Systemic Risk and Capital Adequacy

PRELIMINARY RESEARCH
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Abstract

We assess transmission channels of systemic risk and the effects of capital regulation in the European Banking Union. Two interconnected channels of risk are analysed by employing a data-driven, heterogeneous network model. First, the risk from shocks to corporate, sovereign and retail debt holdings of banks and second, the subsequent contagion effects that spread through the interbank loan market. The effects of both channels are further magnified by the inclusion of default costs. We provide measures and rankings that aim at a realistic review of the resilience and contagion threat from banks, countries and different assets. In addition, we draw policy implications from the effectiveness of regulatory capital requirements by applying treatments to the CT1 capital of individual banks in the network. Our findings suggest that the effect of micro prudential regulations, such as CRD IV, fall short of their expected effectiveness. More specifically, the positive effects of stricter capital regulation are largely compensated by contagion effects.

JEL Classification: G21, D85, G01, F37, G28

Keywords: Systemic Risk, Interbank Network, Contagion Transmission Channels, Bank Regulation

1 Introduction

Stability in financial systems is a prime concern for regulators and policy makers. The assessment of systemic risk is the basis for regulatory concepts that aim at a resilient-yet-efficient banking network. In our sense, systemic risk is the risk of some market participant failing due to an exogenous asset shock which subsequently leads to further defaults through contagion.[1] A landmark example of systemic risk is the default of Lehman Brothers in September 2008. The resulting cascade of asset losses was evident worldwide and highlighted concerns about financial network interconnectedness (De Haas and Van Horen, 2012; Acharya et al., 2014).

Market participants in financial networks consist of many types of institutions, e.g. banks, insurance companies, hedge funds, pension funds or mutual funds. Of these, banks play a key role in financial networks and hence attract special attention by regulators. Among other regulatory efforts, stress tests have been conducted by the European Banking Authority (2011, 2014, 2016) in order to assess several risk scenarios. These stress tests provide a data source

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[1]See Hurd (2015) for a discussion of systemic risk definitions.

of bank level exposures at a granularity that is unparalleled in publicly available data. Most importantly, the reports provide data on banks sovereign, corporate, retail and interbank market exposures. Hence, the reports offer a great platform to employ methods from network theory to actual bank network data.

Despite the granularity of the data, direct links between banks are not observable via public sources. To fill this information gap we utilize a Bayesian methodology in an attempt to model a realistic representation of the European bank network. More specifically, conditional on the observable total interbank liabilities and assets of each bank, a Gibbs-sampler is used, to generate samples from the underlying conditional distribution. The resulting network model represents up to 70% of all European bank assets (see Section 3.4). The model allows to analyse losses and defaults that are caused by different combinations of exogenous shocks, as well as default costs for interbank assets and external assets.

Turning to the regulatory aspects of financial networks, the Capital Requirements Regulation and Directive (currently CRR/CRD IV) is the result of European efforts to implement buffers for loss absorption. Such capital regulations render a primary tool for regulators that focus on systemic stability. Motivated by the sparse empirical evidence that analyses the benefits from capital regulation for systemic stability, we set out to quantify these effects by applying capital treatments to the banks in our network model.

Our findings suggest that the systemic resilience is improving for shocks to retail and corporate assets, whereas shocks to sovereign assets appear as an increasing thereat. Resilience in this sense is the ability of a network to withstand exogenous shocks without an increasing number of nodes defaulting. Furthermore, a velocity measure is defined in order to capture the asset shock sensitivity of the network, after an initial shock absorption threshold is breached. We find that, from 2011 to 2016, this default velocity is decreasing for all transmission channels. In order to assess the "worst-case" scenario, we measure the percentage of defaulting banks in the network, given a very large asset shock. This severity figure is decreasing over the years, where the largest difference is observable for sovereign assets, after the beginning of the European sovereign debt crisis in 2011.

After the initial assessment of the transmission channels for systemic risk, different core tier one equity (CT1) treatments are applied to the networks. The results suggest that the effect of capital regulation on systemic stability is small. More specifically, a treated network is compared to its observed counterpart, revealing that an increasing CT1 ratio does not imply a large reduction of systemic risk. The main effect of capital regulation appears to be on direct defaults, which is nearly fully compensated by interbank network defaults. The clear policy implication is that focus should be on regulatory efforts towards financial networks as a whole. Network focused regulation might for example aim at a reduction of default costs, which would decrease the number of contagion defaults.

On bank level, we provide "first to default" rankings that are based on year and exposure type. Owing to changes in the EBA sampling methods, the comparability of single bank rankings over time is limited. Nevertheless, one finding is that a majority of the top 10 defaulting banks, due to sovereign asset shocks, are consistently based in Germany. More specifically, German state-owned banks, such as e.g. Deka Bank A.G., appear to be heavily exposed to sovereign assets. More detailed scenarios are laid out in the results section.

The remainder of this paper is structured as follows: Section 2 provides a brief review of the relevant literature. The methodology is laid out together with a description of the data in Section 3. The results are presented in Section 4, followed by robustness checks in Section 5. Section 6 concludes.

2 Background and Literature

The 2008 global financial crisis catalysed academic research in systemic risk. Methods from network theory, as a part of graph theory, have since been increasingly employed in financial research to analyse the effects of interconnectedness and contagion in banking systems. The European sovereign debt crisis, which emerged from late 2009 on, shed further light on the interconnectedness of European banks and motivated related research.

The assessment of systemic risk is commonly based on network models,[2] in which banks are represented as nodes and their interbank liabilities as weighted direct edges. A network is stressed by some initial asset shock and allows for a subsequent analysis of resulting contagion effects. This is, nodes that are unaffected or survive the initial shock might still incur losses or default due to other nodes not being able to honour their contractual obligations.

Pioneering the theoretical analysis of systemic risk in finance, Eisenberg and Noe (2001) develop a model of financial institutions as nodes of a network, which are connected by edges that represent their mutual obligations. Conditional on an asset shock to one or more nodes, a vector of payments that clears the network is computed. A core result is that there always exists a clearing payment vector for all participants and their obligations. This vector can then be used to analyse the systemic risk faced by the individual nodes.

Specifying only the degree distribution of their random financial networks, Gai and Kapadia (2010) follow the methodology laid out by Newman (2003) to study contagion effects in arbitrarily structured networks. They find that financial systems tend to be "robust-yet-fragile": Being connected to a high degree results in a low probability of contagion, but once contagion does occur in these networks it is likely to be very severe. A similar assessment is reached by Acemoglu et al. (2015), but within a very different framework. Employing equilibrium theory to set up a network of financial institutions, they show that a highly connected network is robust against negative shocks of limited magnitude/frequency, while sparsely connected networks are very vulnerable. On the contrary, in the presence of large shocks, the sparsely connected ones are the least likely to exhibit systemic failure, while a higher connectivity increases the likelihood of widespread defaults.

Krause and Giansante (2012) also generate random interbank networks, utilizing a Barabási and Albert (1999) scale-free framework, in which crises are triggered by endogenous bank failures. The resulting analysis of contagion effects allows them to draw conclusions on contagion probability as well as post contagion effects. This includes the finding that networks with nodes of homogeneous size are more prone to contagion and highly interconnected networks reduce contagion risk, as losses are spread evenly. On the other hand, highly interconnected networks increase the effects of contagion, similarly to the earlier mentioned results.

Of the more recent contributions, Glasserman and Young (2015) use a methodology that is based on Eisenberg and Noe (2001) to compute expected loss comparisons for different shock distributions as well as losses from network contagion. Their findings suggest that heterogeneous networks have a high likelihood of contagion through spillover effects, particularly when the primary shock hits a large node, a node with high leverage or a node whose majority of liabilities are held by other financial institutions. Anand et al. (2015) employ a minimum density network modelling approach, as opposed to the common maximum entropy method. According to their research, maximum entropy underestimates contagion whereas maximum density is prone to overestimation. Acharya et al. (2014) develop alternative systemic risk measures that are solely based on readily available public information. Their estimated capital shortfall measure (SRISK) is a function of size, market leverage and stock returns under stress that are modeled

[2]See Elsinger et al. (2013) for a technical overview of network models. See Hüser (2015) for an elaborate overview of the literature on interbank networks.

by a Long-Run Marginal Expected Shortfall (LRMES).

Alternative theoretical models investigate the impact of reduced market liquidity on bank failures, where the principal idea is that the liquidation of assets from failing banks depresses the assets of other banks. The asset reduction might subsequently force other banks into default, which gives rise to the idea of contagion through "fire sales", as in Allen and Gale (2000), Diamond and Rajan (2005) along with Upper (2011) and Hurd (2015).

Furthermore, there exists literature on interbank networks with a more data-driven or empirical focus. Paltalidis et al. (2015) base their research on quarterly cross-border interbank exposure data from the Bank of International Settlements, which is fed into a maximum entropy network model. Their findings include that sovereign debt is a dominant factor for determining systemic risk. In addition, the authors find large differences between systemic risk exposure for northern (lower) and southern (higher) European Union countries. Cont and Schaanning (2017) consider another relevant channel of systemic risk, namely, fire-sales that are triggered by banks that de-leverage in order to maintain capital ratios, after an initial asset shock. The authors find that the diversified asset portfolios of large banks increase interconnectedness and thus the impact of fire-sales. Furthermore, this channel exposes banks to assets that are not necessarily part of their own balance sheet; implying that this assets are not considered by the individual bank risk management or RWAs.

Engle et al. (2015) apply SKRISK and LRMES, as discussed in Acharya et al. (2014), to data of the 196 largest European financial firms from 2000 to 2012. They suggest that the taxpayers cost to rescue some domestic banks are so high that some banks might be considered "too big to be saved". According to this research, the countries with the highest exposure to systemic risk are France and the UK, whereas the institutions with the highest exposure are Deutsche Bank, Credit Agricole, Barclays, Royal Bank of Scotland and BNP Paribas.

As this overview of the theoretical and empirical developments suggest, the research on systemic risk in financial networks is far from settling on a final consensus. Motivated especially by the sparse evidence from network models that are calibrated to actual real-world data, we aim at contributing to the literature by applying the laid-out methods to the novel and unique EBA dataset. In particular, to the best of our knowledge, there exists no research that tries to link capital regulation tools to bank exposure data and hence systemic risk.

3 Methodology

3.1 General Model Setup

Let us consider a network of $N \in \mathbb{N}$ banks with indices $I = \{1, ..., N\}$. Figure 1 shows the consolidated balance sheet that describes a bank $i \in I$. Hence, a bank is described by assets $a_i \in [0, \infty)^N$ and liabilities $l_i \in [0, \infty)^N$ that are held within the interbank network, as well as external assets $a_i^{(e)} \in [0, \infty)^N$ and external liabilities $l_i^{(e)} \in [0, \infty)^N$ that refer to entities outside the interbank network. The net worth w_i of bank i for $i \in I$ is equal to the book value of equity if $w_i \geq 0$. In the case of $w_i < 0$, the bank is in fundamental default.

External assets $a_i^{(e)}$ comprise all non-interbank exposures and can be dissected into granular exposures. In our set-up we consider $a_i^{(e)} = a_i^{(sov)} + a_i^{(crl)} + a_i^{(rtl)} + a_i^{(o)}$ as the sum of sovereign exposure $a_i^{(sov)}$, corporate loan exposure $a_i^{(crl)}$, retail exposure $a_i^{(rtl)}$ and other external exposures $a_i^{(o)}$.

The net worth w_i of a bank i is the difference of total assets and total liabilities, hence, $w_i = (a_i^{(e)} + a_i) - (l_i^{(e)} + l_i)$. A shock might transmit to w_i by a direct exposure in $a_i^{(e)}$ or indirect exposure through a_i. A fundamental default of bank i, where $w_i < 0$, could therefore

Bank$_i$	
$a_i^{(e)}$	$l_i^{(e)}$
a_i	l_i
	w_i

Figure 1: Consolidated balance sheet for bank i. Assets and liabilities that are held within the interbank market are denoted as a_i and l_i. External assets and liabilities are denoted as $a_i^{(e)}$ and $l_i^{(e)}$, while equity is the residual w_i.

be a result from direct asset exposure or interbank exposure. In case of a default, the loss can spread to other banks according to their interbank market exposure to l_i. On the interbank side the effect of interconnectedness repeats until the system is cleared, hence, no further defaults or all banks in the system defaulted.

In this set-up we are able to shock external assets of one or more banks in the network. Based on our data, the shocks can be applied to different asset classes from different countries of origin, denoted as $C \in \mathbb{N}$ countries with indices $I_c = \{1, ..., C\}$. We denote the proportional loss on total assets by $s \in [0,1]^N$. For any bank $i \in I$, the remaining external assets after a shock s_i are

$$s_i a_i^{(e)} = \sum_{c=1}^{C} s_c^{(sov)} a_c^{(sov)} + s_c^{(crl)} a_c^{(crl)} + s_c^{(rtl)} a_c^{(rtl)} + a_c^{(o)} \; \forall i \in I. \tag{1}$$

Hence, we are able to analyse shocks $s_c^{(\cdot)}$ and shock combinations on country level for sovereign exposures (sov), corporate loans (crl) and retail assets (rtl). After the shock, the net worth of bank i for $i \in I$ is $w_i(s_i) := (s_i a_i^{(e)} + a_i) - (l_i^{(e)} + l_i)$. The set of all fundamentally insolvent banks after the shock, in other words, the set of immediate defaults, is denoted by

$$\mathbb{D}_0 := \{i \in I | w_i(s_i) < 0\} \tag{2}$$

Spanning the network of interbank assets and liabilities is more involved and will be discussed in Section 3.2. Ultimately the model will enable us to review the direct impact of asset shocks and, in particular, shocks on sovereign, corporate and retail debt exposure. The immediate shock can trigger contagion effects through the interbank network that are also observable through the model. Hence, we will be able to draw an integrated picture on contagion and risk concentration within the considered bank network.

3.2 Network Model for Interbank Liabilities

The links between banks are described by the nominal liabilities $x_{ij}, ij \in I$ of bank i to bank j. $X = (x_{ij}) \in \mathbb{R}^{N \times N}$ is defined as the liabilities matrix if $x_{ij} \geq 0 \; \forall \; i, j \in I$ and $x_{ii} = 0 \; \forall \; i \in I$, i.e. the adjacency matrix of the weighted interbank network. Hence, in the case of $x_{ij} > 0$, there exists a direct edge from node i to node j.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{pmatrix}$$

For any given liabilities matrix X, the column sums denote the total nominal interbank liabilities l_j for bank j,

$$l_j = \sum_{i=1}^{N} x_{ij}, \; j \in I \tag{3}$$

and the row sums denote the total nominal interbank assets a_i of bank i.

$$a_i = \sum_{j=1}^{N} x_{ij}, \; i \in I \tag{4}$$

The total nominal interbank liabilities are equal to the total nominal interbank assets and are given by $L = \sum_{j=1}^{N} l_j = \sum_{i=1}^{N} a_i$.

From the data sources described in Section 3.4, we are able to obtain $a_i, l_j \; \forall \; i, j \in I$ as well as L. The interbank liabilities x_{ij} are in general not known and have to be estimated. With zeros on the diagonal of X, the problem extends to $N^2 - N$ unknowns and cannot be solved analytically for $N > 2$. Since $\sum_{j=1}^{N} l_j = \sum_{i=1}^{N} a_i$, where all l_j and $a_i \in I$ are known, there are a total of $N^2 - 3N + 1$ degrees of freedom available for the estimation of X.

To solve the estimation problem, we follow the Bayesian approach of Gandy and Veraart (2015). In their paper the authors use a Gibbs-sampler to sample from the conditional distribution of X, given its row and column sums. More specifically, first, a generalised version of the Erdős and Rényi (1959) model is used to generate an adjacency matrix $Y = (y_{ij}) \in \mathbb{R}^{N \times N}$. This adjacency matrix is defined by $y_{ij} = 1$ if $x_{ij} \geq 0$ and $y_{ij} = 0$ otherwise. Independent Bernoulli trials generate the directed edges in Y, with probabilities $p_{ij} \in [0, 1] \; \forall \; i \neq j \in I$ and $p_{ii} = 0 \; \forall \; i \in I$. Second, the existing edges are populated with liabilities, which are assumed to follow an exponential distribution. Hence, the model:

$$\begin{gathered} \mathbb{P}(y_{ij} = 1) = p_{ij} \quad \forall \; i \in I \\ x_{i,j} \mid \{y_{ij} = 1\} \sim \text{Exponential}(\varphi_{ij}) \quad \forall \; i \in I \end{gathered} \tag{5}$$

The model is constructed in a way such that the samples maintain the originally observable row and column sums for X. The parameters for the model consist of two matrices, namely, $P \in [0, 1]^{N \times N}$, where the probability of the existence of a direct edge between i and j is denoted by p_{ij}; and $\varphi \in (0, \infty)^{N \times N}$, which describes the distribution of liabilities given that an edge exists.

Under the assumption that all p_{ij} are identical for all $i \neq j$, the network corresponds to the classical Erdős-Rényi model. For our analysis, we calculate the linkage probabilities in a way that reassembles the observable interbank linkages on a country aggregate level. The remaining assumption is that a bank would evenly spread its exposure between available banks from a given country.[3]

[3] A similar assumption is found in e.g. Gai and Kapadia (2010).

The linkage probabilities for our model set-up are derived from the relative weight of interbank exposures, on country aggregate level. Hence, with $a_i^{(c_j)}$ the exposure of bank i to all banks in the country of residency c_j of bank j and $N^{(c_j)}$ the total number of banks in that country, we have,

$$p_{ij} = \frac{a_i^{(c_j)}}{(N^{(c_j)} - 1_{\{c_i = c_j\}})L} \;\forall i, j \in I, \forall i \neq j$$

and at the same time

$$\varphi = \varphi_{ij} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} p_{ij}}{L} \;\forall i \neq j \tag{6}$$

to ensure that

$$\mathbb{E}\left[\sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij}\right] = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{p_{ij}}{\varphi_{ij}} = L \tag{7}$$

With this parametrization we utilize the Gibbs sampling method from Gandy and Veraart (2015) to produce 20.000 samples of liability matrix X. More specifically, through the chain of the Gibbs sampler, we disregard the first 10.000 steps as burn-in and afterwards retain one sample every 10.000 steps until a sample size of 20.000 is reached.

Later on, the assumption on equally weighted exposures within a given country will be relaxed by weighting the exposure probability of banks based on their respective interbank assets. Interbank assets in this sense aid as an indicator for interbank market activity. Hence, we postulate that a large fraction of e.g. HSBC's German interbank liabilities come from the bank with the largest amount of interbank assets in Germany.

3.3 Shock Propagation

The literature follows two common approaches to model the shocks that run through the network. *Sequential default algorithms*, assume that the bank pays $(1 - \mathrm{Recovery_j})l_j$ in case it is in fundamental default, which is if the net worth $w_j < 0$. After a given asset shock, the algorithm runs for a maximum of $n - 1$ iterations until no further interbank market contagion defaults occur, see e.g. Anand et al. (2015), Mistrulli (2011), Amini et al. (2016) and references therein. In this set-up, the recovery rate would have to be assumed, while it does not incorporate the possibility that the default of a bank could impact the losses of another defaulting bank during its insolvency phase. Eisenberg and Noe (2001) discuss a modified version of the sequential default algorithm, where the recovery rate is endogenous.

Alternatively, a *clearing mechanism* can be utilized to directly model payments in the interbank market without any exogenous assumptions on recovery. Originally discussed by Eisenberg and Noe (2001), the core idea is that banks, once defaulted, use all available assets to repay their liabilities proportional to their original debt distribution. A generalization to this approach that allows to incorporate default costs was proposed by Rogers and Veraart (2013). More specifically, the authors define, for a shock realisation $s = (s_1, ..., s_N)^\top \in [0, 1]^N$, the clearing vector $c^*(s) \in [0, l_i^{(e)} + l_i]^N$ as a solution to $c^*(s) = \Phi(c(s))$, where

$$\Phi(c(s))_i = \begin{cases} l_i^{(e)} + l_i & \text{, if } l_i^{(e)} + l_i \leq \sum_{j=1}^{N} \prod_{ij} c_j(s) + s_i a_i^{(e)} \\ (1-\beta) \sum_{j=1}^{N} \prod_{ij} c_j(s) + (1-\alpha) s_i a_i^e & \text{, else.} \end{cases} \tag{8}$$

The constants $\alpha, \beta \in [0, 1]$ model default costs. The special case of $\alpha = \beta = 0$ yields the classical clearing vector approach as introduced by Eisenberg and Noe (2001). A formal proof on the existence of a (greatest) clearing vector is provided in Rogers and Veraart (2013), which relies on the limiting assumption that all liabilities can be cleared at the same time.

To find α, β we turn to the academic literature that aims at analysing the asset loss that is a result of the default of a company. Early work in this direction was published by Andrade and Kaplan (1998) who find asset losses of 10% to 25% on highly leveraged transactions. Davydenko et al. (2012) provide empirical evidence on default costs, depending on the rating, of 19.9% to 31%. A recent simulation study by Glover (2015), analysing firms from all sectors, found asset losses in the range of 35% to 53.2%. Empirical evidence on the default costs of banks is presented by Kang and Maziad (2012), the authors find default related asset losses of around 30%.

In the following section, we analyse transmission channels of systemic risk for the European banking union as a whole as well as countries and single banks. For our base model, we assume default costs of 30%. This is within the range of overall empirical evidence and the mean result of Kang and Maziad (2012) who were focusing on banks in particular. In addition to default frequencies and losses, measures for systemic resilience, default velocity, and crash severity are presented. Later on, we will run robustness tests with a focus on potential model miss-specification issues.

3.4 Data

Data is collected primarily from the European Banking Authorities' (EBA) stress test reports for 2011, 2014 and 2016, which shed light on bank level exposures at an unparalleled granularity for publicly available data.

Bank coverage is driven by the sample selection mechanisms of EBA. In European Banking Authority (2011) the criterion was to cover at least 50 percent of each national banking sector in terms of total consolidated assets (as of end 2010), covering in total 65 percent of the EU banking system total assets. The European Banking Authority (2014) criterion was to cover at least 50 percent of each national banking sector in terms of total consolidated assets (as of end of 2013), while additional banks could be added by authorities such as the ECB if deemed necessary. The 2014 sample covers more than 70 percent of the total banking assets in the EU. European Banking Authority (2016) includes banks with a minimum of EUR 30 bln in assets, which results in a sample covering approximately 70 percent of each national banking sector in the Eurozone, each non-Eurozone EU member, and Norway.

Table 1: Sample Overview. Based on EBA stress test banks from 2011, 2014 and 2016.

	2011	2014	2016
EBA Banks	91	123	51
Countries	21	22	15

For interbank network exposures, the EBA data is granular to the country-of-exposure level for every considered bank. For instance, we are able to observe the interbank market exposure of Deutsche Bank against the country-level aggregate of banks in up to 22 European countries.

As transmission channels for systemic risk, we consider exposures with respect to sovereign debt, corporate debt (exclusive of real estate) and retail debt. Analogue to the interbank network exposures, this data is available as exposure against a country of origin. The remaining data is collected from Bankscope, OECD, SNL and Bloomberg, including GDP, tier one capital, risk-weighted assets and other balance sheet items.

4 Results

For our bank networks as of 2011, 2014 and 2016 we simulate shocks as a reduction of 1) sovereign assets, 2) corporate assets and 3) retail assets. Following mark-to-market accounting standards, losses are deducted from asset values and possibly reduce capital buffers until a default occurs. The clearing vector mechanism from Section 3.3 is used to compute contagion losses and defaults. The goal is to analyse losses and the paths that spread contagion; hence, we do not model any form of government or central bank intervention.[4] This is, the tools and information that are provided in this paper aim at assessing the market situation and scenarios free of countermeasures.

In the first part of this section presents a review of the European bank network as a whole. Results are compared by measures of systemic resilience, default velocity as well as contagion severity. In the following part, the focus is on single countries and banks. Countries that pose the biggest threat to the European bank network are presented together with countries that incur the largest impacts from contagion. After reviewing the observable networks, the last part of this section presents results that are derived from simulating the systemic risk profile of networks under different regulatory capital treatments.

4.1 Transmission Channels of Systemic Risk

Figure 2 shows the core-periphery network structure of European interbank liabilities as of 2011. Multiple, color-coded layers of arrows represent weighted ties and exposure direction between nodes. Nodes are grouped based on the strength of their ties. This automatically results in most nodes being grouped by countries. Additionally, the United Kingdom (London), being the largest financial hub in Europe, is placed in the middle of the graph. An exception to the heavily interconnected European market is Spain. The Spanish savings bank 'Caja' system shows weaker interconnectedness with banks outside the local market, of which most run through Banco Santander (ES05).[5]

To analyse the transmission channels of systemic risk we, ceteris paribus, apply Europe-wide shocks $s^{(\cdot)} \in [0, 0.5]$ with 0.5 being a 50% loss in the respective asset (sovereign, corporate and retail). Figure 3 shows the relative number of defaults (percentage of banks in the network). Intuitively, defaults as a function of asset shock follow a sigmoid shape. This is, after some initial interval of shock resistance is breached, the number of losses increases until some upper level is reached. The upper boundary might simply be a total wipe-out of the network.

Based on the observation that defaults, as a function of the initial percentage shock to an external asset $s^{(\cdot)} \in [0, 0.5]$, have a sigmoid shape, we fit:

$$D_{\gamma,\lambda,\delta}(s^{(\cdot)}) = \frac{\gamma}{1 + \exp(\lambda - \delta s^{(\cdot)})} \tag{9}$$

When comparing networks, the fitted parameters of this function allow for the following interpretations; λ provides an indication on the shock that the network can resist without an accelerating number of defaults. Default velocity is captured by δ as some form of steepness. Resistance and velocity can be combined to a resilience index, given by the fraction λ/δ, where a higher number indicates a higher systemic risk. The limiting number of defaults in the network

[4] The history of financial markets provides several occasions, e.g. the recent 2008 financial crisis or 2011 government debt crisis, that allow us to observe these actions in the form of e.g. bail-out programs, liquidity facilities or forced mergers.

[5] Banco Santander S.A. is the largest Spanish bank with total assets amounting to 1,223.267 bln as of 2011. In contrast to the locally focused savings banks, Santander has a large international presence.

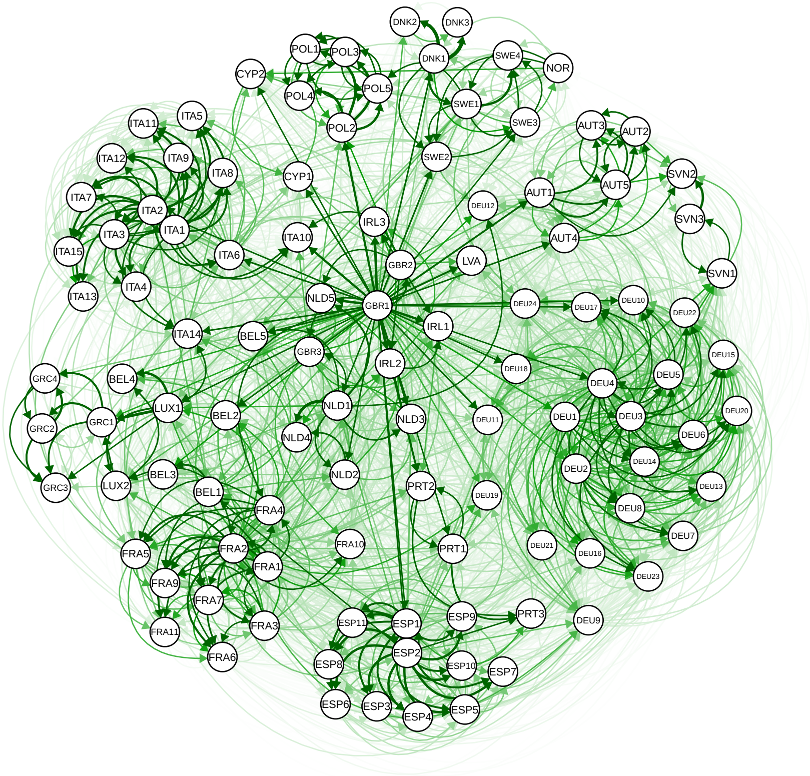

Figure 2: Network representation of the European interbank market as of 2014. Linkage probabilities for a given country are weighted based on the interbank market assets of each bank. The data shows the intuitive result that some countries (e.g. United Kingdom) act as a hub and hence occupy a central position in the system, whereas other local banking systems (e.g. Spain) show weaker links to the overall European system. Banks are represented by the ISO3 code and asset size rank of their country of residency. The following banks have a rank of 1 in their respective country of residency: Erste Group (AUT1), Dexia (BEL1), Bank of Cyprus (CYP1), Deutsche Bank (DEU1), Danske Bank (DNK1), Banco Santander (ESP1), BNP Paribas (FRA1), HSBC (GBR1), Bank of Ireland (IRL1), UniCredit (ITA1), Banque de l'Etat (LUX1), ABLV (LVA1), ING (NLD1), DNB (NOR1), Getin Noble (POL1), Caixa Geral de Depositos (PRT1), Nova Ljubljanska (SVN1), Nordea (SWE1).

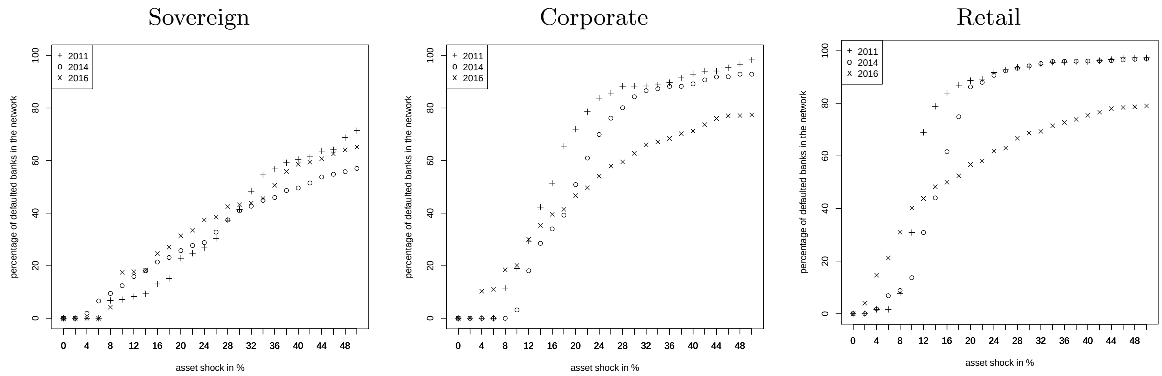

Figure 3: Percentage of defaulting banks in the network as a result of asset shocks $s^{(\cdot)} \in [0, 0.5]$. Direct defaults result from the shock itself, total defaults include additional defaults that are caused by contagion through the network.

in percent is captured by γ. This measures help to compare networks through time and between risk transmission channels.

Table 2 shows the fitted parameters from Equation (9). In 2011, the network appears most resilient to shocks in sovereign assets, followed by corporate and retail assets. Between 2011 and 2014, the systemic risk from corporate and retail assets is decreasing whereas the risk from shocks to sovereign assets is increasing. This is likely the result of banks shifting their exposure to European sovereign assets[6], as a result of stricter capital regulation for non-sovereign assets.

The worst case impact, as measured by γ, of sovereign asset write-downs decreases from 2011 onwards. On the other hand, the resistance of the network is decreasing as well. The largest change, especially for corporate and retail exposure, is their reduced default velocity. The 2016 sample of large banks probably results in a naturally reduced retail exposure, relative to other balance sheet items. Hence, a seemingly reduced impact from retail assets.

Table 2: Fitted parameters from Equation (9). The ability to resist asset shocks is measured by λ, the velocity of defaults by δ and γ is a measure of severity. For this analysis, the network is shocked by $s^{(\cdot)} \in [0, 0.5]$ with default costs of 30% (see Section 3.2).

	2011		2014		2016	
Paramter	Estimate	SE	Estimate	SE	Estimate	SE
Sovereign exposure						
Resistance (λ)	3.7998	0.1560	2.5709	0.1276	2.6681	0.2230
Velocity (δ)	0.1406	0.0071	0.1131	0.0075	0.1179	0.0128
Severity (γ)	71.1764	1.5366	57.9938	1.6603	64.9655	2.9245
Resilience (δ/λ)	0.0370		0.0440		0.0442	
R^2	0.9979		0.9969		0.9915	
Corporate exposure						
Resistance (λ)	4.1391	0.2316	4.4655	0.2401	2.3395	0.1477
Velocity (δ)	0.2740	0.0155	0.2369	0.0131	0.1390	0.0098
Severity (γ)	92.4019	0.8903	90.7940	1.0297	75.4984	1.5157
Resilience (δ/λ)	0.0662		0.0530		0.0594	
R^2	0.9985		0.9982		0.9968	
Retail exposure						
Resistance (λ)	7.4849	0.7147	5.1056	0.1407	1.8320	0.1849
Velocity (δ)	0.6830	0.0650	0.3552	0.0098	0.1533	0.0155
Severity (γ)	93.7118	0.8306	95.6304	0.3776	75.5145	1.6710
Resilience (δ/λ)	0.0912		0.0696		0.0837	
R^2	0.9984		0.9997		0.9949	

[6]For the entire sample period, sovereign assets in the European Union are treated with a risk weight of 0%, regardless of their individual credit rating (European Comission, 2015).

4.2 Country Level Contagion

In this section, we focus on contagion effects for European countries as well as individual banks. On one hand, the loss impact for countries in Europe, from shocks to banking assets and contagion, is analysed. On the other hand, we rank banks by their network resilience; hence, ability to withstand shocks from different transmission channels.

For the 21 (2011), 22 (2014) and 15 (2016) countries in the sample, the following analysis is conducted, in order to compare contagion threats from single countries. First, all assets that origin in one single country are shocked by 60%.[7] Second, we record the total asset loss that subsequently occurs in the remaining countries. The results are used to rank countries according to their contagion thread towards other EU countries.

Figure 4 shows the results as a ranking of European countries. A darker colouring depicts a larger contagion impact. It is clear and well researched that the relative size of a network node or group of nodes (i.e. country) has a major impact on systemic stability. Besides the absolute impact, the relative impact could be considered. In our sense, relative impact is the severity of contagion relative to the economic output of the country. Hence, the second row of graphics in Figure 4 shows the results relative to the GDP of the shocked country. Despite the size, the primary factors that drive country contagion are debt-holdings from foreign banks and network connectedness.

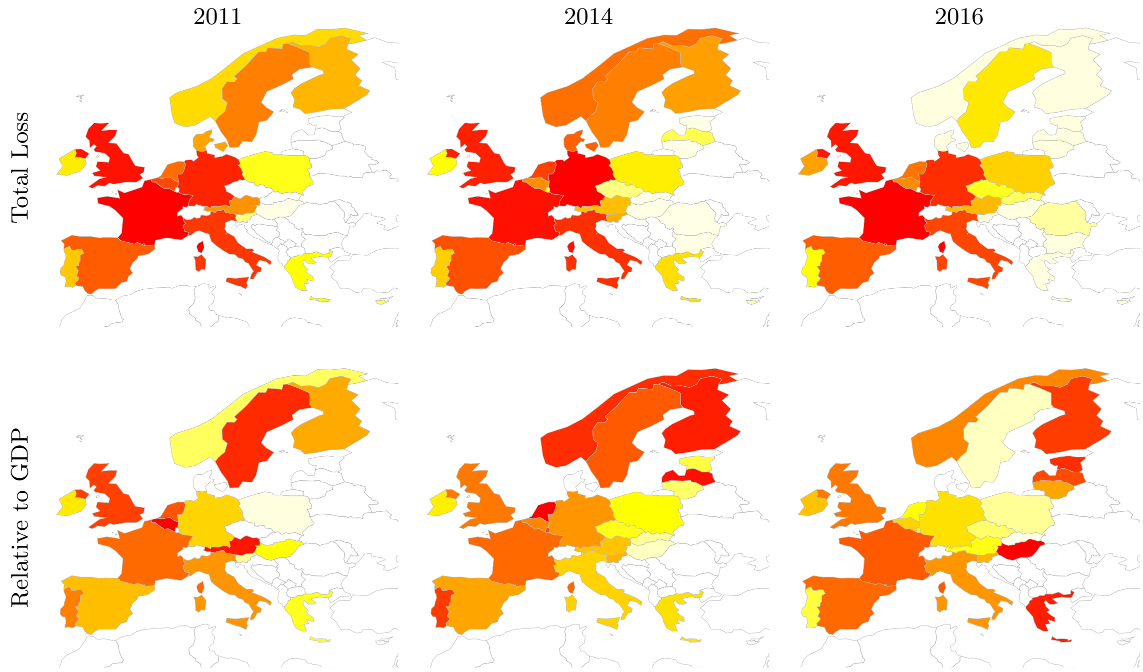

Figure 4: Contagion threat from countries in the EU. A darker colouring indicates a larger contagion threat to other countries. The ranking is based on total losses (first row) and losses relative to GDP (second row). Maps from left to right display results for 2011, 2014 and 2016. Countries that are not represented in the dataset are left blank (white).

To assess how individual countries are affected by incoming contagion from the European bank network, the following analysis is conducted. First, all assets that origin in one single country are shocked by 60%. Second, the subsequent losses in the other, non-shocked, countries are recorded relative to their GDP. In contrast to the previous analysis, the incoming losses are

[7]The choice of a 60% asset loss, i.e. 40% recovery, is somewhat arbitrary. However, the resulting numbers are used in a ranking, which relativises the precise asset shock.

accumulated on a country level. The results are presented relative to GDP, which aids as an indicator of an economies ability to sustain losses in the banking system. Hence, we provide an indication of how severely a given country is affected. This process is repeated for all countries in the network. The results are shown in Figure 5.

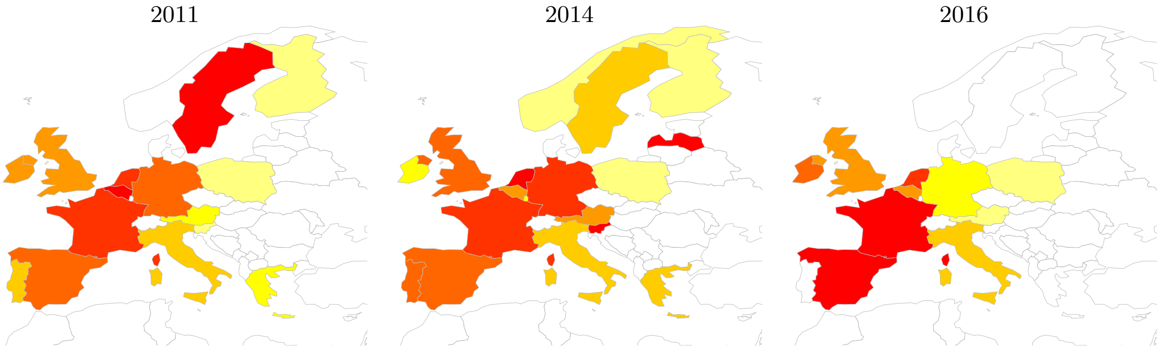

Figure 5: Impact severity from contagion in Europe. A darker colouring indicates a larger incoming contagion effect relative to GDP. Maps from left to right display results for 2011, 2014 and 2016. Countries that are not represented in the dataset are left blank (white).

The 2011 and 2014 sample is comparable with regards to sample size as well as sample selection mechanism. For 2016, comparability is limited, which is owed to the exclusion of several banks from the dataset, see Section 3.4. When comparing the outgoing contagion threat from a country to the incoming thread it is worth mentioning that the losses can only spread through the banking system. For example, Banks in 2011 had Norwegian asset exposure but the sample did not include Norwegian banks. Thus, Norway has a risk contribution but appears to be unaffected by incoming contagion.

4.3 Single Bank Defaults and Systemically Relevant Institutions

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This section (4.3) will be restructured. We are currently working on a different implementation of the single bank default mechanism. One goal is to use our network model to identify critical institutions and compare the results to banks that are identified as systemically relevant by regulatory authorities.

Table 3 shows a fraction of a single bank default resilience ranking. More specifically, the first 10 banks to default from a Europe-wide asset shock are displayed. For sovereign exposures, the top 10 is dominated by medium-sized German state-owned banks ("Landesbank"). On one hand, these banks have a comparatively strong exposure to sovereign debt; on the other hand, they appear to be closely interconnected through the interbank market.

It is important to note that these rankings are based on current market data and severe loss scenarios. For example, among the first to default from shocks to retail assets are several covered bond banks. This is not surprising as retail exposure consists largely of mortgages. Hence, our retail shocks imply a shock to the covering mortgage asset values. Nevertheless, in lieu of the 2008 financial crisis, such shocks might not be completely unrealistic.

The large international banks appear less severely impacted, simply because their assets pools spread to regions that are not considered in our analysis. When stressing European sovereign, corporate and retail assets simultaneously, we find these large international institutions such as HSCB, Barclays, Societe Generale, Commerzbank, Banco Santander, RBS and Deutsche Bank among the most resilient network nodes.

Table 3: First 10 banks to default from shocks to sovereign, corporate and retail asset exposure in 2011, 2014 and 2016.

2011	Sovereign		Corporate		Retail
ITA	Intesa Sanpaolo	FRA	CREDIT AGRICOLE	ESP	CAJA DE AHORROS Y PENSIONES DE BARCELONA
DEU	DekaBank	ITA	INTESA SANPAOLO S.p.A	ESP	BANKINTER, S.A.
AUT	Oesterreichische Volksbank	ITA	BANCA MONTE DEI PASCHI DI SIENA S.p.A	ESP	CAJA DE AHORROS Y M.P. DE ZARAGOZA, ARAGON Y RIOJA
NLD	SNS Bank	ITA	BANCO POPOLARE - S.C.	GBR	LLOYDS BANKING GROUP plc
DEU	Bayerische Landesbank	ITA	UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)	IRL	ALLIED IRISH BANKS PLC
DEU	Landesbank Berlin	PRT	BANCO COMERCIAL PORTUGUS, SA (BCP OR MILLENNIUM BCP)	ITA	BANCA MONTE DEI PASCHI DI SIENA S.p.A
DEU	DZ BANK	SVN	NOVA LJUBLJANSKA BANKA D.D. (NLB d.d.)	NLD	ABN AMRO BANK NV
DEU	Hypo Real Estate	DEU	Norddeutsche Landesbank -GZ	PRT	BANCO COMERCIAL PORTUGUS, SA (BCP OR MILLENNIUM BCP)
ITA	Banca Monte Dei Paschi	ESP	BANCO DE SABADELL, S.A.	SWE	Swedbank AB (publ)
DEU	Norddeutsche Landesbank	ESP	BANKINTER, S.A.	NLD	SNS BANK NV
2014	Sovereign		Corporate		Retail
DEU	Mnchener Hypothekenbank eG	ITA	Banca Monte dei Paschi di Siena S.p.A.	IRL	Permanent tsb plc.
DEU	Hypo Real Estate Holding AG	ITA	Banco Popolare - Societ Cooperativa	NLD	ABN AMRO Bank N.V.
DEU	DekaBank Deutsche Girozentrale	NLD	Bank Nederlandse Gemeenten N.V.	NLD	SNS Bank N.V.
DEU	Wstenrot Bausparkasse AG	SWE	Nordea Bank AB (publ)	POL	BANK OCHRONY SRODOWISKA SA
DEU	DZ Bank AG Deutsche Zentral-Genossenschaftsbank	SWE	Skandinaviska Enskilda Banken AB (publ) (SEB)	POL	GETIN NOBLE BANK SA
DEU	WGZ Bank AG Westdeutsche Genossenschafts-Zentralbank	SWE	Svenska Handelsbanken AB (publ)	SVN	SID - Slovenska izvozna in razvojna banka
BEL	Belfius Banque SA	DEU	Mnchener Hypothekenbank eG	BEL	AXA Bank Europe SA
DEU	Landwirtschaftliche Rentenbank	DEU	Landesbank Hessen-Thringen Girozentrale	DEU	Mnchener Hypothekenbank eG
DEU	Landesbank Hessen-Thringen Girozentrale	ITA	Banca Carige S.P.A. - Cassa di Risparmio di Genova e Imperia	DEU	Wstenrot Bank AG Pfandbriefbank
FRA	Socit de Financement Local	POL	BANK OCHRONY SRODOWISKA SA	DEU	Landesbank Hessen-Thringen Girozentrale
2016	Sovereign		Corporate		Retail
FRA	La Banque Postale	NLD	N.V. Bank Nederlandse Gemeenten	ESP	Banco Bilbao Vizcaya Argentaria S.A.
DEU	Landesbank Baden-Wrttemberg	IRL	The Governor and Company of the Bank of Ireland	POL	Powszechna Kasa Oszcz?dno?ci Bank Polski SA
DEU	NRW.BANK	DEU	NRW.BANK	IRL	The Governor and Company of the Bank of Ireland
NLD	N.V. Bank Nederlandse Gemeenten	ITA	Banco Popolare - Societ Cooperativa	DEU	Volkswagen Financial Services AG
POL	Powszechna Kasa Oszcz?dno?ci Bank Polski SA	FRA	La Banque Postale	FRA	Groupe Crdit Mutuel
NLD	ABN AMRO Group N.V.	DEU	Volkswagen Financial Services AG	NLD	ABN AMRO Group N.V.
BEL	Belfius Banque SA	POL	Powszechna Kasa Oszcz?dno?ci Bank Polski SA	BEL	Belfius Banque SA
DEU	DekaBank Deutsche Girozentrale	NLD	ABN AMRO Group N.V.	DEU	DekaBank Deutsche Girozentrale
DEU	Volkswagen Financial Services AG	BEL	Belfius Banque SA	DEU	NRW.BANK
IRL	The Governor and Company of the Bank of Ireland	DEU	DekaBank Deutsche Girozentrale	NLD	N.V. Bank Nederlandse Gemeenten

4.4 Capital Regulation and Systemic Stability

In this section we asses the ceteris paribus impact of capital regulation on systemic stability. More specifically, the CT1 capital ratios of banks in the network are elevated by injecting additional CT1 capital, while the network topology and remaining asset exposures remain unchanged. This allows to compare the different networks through time on the basis of equal CT1 capital. The actual effect of increased capital ratios is driven by several choices regarding the implementation of higher capital requirements[8]. Owing to their preferential regulatory treatment, it is likely that some fraction of assets will be shifted into sovereign assets instead of plain cash holdings, this is currently not considered by this simulation study. In this sense, the presented figures can be seen as best-case scenarios from a regulatory perspective.

Before proceeding with the analysis, a concise overview of the discussion on capital regulation as of 2017 is presented. The Capital Requirements Regulation and Directive (CRR/CRD IV) implements a set of capital regulations for European banks. A central part of this regulation is the definition of capital buffer requirements. Figure 6 provides an overview of currently implemented and discussed capital buffers. The top layer of capital requirements is the attempt to specifically target systemically relevant banks in order to reduce the risk from central network nodes. Hence, capital regulation is evidently used as a tool for systemic bank regulation. Therefore, the focus of this section is on assessing the theoretical and actual impact of such regulatory efforts. The average CT1/RWA capital ratios that are observed in the data for all banks in the sample are presented in Figure 7 together with the related milestones from the adoption of the Basel regulatory Framework.

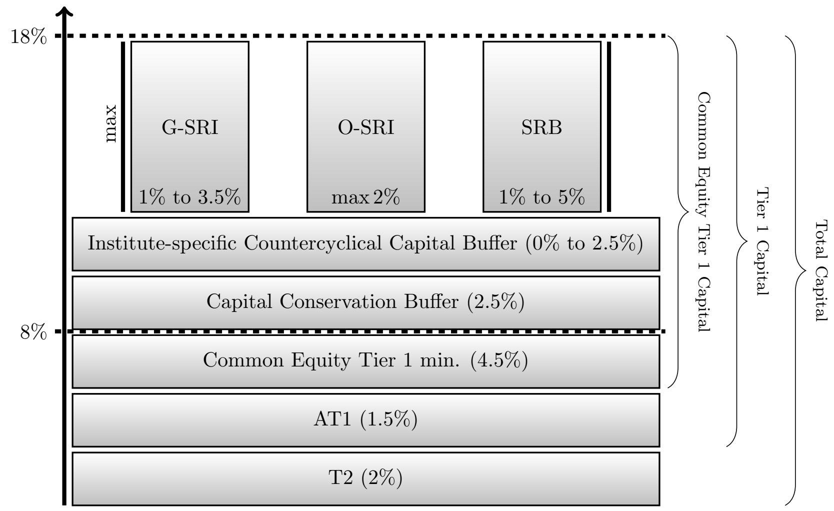

Figure 6: Overview of implemented and discussed regulatory capital buffers. G-SRI refers to global systemically relevant institutions, O-SRI to other systemically relevant institutions and SRB to systemic risk buffer. Source: BIS (2016).

Let us begin with the network as of 2011 and increase CT1 capital to match the 2014 average ratio. Therefore assessing the systemic risk profile of the 2011 network with the capital requirements of 2014[9]. The capital injection is implemented as a floor on CT1 capital. Hence,

[8]In practise, banks can reduce risk-weighted assets (RWA) or increase CT1 capital through e.g. issuing additional equity or contingent convertible bonds. Especially the reduction of RWA might change the asset exposure in the system. For most banks, shifting assets into sovereigns would decrease RWA; however, this preferential regulatory treatment of sovereign exposure is currently under review (Weidmann, 2013).

[9]This is repeated for any combination of 2011, 2014 and 2016 data. The results are similar, however, the

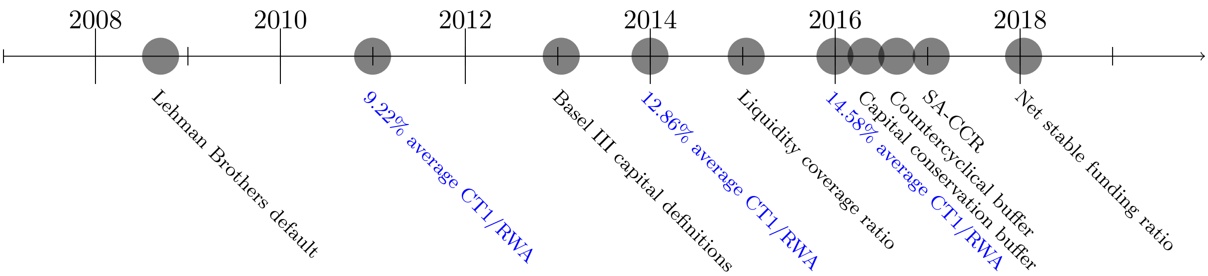

Figure 7: Risk based capital and liquidity standards related adoption of the Basel regulatory framework (BIS, 2016). The average CT1/RWA ratio for banks in our sample is depicted in blue.

all individual banks receive additional CT1 capital until they obey the desired ratio. In practise, a bank would aim at increasing its capital ratio to a slightly higher value than the regulatory threshold. Assumptions on this additional buffer are avoided by using the actually observed capital ratios.

The results for '11/'14 are shown in Figure 11. The first column of graphs shows direct defaults and total defaults as a function of a Europe-wide shock in sovereign, corporate and retail assets. The second column shows the same 2011 network with a capital treatment to match the 2014 CT1 ratio. The third column shows the actually observed network as of 2014. The idea of capital regulation is to provide a larger buffer for asset losses before defaults occur. Thus, we would expect that the networks in column 2 and 3 are more resilient, due to theoretically and actually increasing capital requirements.

In Figure 11, the top row of figures shows the effects of shocks to sovereign assets. The 2011 network with treated capital appears to be more resilient. Hence, the tipping point, where bank defaults start to accelerate, moved right on the x-axis. In contrast to this simulated result, the actual observed network in 2014 appears nearly identical to the original 2011 network. Furthermore, the network appears slightly less resilient on the short end, when considering the tipping point. This is not surprising as the 0% risk-weight for European sovereign bonds provides a strong incentive to shift assets into this class. Thus, the increase in regulatory capital requirements, among other factors, might have triggered an actual increase in risk from this transmission channel.

In the second row, shocks to corporate assets are simulated. As expected, the treated network shows greater resilience. However, despite an actual change in CT1 ratio from 9.22% to 12.89%, the default profile does not show any noteworthy changes for total defaults. It appears that the lower defaults from direct exposure are fully compensated by network defaults through the interbank market.

The results for retail assets in row three are similar. Most notably, the direct defaults from retail asset losses decrease from 2011 to 2014. However, that reduction is fully compensated by network defaults. This result is clearly affected by our assumptions on default costs (see Section 3.2), we address this issue of robustness in Section 5.

On paper, increased capital requirements and hence larger buffers for shock absolution should yield a more resilient financial network. According to our analysis, the theoretical benefits from increased capital requirements are higher than the actually observed effects. For all three considered transmission channels, the simulated networks are more resilient than the network under the actual capital regulation. The lag of effectiveness in a systemic risk sense is likely due to the actual implementation of capital regulation.

changes to the dataset between 2014 and 2016 reduce the informative value of combinations that include 2016 data (see Section 3.4 for a detailed description of the data). Results are presented in Appendix A.

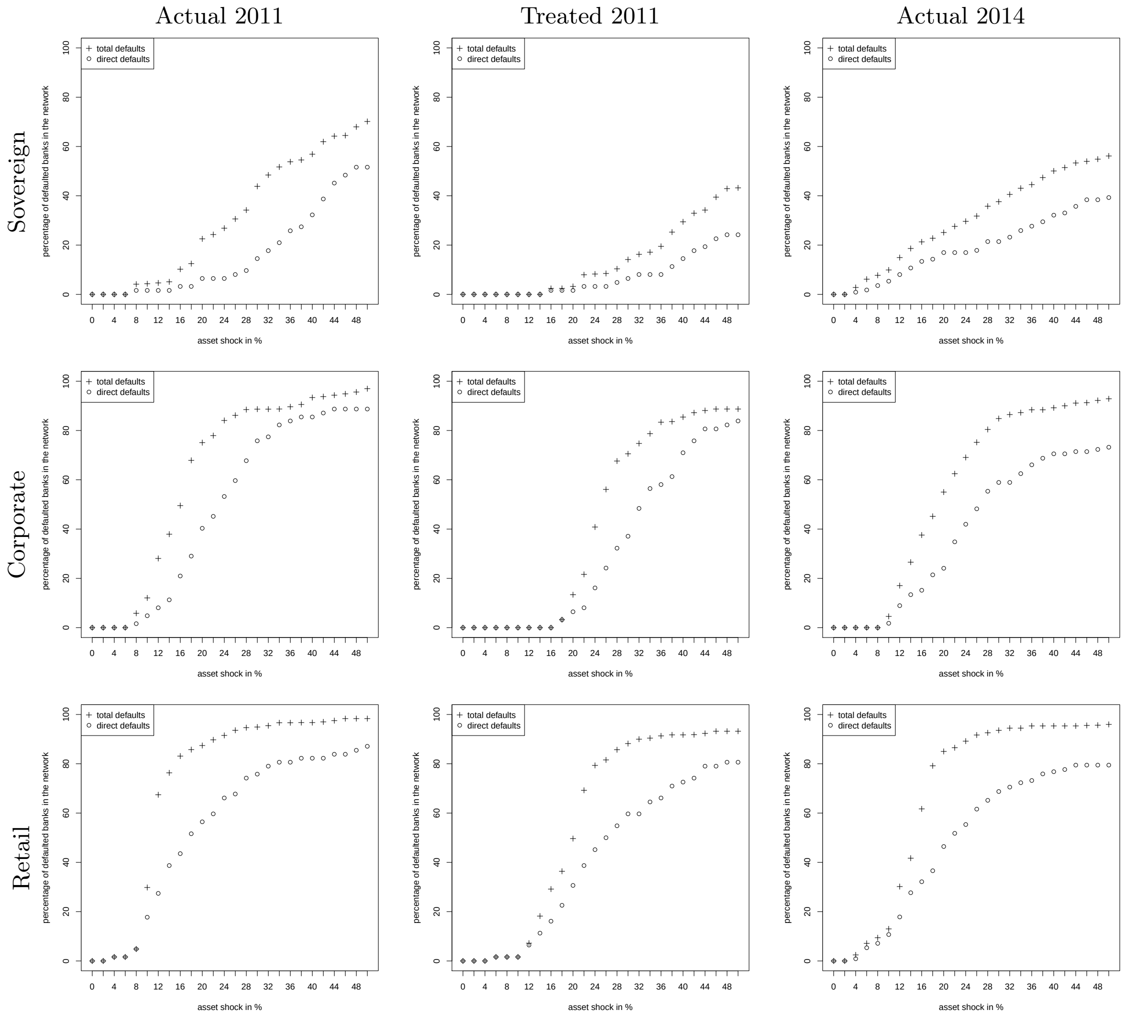

Figure 8: Percentage of defaulting banks in the network as a result of asset shocks $s^{(\cdot)} \in [0, 0.5]$ to CT1 treated and untreated networks. Direct defaults result from the shock itself, total defaults include additional defaults that are caused by contagion through the interbank network. Top to bottom: sovereign, corporate, retail asset shocks.

The finding that a reduction of direct defaults is compensated by network effects is particularly relevant. In this paper we only focus on one network contagion channel, namely, the interbank market. Another relevant channel can be identified as fire-sales that are triggered by banks that de-leverage in order to maintain capital ratios, after an initial asset shock. The diversified asset portfolios of large banks increase interconnectedness and thus the impact of fire-sales. Cont and Schaanning (2017) show that this channel exposes banks to assets that are not necessarily part of their own balance sheet; implying that this assets are not considered by an individual banks risk management or RWAs. Hence, the network risk in this paper is likely to be underestimated and the actual effect should be much higher. Together this creates a strong argument in favour of comprehensive network regulation over individual bank regulation.

5 Robustness

This paper aims at drawing a realistic picture of systemic risk in the European bank network. Most results are based on comparisons of outputs from models that are created under the same set of assumptions. This includes in particular assumptions on linkage probabilities and default costs, as explained in Section 3.2.

To understand the impact of default costs on systemic stability we repeat the network analysis with default costs of 15% and 45%. The results are shown in figure Figure 9. Contagion defaults play an important role for shocks in the range of 0% to 30%, afterwards most nodes would simply default on their direct (non-interbank) asset exposure, see Figure 11. Hence, it is not surprising that a reduction in default costs leads to a more shock resistant bank network.

This is relevant from a regulatory perspective when considering the previous result that capital regulation appears to have an impact on direct defaults, which is compensated by network defaults. Thus, regulatory efforts towards the reduction of bank default costs would help to create more resilient financial networks.

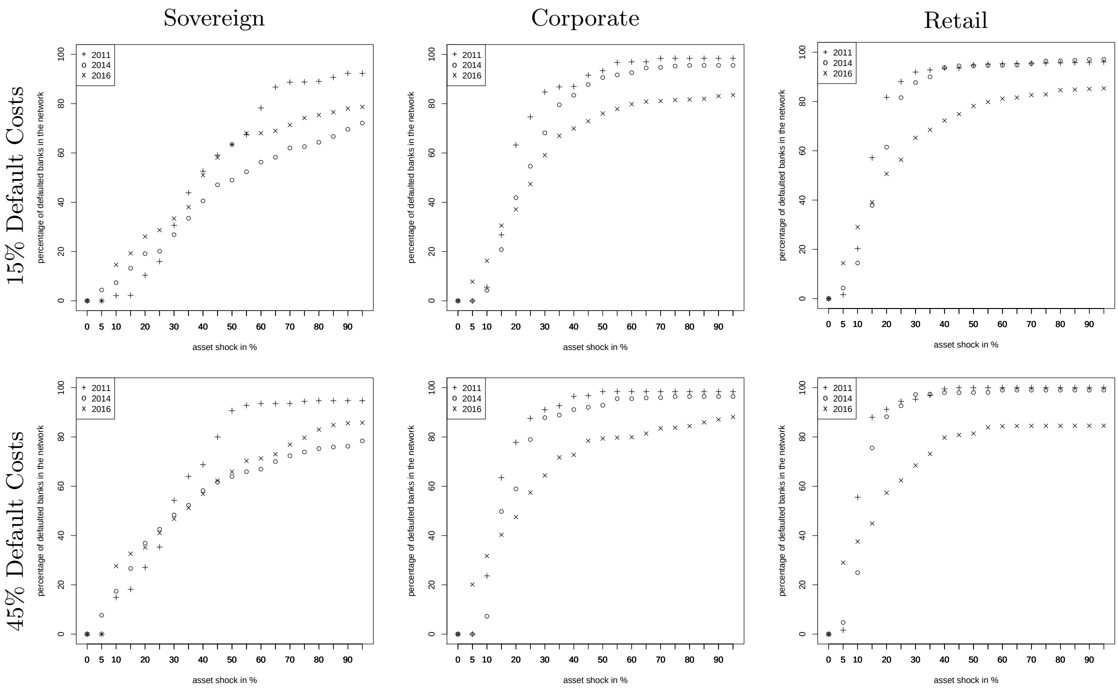

Figure 9: Percentage of defaulting banks in the network as a result of asset shocks. Direct defaults result from the shock itself, total defaults include additional defaults that are caused by contagion through the network. The default costs are 15% for the first row of graphics and 45% for the second row.

6 Concluding Remarks

We endeavoured into the analysis of systemic risk with the particular aim of measuring the impact of capital based regulation. This research is based on a data-driven, heterogeneous network model that represents up to 70% of European bank assets. A Gibbs-sampling method is used to fill the missing links in the data and provide an accurate yet computationally efficient representation of the network. This set-up can be adjusted to shed light on several aspects that affect systemic stability. As presented, we start from a highly granular representation of the whole network before analysing country level aggregates and finally single banks. Capital treatments are applied to banks in the system in order to assess the impact of capital regulation.

Our findings suggest that systemic resilience is improving for shocks to retail and corporate assets, whereas shocks to sovereign assets appear as an increasing thereat. This observation is likely owed to the preferential treatment of European sovereign assets, which as of 2017 carry a risk weight of 0%. Some results from the previous literature can be confirmed, this includes the identification of France, the UK and Germany as the nodes that would generate the largest contagion impact. Largely due to their size and the number of links to other economies.

After an initial assessment of the European bank network, we applied different treatments to CT1 capital. The findings from this analysis suggest that the effect of capital regulation on systemic stability is comparably small. More specifically, we compare a treated network to its observed counterpart and find that an increasing CT1 ratio does not necessarily yield a large reduction of systemic risk. The main effect of capital regulation appears to be on direct defaults, which is almost fully compensated by interbank network defaults. The clear policy implication is that a strong focus should be on regulatory efforts towards financial networks as a whole. The literature is in agreement that network structure has a significant impact on systemic risk. In addition, we find that a reduction of default costs would likely increase the effectiveness of capital regulation.

On country level, we find that the impact of contagion is particularly high for central and southern European countries when ranking the impact relative to GDP. On bank level, we provide "first to default" rankings that are based on year and exposure type. Owing to changes in the sampling methods of EBA, the comparability of single bank rankings over time is limited. Nevertheless, one finding is that a majority of the top 10 defaulting banks, due to sovereign asset shocks, are consistently based in Germany. More specifically, German state-owned banks, e.g. Deka Bank A.G., appear to be heavily exposed to sovereign assets. It is, however, important to note that for this ranking we applied an even shock to all sovereign assets in the network.

Several aspects of the analysis can be refined. Relaxing the assumption of evenly spread exposure within a given country would result in a more realistic representation of the network. The simple capital treatments can be refined to include more details from CRD IV, including special capital rules for systemically relevant banks, as laid out in Figure 6. Additionally, there exists a certain degree of freedom around the implementation of capital rules. Some of this implementation choices could be captured by a modified version of the presented method. Finally, including additional channels of network risk such as fire-sales or bank runs, would likely amplify the results that are presented in this paper.

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A Capital Regulation and Systemic Stability cont'd

A.1 2014 vs 2016

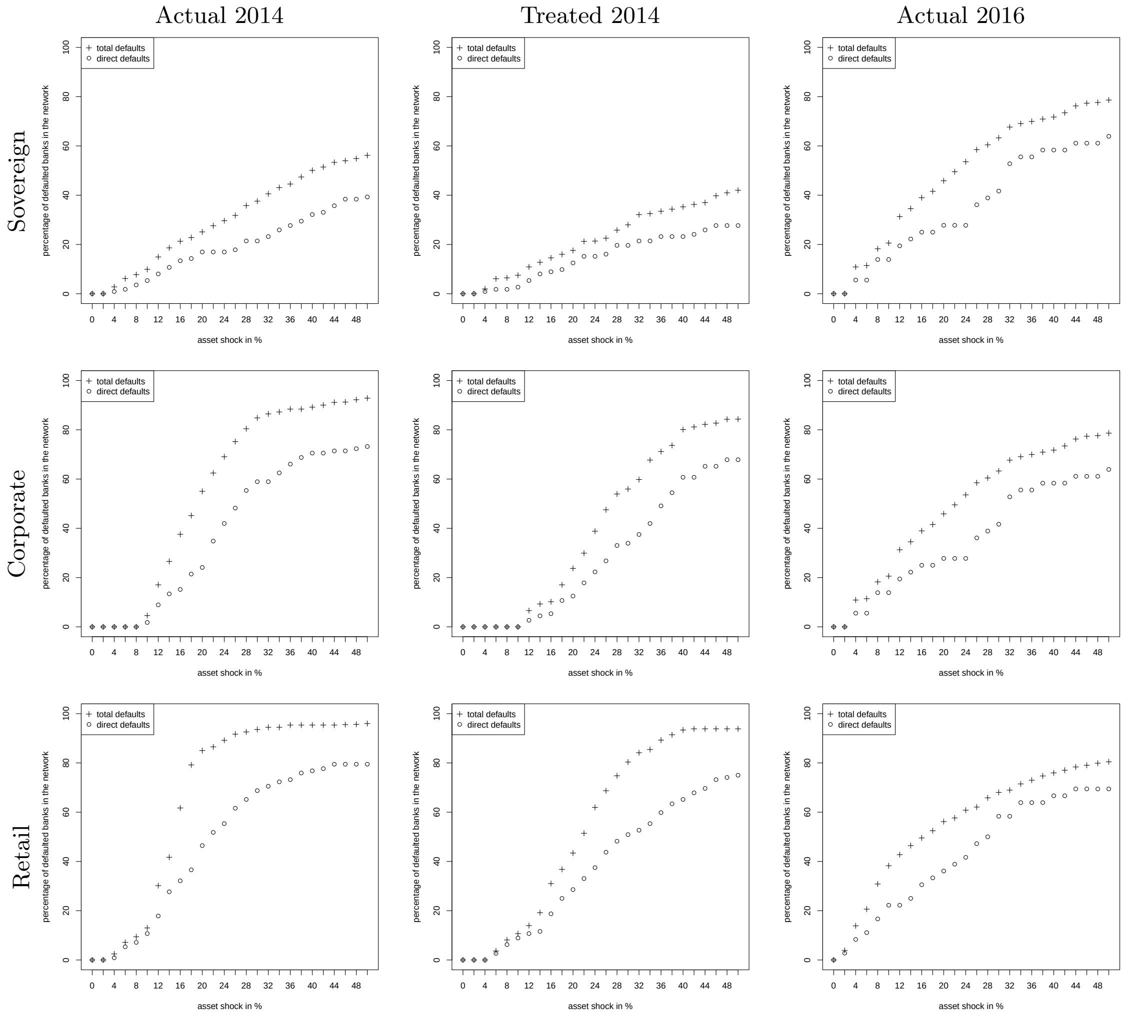

Figure 10: Percentage of defaulting banks in the network as a result of asset shocks $s^{(\cdot)} \in [0, 0.5]$ to CT1 treated and untreated networks. Banks in the 2014 treated network are endowed with additional CT1 capital in order to match the average 2016 CT1 capital ratio of 14.47%. Direct defaults result from the shock itself, total defaults include additional defaults that are caused by contagion through the interbank network. Top to bottom: sovereign, corporate, retail asset shocks.

A.2 2011 vs 2016

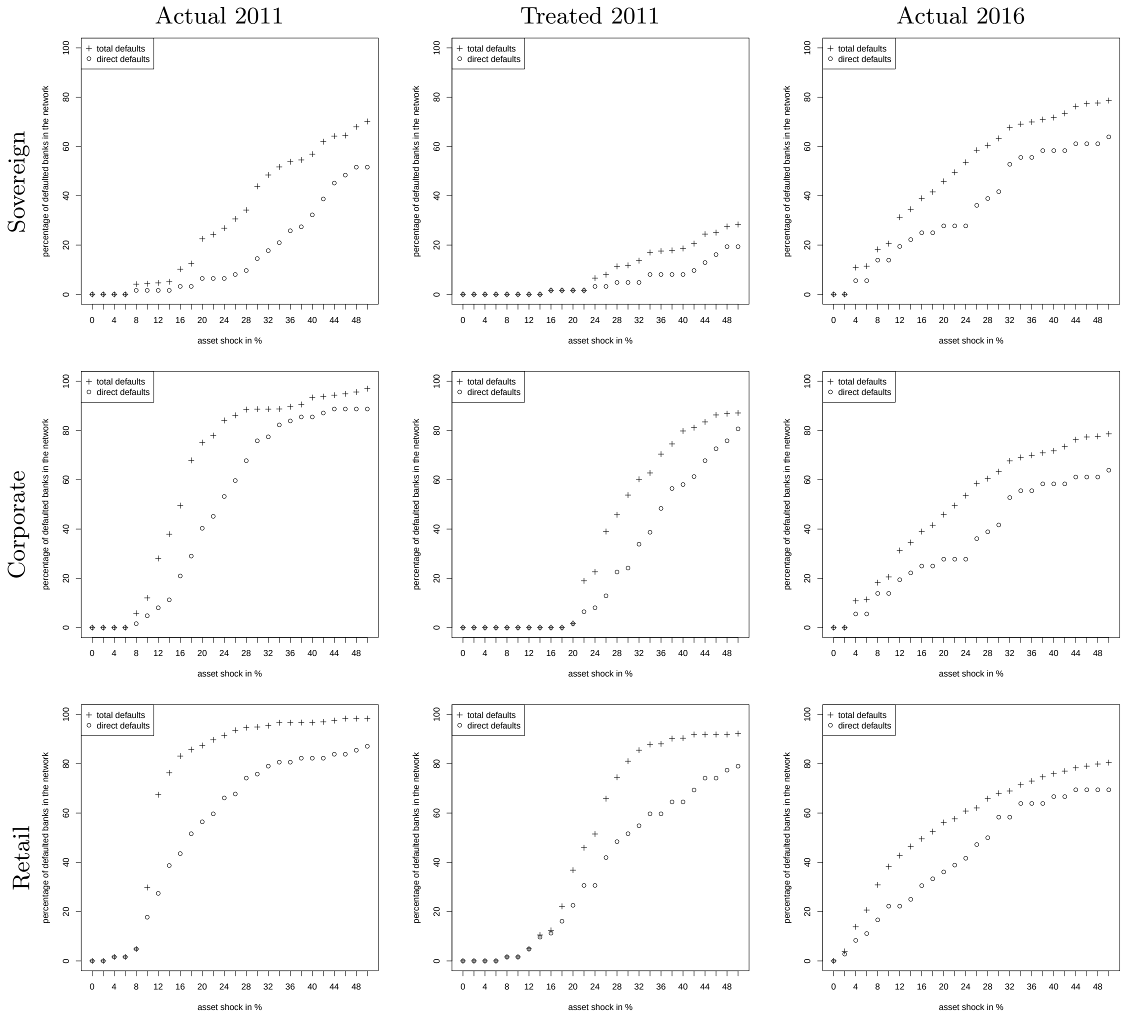

Figure 11: Percentage of defaulting banks in the network as a result of asset shocks $s^{(\cdot)} \in [0, 0.5]$ to CT1 treated and untreated networks. Banks in the 2011 treaded network are endowed with additional CT1 capital in order to match the average 2016 CT1 capital ratio of 14.47%. Direct defaults result from the shock itself, total defaults include additional defaults that are caused by contagion through the interbank network. Top to bottom: sovereign, corporate, retail asset shocks.