adjustments as actual regulatory instrument – not least because some features such as determining the optimal macroprudential capital allocation from a social planner's perspective is possible in our model but would be difficult in reality. Nevertheless, our SVaR exercise highlights potentially conflicting goals in actual macroprudential regulation. The arguments provided in our SVaR analysis as well as the mechanisms behind our results also apply to highly complex financial systems.

Following our results, setting banks' macroprudential capital requirements proportionally to their contribution to systemic risk can be inconsistent or inefficient. One might argue that this result is akin to the so-called Tinbergen rule. The rule states that consistent economic policy requires the number of independent policy instruments to be at least equal to the num-

[56] For example, in the baseline specification, banks' capital requirement ratio (γ) is set to 8% while in the random experiment it is drawn from a uniform distribution ranging from 6% to 10%.

[57] See, for example, Acemoglu et al. (2013) and Bluhm et al. (2013).

ber of different policy targets.[58] In our systemic risk management approach, a consistent and efficient economic policy pursues two separate policy targets: first, a certain ceiling on admissible systemic risk, measured by the SVaR, and, second, the internalization of systemic risk contributions at the firm level, by stipulating a fair risk charge. Though ultimately related, both targets can become distinct when the risk-channels through which banks contribute to systemic risk are affected by the instrument to achieve systemic stability to a different extent. In case the risk-channels are indeed affected differently by additional capital injections, merging the two instruments can be dysfunctional, setting the wrong incentives with respect to systemic risk reductions or resulting in a sub-optimal capital allocation. A possible solution to this policy 'dilemma', or rather this goal-conflict, has been embedded in our analysis already. Namely, the use of two separate instruments, a bank levy to fulfill the incentive requirement[59] and a bank capital injection (or enhancement) to guarantee systemic stability.

4.2 Robustness Checks

The value at risk and conceptually similar approaches have been criticized for not being coherent risk measures.[60] For this reason and as a robustness check we carry out an analysis similar to the SVaR, using the concept of expected shortfall which is a coherent risk measure. Expected shortfall is defined as the expected loss incurred in the $(1-p)\%$ worst cases of a portfolio.[61] In analogy to the SVaR, we define the System Expected Shortfall (SES) as the expected proportion of the financial system in default in the worst scenarios covered by the q^{th} quantile, with $q = 1 - p_{SVaR}$. That is, the SES quantifies expected systemic risk conditional on the SVaR being exceeded.[62] Repeating our previous analyses for the SES defined as 'The SES

[58]See Tinbergen (1952).

[59]Note that in our analysis we do not consider the endogeneity of portfolio choices, that is, how the introduction of a systemic risk charge will –once it has been introduced– affect banks' chosen balance sheet composition. Exploring these endogenous portfolio reactions is beyond the scope of this paper. For an analysis of banks' endogenous portfolio choice in relation to macroprudential requirements see Bluhm et al. (2013).

[60]See Acharya et al. (2011) and Artzner et al. (1999).

[61]See Acerbi and Tasche (2002).

[62]Note that our measure is not the same as Acharya et al. (2011)'s Systemic Expected Shortfall for which the authors use the same acronym. Acharya et al. (2011)'s SES is defined as the "propensity to be undercapitalized when the system as a whole is undercapitalized". Our SES measure is conceptually closer related to the market-based SRISK measure from Brownlees and Engle (2012) as well as Acharya et al. (2012). The authors define SRISK as the capital that a firm is expected to need if there is another financial crisis. It is computed using the average of the fractional returns of the firm's equity in crisis scenarios. This capital shortfall approach is then used to determine firm-specific capital requirement or leverage ratios. While our SES approach determines macroprudential capitalization based on an optimization approach to achieve a specific tail risk and charges banks according to their contribution to systemic risk, the SRISK approach sug-

in the 3% worst outcomes shall not exceed 36%' yields the results displayed in Table 3.

Contribution to Systemic Risk of Bank 1 (Percentage Points)	32.1
Contribution to Systemic Risk of Bank 2 (Percentage Points)	31.6
Contribution to Systemic Risk of Bank 3 (Percentage Points)	35.6
Systemic Risk	99.3
Capital Injected to Bank 1 (% of System Equity)	21.2
Capital Injected to Bank 2 (% of System Equity)	44.5
Capital Injected to Bank 3 (% of System Equity)	39.2
Minimum Capital Required for Systemic Risk Fund (% of System Equity)	105.0
Bank 1's Risk Charge (% of System Equity)	33.9
Bank 2's Risk Charge (% of System Equity)	33.4
Bank 3's Risk Charge (% of System Equity)	37.7

Table 3: Results of the Systemic Risk Fund Exercise Using the SES Approach
Results are obtained by carrying out the ESS analysis in financial system matrix 23* (See the Appendix for an outline of financial system matrix 23*.)

The result is qualitatively similar to our SVaR analysis with the correlation between between the vectors of contribution to systemic risk (rows 1 to 3) and optimal macroprudential capital injections (rows 5 to 7) equal to 0.20. Note that the capital injections required under the SES approach are slightly higher than under the SVaR approach, that is, the expected tail risk using the optimal injections from the SVaR analysis exceeds the expected tail risk using the optimal capital injections from the SES analysis. Repeating our simulation exercise, generating 1000 random financial systems, the average correlation between banks' contribution to systemic risk and their optimal macroprudential capitalization as indicated by the SES equals 0.06 with a standard deviation of 0.71. Taking conventional statistical confidence levels, all correlations from perfectly negative to positive are possible. Overall, our robustness analysis using SES as a related coherent macroprudential risk management approach therefore confirms our previous findings. The next section concludes.

5 Conclusion

In this paper we set up a framework which allows for analyzing some puzzling features of systemic risk, as it has emerged during the deep financial crisis of 2007-2009. These features concern the interplay of the main channels of systemic risk among financial institutions, namely bank balance sheets, direct

gests requiring banks to hold enough capital to ensure that their expected capital shortfall –which may arise as an externality from other banks– is zero.

interconnections through assets and liabilities, and indirect interdependencies through non-liquid asset fire sales, and generic portfolio correlations. Our model provides insights to systemic risk and banks' contribution to it and allows for investigating a novel macroprudential risk management approach, the SVaR.

With respect to systemic risk and banks' individual contributions, we offer two important insights. First, relying on the model's baseline setting, we find that direct interconnections between financial institutions are a dominant driver of systemic risk. Though non-monotonic, increasing interconnectedness tends to be associated with increasing levels of systemic risk and banks' contribution to it. The interbank market thus deserves high attention in any systemic risk analysis. Second, the fire sale channel is an important amplifier of exogenous shocks and can strongly influence outcomes. Depending on the price sensitivity to non-liquid asset sales, even tiny shocks may be amplified by this indirect contagion channel, putting the entire financial system at risk. In light of this result, marking-to-market accounting in times of financial turmoils may amplify distress risk in the financial system. However, our analyses also provide evidence that ceteris paribus increasing banks' holdings of liquid assets alleviates the contagious effects of the fire sale channel.

Furthermore, we propose a new metric, a system-wide value-at-risk calculation. We look at two policy instruments, a special bank levy and a mandatory capital injection into individual financial institutions and assume the regulator to invest no funds of its own, nor to keep any levies generated by the charge on its own account. In other words, the macroprudential supervisor invests the systemic risk levy into the banking system in order to fulfill its macroeconomic objective. Based on this assumption, we investigate whether the capital injection and the risk charge are congruent.

Our analyses provide evidence that these two payments, that is, the individual charges flowing from the banks to the supervisor, and the optimal capital injection flowing from the supervisor to the banks, will typically not be equal. Based on the parameters in our simulations, we rather find a net transfer of (additional) funds from some banks, namely those which mainly contribute to systemic risk via channels that are not affected by the macroprudential policy instrument, to other banks, namely those which contribute to systemic risk via channels that can be effectively dampened via the macroprudential policy instrument. The net transfer is achieved through the separation of the risk charge and the macroprudential capital injection.

On a general level, our analysis suggests the need to distinguish carefully between a bank's negative externality vis-a-vis the financial system, the corresponding risk charge levied by the supervisor, and the intended macroprudential capitalization. It seems as if the well-known Tinbergen rule of public policy is also applicable to macroprudential policy instruments: the number of policy instruments should equal the number of distinct policy goals.

The results presented in this paper are a first step towards a fuller modeling of a banking network. For now, we have taken banks to respond rather mechanically to asset value shocks. This is in line with the literature. However, a possible future setup will model banks as optimizing agents in a more comprehensive sense. For instance, individual banks in a network will pursue a profit motive, such that their investment and funding decisions are efficient, that is, fulfill the rational expectations requirement. In such a model, behavioral biases can also be incorporated. Furthermore, interconnections may not only result from loan exposures, but also from derivative contracts, that is, payments conditional on state realizations. Equally, direct interconnections between banks may be intertwined with asset markets, for example, if repo markets are integrated into the model. Or, correlations between underlying portfolio assets (of banks in our model) may be altered by hedging operations which, in turn, introduce counterparty risk into the network structure. In addition to these extensions, we have pointed to a number of possible further extensions in our exposition of the model and interpretation of analyses. These include modeling asset market freezes on the market for non-liquid assets as were witnessed during the recent financial crisis, extending the model for different shock origins and comparing differences in effects on systemic stability, extending the model to an intertemporal setting in which raising new equity as an additional means of re-capitalisation could be investigated, and extending the model to investigate further risk dimensions such as banks' non-interest rate income and their funding fragility.

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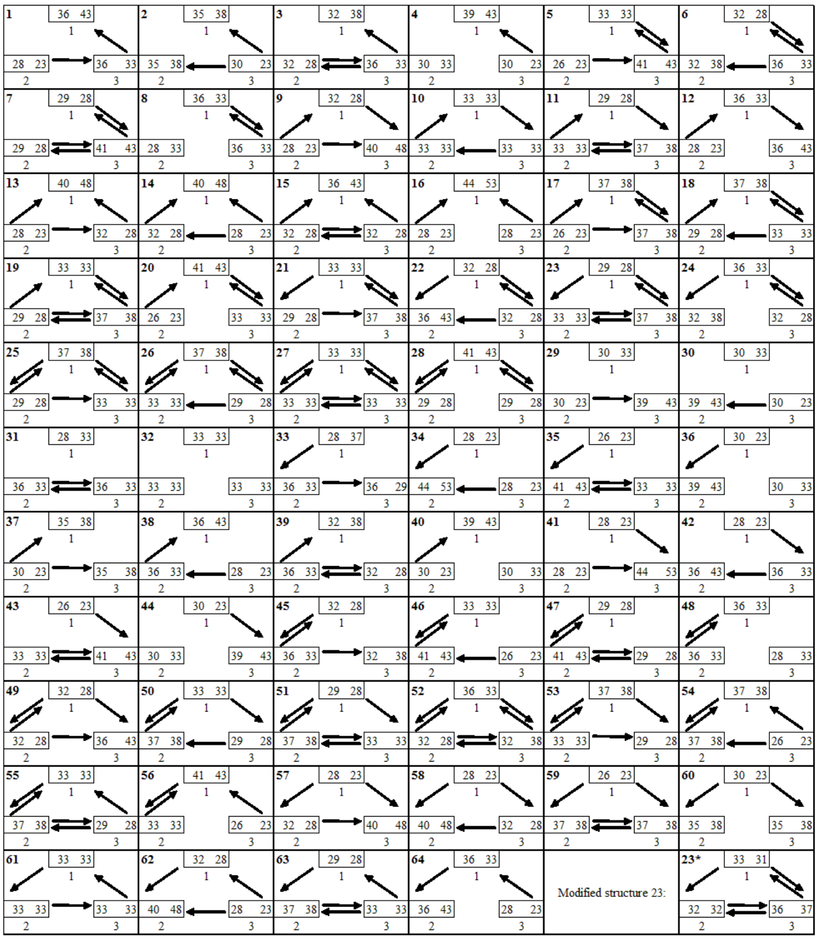
Appendix: Financial System Matrices[63]



[63]The figure gives a compact overview on all financial system matrices investigated in the baseline scenario (see Section 3.1). Different financial system matrices emerge through the possible combinations of lending and borrowing relationships as indicated by an adjacency matrix. Given that there are three banks in the financial system and banks can borrow as well as lend, there are 2^6 different financial system matrices. On each sub-panel, the bold-typed number assigns a unique number to a given financial system matrix. The three banks are represented by the three small boxes, with the bank's identifier below the box. Inside each bank's box, the left number (rounded) indicates the bank's size with respect to the financial system, computed as the ratio of its assets relative to the sum of all assets in the financial system, and the right number (rounded) indicates the proportion of the bank's non-liquid asset holdings relative to the sum of non-liquid asset holdings of all three banks. An arrow from a bank to another bank indicates that this bank has exposure to the other bank through interbank lending. Note that financial system matrix 23* on the bottom right is used for the SVaR and SES analyses in Section 4.