2021-02

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Irena Vodenska, Hideaki Aoyama, Alexander P Becker, Yoshi Fujiwara, Hiroshi Iyetomi, Eliza Lungu. 2021. "From stress testing to systemic stress testing: The importance of macroprudential regulation." Journal of Financial Stability, Volume 52, pp. 100803 - 100803. https://doi.org/10.1016/j.jfs.2020.100803
https://hdl.handle.net/2144/43042

Journal of Financial Stability 52 (2021) 100803

Contents lists available at ScienceDirect

Journal of Financial Stability

journal homepage: www.elsevier.com/locate/jfstabil

From stress testing to systemic stress testing: The importance of macroprudential regulation

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ARTICLE INFO

Article history:
Available online 17 October 2020

Keywords:
Bank network
Portfolio overlap
Basel III
Macroprudential regulation

ABSTRACT

Stability of the banking system and macroprudential regulation are essential for healthy economic growth. In this paper we study the European bank network and its vulnerability to stressing different bank assets. The importance of macroprudential policy is emphasized by the inherent vulnerability of the financial system, high level of leverage, interconnectivity of system's entities, similar risk exposure of financial institutions, and susceptibility for systemic crisis propagation through the system. Current stress tests conducted by the European Banking Authority do not take in consideration the connectivity of the banks and the potential of one bank vulnerability spilling over to the rest of the system. We create a bipartite network with bank nodes on one hand and asset nodes on the other with weighted links between the two layers based on the level of different countries' sovereign debt holdings by each bank. We propose a model for systemic risk propagation based on common bank exposures to specific asset classes. We introduce the similarity in asset distribution among the banks as a measure of bank closeness. We link the closeness of asset distributions to the likelihood that banks will experience a similar level and type of distress in a given adverse scenario. We analyze the dynamics of tier 1 capital ratio after stressing the bank network and find that while the system is able to withstand shocks for a wide range of parameters, we identify a critical threshold for both asset risk and bank response to a shock beyond which the system transitions from stable to unstable.

1. Introduction

In today's interconnected world the financial system with increased global reach is becoming more vulnerable to international corporate, household, and sovereign exposures. Drawing national business boundaries for banks has become a difficult task. Even though in general banks still have significant exposures to domestic economies, the largest financial institutions have a substantial international presence. Systemic risk describes the vulnerability of a system, like the bank network, as a whole to exogenous and endogenous shocks. If not understood and closely monitored, these shocks can wipe out significant parts of a system. Therefore, monitoring the vulnerabilities of banks globally is highly important for policymakers. Stress tests are an important tool for determining the fragility of banks under adverse scenarios. While there are many factors that determine the health of financial institutions, (i) adequate level of capital and (ii) high quality liquid assets are two main aspects to consider when assessing banks' stability. Additionally, (iii) examining the interconnectivity among banks plays an important role in determining the macroprudential fragility of the network.

In this paper we address all three important factors from above and demonstrate that if banks are well capitalized, hold liquid high quality assets, and maintain well-balanced portfolios in relation to other banks, we can expect better overall stability of individual banks as well as the banking system as a whole. While the first two factors are well studied (Moyer, 1990; Beltratti and Stulz, 2012; Calice et al., 2013; Distinguin et al., 2013; Miles et al.,

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https://doi.org/10.1016/j.jfs.2020.100803
1572-3089/

2013; European Central Bank, 2014; DeYoung and Jang, 2016), we offer a novel insight into the importance of the network structure and dynamics of the system of international financial institutions through the study of the third factor.

We propose a bipartite network model of banks on one hand and assets on the other and test the stability of the network under specific adverse scenarios. The links between the banks are established indirectly through common exposures to asset classes such as corporate loans or commercial real estate loans, and the weights of the links are approximated based on bank exposures to sovereign debt of different countries. Our model has two parameters: (i) size of the initial shock to the banking system, and (ii) spreading or spillover parameter, which we identify as a measure of systemic risk. The initial shock reduces bank capital or increases the risk weights of bank assets. Both types of shocks cause a deterioration in the tier 1 capital ratio, which is used as benchmark to assess proper capitalization of financial institutions. This deterioration prompts a response from the affected banks which can further distress other parts of the system. We confirm, in accordance with Eisenberg and Noe (2001) and Glasserman and Young (2015), that any spillover effect in a linear system is not significant, and it is bounded by the initial shock to the system, i.e., no systemic effect is observed through network spreading dynamics. To investigate the conditions when systemic risk propagates through the banking network, we introduce non-linearity in our model. We simulate a non-linear bank response to a loss of equity or an increase of specific asset risk weights. In the non-linear scenario, we observe increased fragility of the banking system. The spreading parameter which describes asset vulnerability to risk is a critical parameter that separates the stable from the unstable regime of the system.

2. Literature review

Central banks often work in concert to steer the financial system towards stability. Just recently, researchers from 13 central banks joined efforts to study data from 25 different markets to understand how to reconstruct exposures in financial networks (Anand et al., 2017). Financial crises such as the sub-prime credit crisis of 2007–2009 and the European sovereign debt crisis of 2010–2012 have revealed weaknesses in bank risk management practices as well as softness in the global regulatory framework. As a response to the economic system instabilities, regulators have focused on strengthening liquidity and capital requirement rules to increase the stability of the financial system and reduce the possibility of major negative impact on global economy (Committee et al., 2010; One Hundred Tenth Congress, 2010).

The Basel Committee on Bank Supervision has developed the first Basel Capital Accord in 1988 to address apprehensions arising from financial deregulation. The Basel III accord (endorsed by the G20 countries in November 2010) responds to the need for effective regulation to maintain the stability of the financial system in times of economic downturns, such as the financial crisis of 2007–2009. More specifically, Basel III calls for improvement in quantity and quality of capital, redefines tier 1 capital, weighs on banks' risk management, and calls for capital buffer requirements to increase the stability of the entire financial system (macroprudential regulation). Previous Basel regulations (I and II) have focused on the stability of the financial system's entities (microprudential regulation), disregarding the systemic risk and the vulnerability of the financial system to cascading failures. Similarly to Basel I and II, Basel III maintains the requirement that banks hold total capital of 8 percent of their risk-weighted assets (RWA). One of the main differentiating aspects of Basel III however is the introduction of a more stringent definition of tier 1 capital as a "going-concern" capital comprised mostly of common equity (common stock, common stock surplus, and retained earnings). Additionally, according to Basel III, 75 percent of the total banks' capital should consist of tier 1 capital. Common equity tier 1 capital should account for at least 4.5% of RWA of the bank.

The RWA are a fundamental input for Basel III capital requirements and are determined by an internal rating-based (IRB) approach that assesses counterparty credit risk (CCR). The majority of banks use external credit ratings attributed to their counterparties. Large banking institutions, however, may choose to use internal risk models to determine the capital needed to offset specific RWA, based on their estimates of exposures to loss or likelihood of loan defaults. (King and Tarbert, 2011; Padgett, 2012).

One of the challenges in macroprudential regulation is proper risk assessment of financial institutions and ensuring that, on a systemic level, the risk of network failure is minimized. Since the bank risk is based on exposures to different sectors of the main economy as well as the liquidity of the rest of the financial system, having an accurate assessment of asset risk factors as well as ensuring high quality tier 1 capital is essential. The Basel Committee on Banking Supervision introduced the Basel III reforms in 2010 to address the vulnerabilities in the financial system focusing on the liquidity requirements expressed through the Liquidity Coverage Ratio (LCR) and the Net Stable Finding Ratio (NSFR). Basel III stirred numerous arguments between supporters of the reforms who argue that Basel III will increase the stability of the financial system and opponents who claim that the reform will reduce credit availability and economic activity (Admati et al., 2011; Admati and Hellwig, 2011; Allen et al., 2012; King, 2013; Miles et al., 2013).

Given that certain banks are allowed to use internal models for calculating risk-weighted assets (RWA), and hence influence their tier 1 capital ratios, it is not always possible to state the proper capitalization of banks with great confidence. The banks can influence tier 1 capital ratios by holding assets weighted with a low risk that actually have higher risk. Additionally, there is a risk that asset risks might change over time. Moreover, correlations of banks' shared portfolios are prone to increase and contribute to higher risk in the banking system (Engle, 2009; Acharya et al., 2014; Caccioli et al., 2014; Brownlees and Engle, 2015; Corsi et al., 2016).

The establishment of the European Single Supervisory Mechanism (SSM) in November 2014 opened a new era of bank supervision in the euro zone. The intention of the SSM has been to harmonize key areas of bank supervision and to contribute significantly towards the safety and resilience of the European banking system. By conducting a comprehensive assessment of 130 banks in the euro area, the European Central Bank (ECB) has addressed several important objectives including: (i) strengthening bank balance sheets, (ii) enhancing transparency and improving quality of information regarding bank conditions, as well as (iii) building confidence by assuring banks' appropriate capitalization after completion of necessary corrective actions. The 130 banks, involved in the comprehensive assessment, account for € 22 trillion total assets or over 80% of total assets in the SSM as of December 2013 (Authority, 2016). Similar efforts to regulate the financial system have been made in the US, most prominently in form of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (One Hundred Tenth Congress, 2010). More recently though, there have been significant efforts by the new US administration to revoke some of the regulations put in place by this bill (Rapperport, 2017). This shows that there is a significant political component to regulation, specifically regarding how much or how little regulation is appropriate. The focus, however, should not necessary be on more or less regulation, but rather better regulation in order to curb banking crises or reduce systemic distress in the financial network.

This is all the more urgent as banking crises have been more frequent than expected in both developed and emerging market economies with an annual probability of a crisis of approximately 4–5% (Walter, 2010).

Stability of financial institutions has attracted the attention of many economists who have offered insight into financial system fragility, measures of systemic risk as well the impact of regulation on systemic risk. In addition to central banks' stress test methodologies, Acharya et al. (2014) have proposed an alternative approach to measuring systemic risk (SRISK) by offering an insight into how much capital a financial institutions will need to raise during economic crisis to bring their capital up to regulatory levels.

Comparison studies between regulatory stress tests and stress tests that use only public market data reveal that approaches used to weight assets by risk are not correlated with market measures of risk. The well capitalized banks also have not fared better than the rest of the European banks in light of the European sovereign debt crisis of 2011 (Acharya et al., 2012, 2014; Lucas, 2014a). On the other hand, Yan et al. (2012) find Basel III reforms to have significant long-term positive effects on the UK economy. Lucas argues that in addition to financial institutions, which are tightly interlinked with the main economy, the Government is also a significant source of systemic risk. While other factors such as lack of transparency of government actions and the scope of government's involvement in financial markets can contribute to overall systemic risk buildup in the economy, a notable systemic characteristic of the government is its enormous size as financial conglomerate. When considering the traditional credit programs, Fannie Mae, Freddie Mac, the Federal Home Loan Banks, deposit insurance, the Federal Reserve System, and the Pension Benefit Guarantee Corporation, the government becomes a $20 trillion financial institution (Lucas, 2014b). The government, on the other hand, can also serve as an essential contributor to financial stability in times of crises undertaking appropriate actions carried out swiftly. Both aspects of government, carrying significant costs, may contribute to rethinking the notion that government debt is risk-free and hence reconsider sovereign debt risk weights used to determine banks' RWA.

To incorporate the complexity of the financial system, interdisciplinary approaches have been proposed. Understanding the interconnections among financial institutions as well as interlinks between bank networks and the main economy have been a focus of many researchers during the past two decades starting with Eisenberg and Noe (2001) and Furfine (2003). Using tools from network science, researchers have studied the likelihood of contagion (Upper, 2011; Glasserman and Young, 2015), developed systemic risk measures (Battiston et al., 2012b), and analyzed specific banking systems (Van Lelyveld and Liedorp, 2004; Upper and Worms, 2004). Other approaches include the study of robustness, the cost of repair, and topological properties and their consequences for systemic risk (Battiston et al., 2012a, 2016; Caldarelli, 2007; Dehmamy et al., 2014; Elsinger et al., 2006; Garlaschelli and Loffredo, 2004, 2005; Huang et al., 2011; Iori et al., 2008; Joseph et al., 2014; Majdandzic et al., 2016; Piškorec et al., 2014; Vitali et al., 2011; Vodenska et al., 2016, 2020).

Following a shock, the natural response of financial institutions includes reducing losses by selling assets, which most likely trade at depressed prices: due to the distress, liquidity may dry out and a lack of buyers reduces market value. (Huang et al., 2013; Greenwood et al., 2015; Sakamoto and Vodenska, 2016, 2017). Previous studies have considered fire sale dynamics, in which banks attempt to unload their assets as efficiently as possible, leading to a downward spiral exacerbated by overlapping portfolios (Duarte and Eisenbach, 2015; Cont and Schaanning, 2017). We expand upon this approach and introduce a behavioral component by including the risk tolerance of banks, modeling financial institutions' inclination to induce a fire sale. We suggest that by being able to monitor the dynamics of links in the bank network, regulators might be able to foresee specific bank network vulnerabilities in light of certain exogenous or endogenous economic shocks, and engage in mitigation activities such as in Smolyak et al., 2020, to improve the stability of the financial network.

The rest of the paper is organized as follows: In Section 3 we describe the data that we use for empirical analysis. In Section 4 we introduce the simulation model of systemic risk propagation through the bipartite network of banks and assets, while in Section 5 we present the results of the simulation using the European Banking Authority stress test results data. Here we highlight the effect of inter-connectivity of the banks through shared portfolio networks. In Section 6 we discuss the regulatory implications of our results and offer our concluding remarks.

3. Data

We use data from the 2011 European Banking Authority (EBA) stress test. This data offers insight into asset portfolios of European banks. It shows the total exposure of 90 different banks in the following seven investment categories: sovereign debt, financial institutions, corporate, retail residential mortgage, retail revolving, retail small and medium-sized enterprises (retail SME), and commercial real estate (CRE). Fig. 1 shows the structure of the banks' holdings. For each of the seven asset classes we plot the histogram of the percentage they make up in the banks' portfolios.

We observe that banks tend to hold large amounts of corporate loans and assets in the residential retail sector. Sovereign debt and loans to the financial sector play a smaller roll, while retail revolving, retail SME, and commercial real estate tend to make up the smallest part of the banks' portfolios. This is reflected by the means, indicated by dotted lines in the plot. An average bank portfolio is comprised of roughly 14% sovereign debt, 15% loans to financial institutions, 30% corporate loans, 26% residential mortgage, 3% revolving retail, 5% retail SME and about 7% commercial real estate.

The data set also details which kind of country's sovereign debt each bank holds. These countries include 30 European nations, the United States and Japan as well as a category “other”.

Fig. 2 represents a network representation of the portfolio similarity of the banks. Since all banks exhibit a certain overlap in portfolio, we filter the network using a method introduced by Tumminello et al. (2005). Such a planar maximally filtered graph (PMFG) reduces the number of edges for information filtering and better graphical representation. A link, drawn in gray, between two banks indicates that there exists a significant overlap between their respective sovereign debt portfolios. The minimum spanning tree Kruskal (1956) of the graph is indicated by the thicker, solid edges. We define the overlap of two portfolios as their cosine similarity: given portfolios A and B with weights a_i, b_i distributed among asset classes $i = 1, \ldots, N$ and $\Sigma_i^N a_i = \Sigma_i^N b_i = 1$, the cosine similarity is given by

$$\text{similarity} = \frac{\sum_{i=1}^{N} a_i b_i}{\sqrt{\sum_{i=1}^{N} a_i^2}\sqrt{\sum_{i=1}^{N} b_i^2}}, \tag{1}$$

which is the normalized inner product of the relative weights of portfolio A with the relative weights of portfolio B. This product yields a number between 0 and 1 where a value of 0 means that portfolio A does not contain any asset that is in portfolio B and vice versa, and a value 1 means that both portfolio holders allocate their resources equally among the available assets. The size of the nodes and their color correspond to the value of all assets in the respective bank's portfolio and to the country or region in which it is headquartered.

The largest banks by asset value, listed in Table 11 in the appendix, are positioned at the center of the minimum spanning tree. The French bank Société Générale, which is the 11th largest

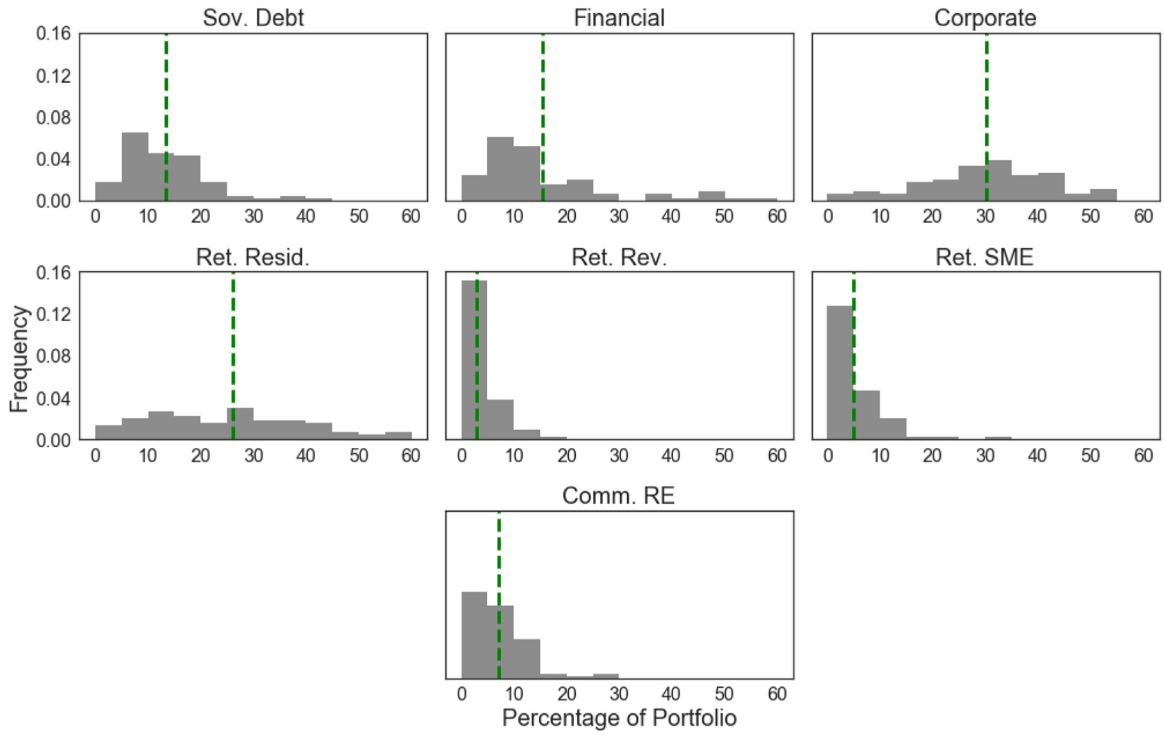

Fig. 1. Histograms of bank holdings where the *x*-axis is the percentage of a bank's portfolio an asset makes up. The dotted line indicates the mean value of the distribution.

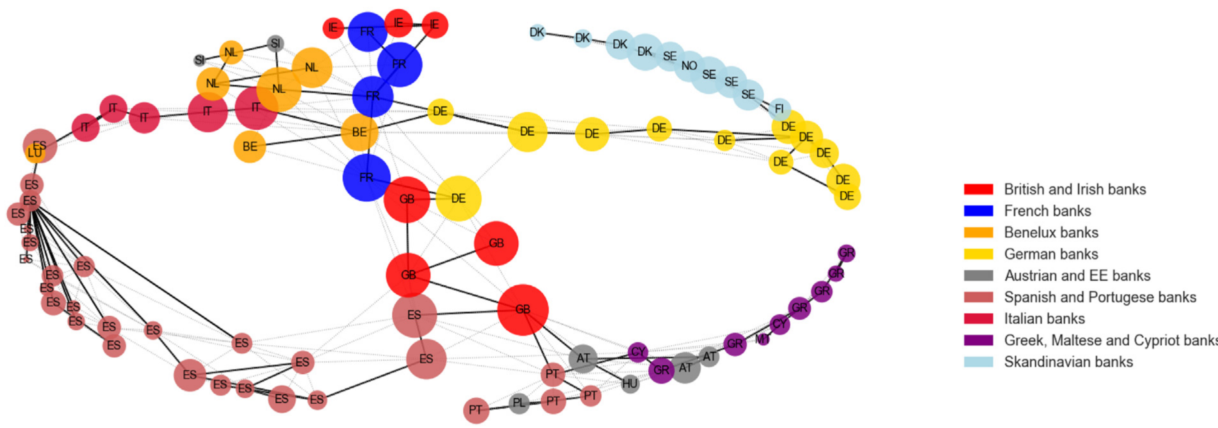

Fig. 2. PMFG (Planar Maximally Filtered Graph) and MST (Minimum Spanning Tree) network representation of portfolio overlap of banks considering sovereign debt. Banks from different countries and regions are color-coded. British and Irish banks (bright red), French banks (blue), banks from the Benelux countries (orange), German banks (yellow), Austrian and Eastern European banks (gray), Spanish and Portuguese banks (light red), Italian banks (crimson red), Greek, Maltese and Cypriot banks (purple), Scandinavian banks (light blue). The size of the node represents the value of all assets a bank holds as a proxy for the size of the bank. The largest banks are at the center of the network. We observe that banks from the same country cluster, indicating that their portfolios are similar due to home and regional bias. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

bank, has the most connections to non-domestic banks (13). The French bank BNP Paribas (2nd largest), the Belgian bank Dexia (17th largest), and the British bank HSBC (largest bank in the data set) follow in second place with 10 connections to banks from other countries. We can roughly separate the banks into two groups. On the one hand we have around 20 of the largest banks which show significant portfolio overlap with banks from other countries, indicating a broad and international portfolio of sovereign debt. On the other hand we find the remaining banks sharing a larger overlap with banks from their own country or neighboring countries. For example, sovereign debt holdings by Danish banks tend to be more similar to sovereign debt holdings of other Scandinavian banks as compared to the portfolios of banks from other European countries. These home and regional biases may be due to regulatory requirements such as Basel II, which have allowed to favor domestic sovereign debt,[1] and probably reflect the focus of a bank's business operations. We use this insight later to approximate the bank holdings in other asset classes.

The EBA data also details the tier 1 capital ratios of banks which is defined as the ratio of tier 1 equity and the sum of the risk-weighted assets of a bank. The risk-weighted assets of a bank are calculated by weighting the exposure to an asset by an estimate of their riskiness. Until 2013 Basel III has required banks to maintain a tier 1 capital ratio of at least 4.5 percent at all times. In line with the phase-

[1] http://www.bis.org/publ/bcbs128b.pdf.

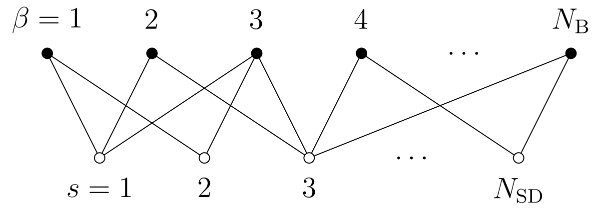

Fig. 3. Bipartite network of the banks β and sovereign debts s.

in arrangements of the Basel III framework,[2] the requirements are currently higher than that; however we recognize that we need to compare the situation of the banks in our data set with the regulations at the time. The 2011 EBA report includes two banks that have a capital of less than 4.5 percent already, however, which we have to remember in the analysis of the results of our simulations. These banks are the Allied Irish Banks (tier 1 capital ratio of 3.7%) and the Spanish Caja de Ahorros (3.8%). Hypo Real Estate exhibits the largest value among all banks, with a tier 1 capital ratio of 28.4 percent. The mean and median capital ratio of the banks in the data set are 9.3 percent and 8.7 percent, respectively.

4. Simulation model

While the EBA data details the origin of sovereign debts in a bank's portfolio, it does not identify the origin of other assets, that is, financial institutions, corporate, retail residential mortgage, retail revolving, retail SME, and commercial real estate. We make the assumption that the distribution of sovereign debts of a given bank is a good proxy for the entire portfolio of that bank. In other words, if half of a given bank's sovereign debt exposure comes from German bonds, we assume that also half of its exposure to financial institutions, corporate, etc., comes from Germany. The static balance sheet and distribution of bank portfolio assumptions are based on the bank balance sheet characteristics, where the credit exposures that banks have on one hand (the asset side) and the financing, i.e., short and long term debt on the other (the liability side) of the balance sheet are usually quite stable over extended periods of time. Bank leverage (or the equity level of the bank) is also quite invariant and it is regulated by international regulatory frameworks such as Basel III.

This allows us to construct a complete bipartite network, in which banks and assets interact back and forth, as illustrated for the case of sovereign debts in Fig. 3. Let us first define variables on the bank layer and the asset layer, and then the risk propagation procedure.

4.1. Modelling a bank's exposures

A bank $\beta \in [1, 2, 3, \ldots, N_B(=90)]$ is invested into different asset subcategories $a \in [1, \ldots, N_A(=7)]$ from different countries $s \in [1, \ldots, N_{SD} = 32]$. We define the following financial variables for bank β:

$$\mathbf{A}_\beta = \left.\underbrace{\begin{pmatrix} S_{\beta,1} & \cdots & S_{\beta,N_{SD}} \\ A_{\beta,2,1} & A_{\beta,2,2} & \\ \vdots & \ddots & \\ A_{\beta,N_A,1} & A_{\beta,N_A,N_{SD}} & \end{pmatrix}}_{\text{Countries}}\right\}\text{Asset Classes}$$

[2] http://www.bis.org/bcbs/basel3/basel3_phase_in_arrangements.pdf.

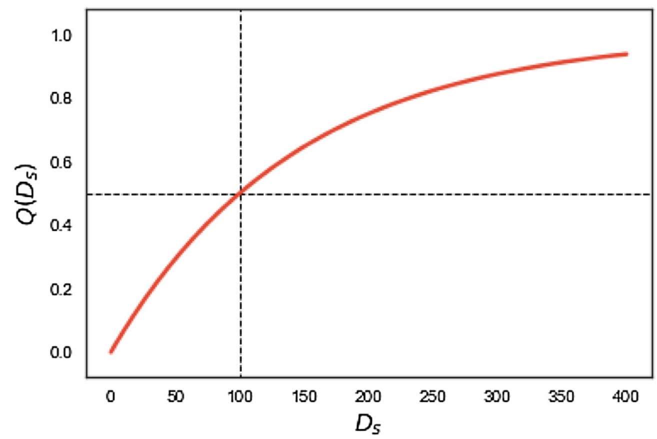

Fig. 4. Spreading parameter $Q(D_s)$ where D_s is the CDS spread in basis points for a given sovereign debt s. The function $Q(D_s) = 1 - 2^{-D_s/100}$ is selected such that its value is between 0 and 1 and that a spread of 100 basis points corresponds to a value of 0.5. A CDS spread of 0 corresponds to a Q value of 0, and as the CDS spread grows, Q approaches 1. Note the similarity of the function $Q(D_s)$ with the default probability derived from a CDS spread for some maturity and recovery rate.

$\mathbf{A}_\beta$ — $N_A \times N_{SD}$ matrix detailing the exposures to different asset classes from different countries:

$$\mathbf{A}_\beta = \left.\underbrace{\begin{pmatrix} S_{\beta,1} & \cdots & S_{\beta,N_{SD}} \\ A_{\beta,2,1} & A_{\beta,2,2} & \\ \vdots & \ddots & \\ A_{\beta,N_A,1} & A_{\beta,N_A,N_{SD}} & \end{pmatrix}}_{\text{Countries}}\right\}\text{Asset Classes}$$

$S_{\beta,s}$ — The first row of the matrix $\mathbf{A}_\beta$, contain the exposure to all sovereign debt SD held by this bank. An individual sovereign debt s is therefore $S_{\beta,s} = \left(\mathbf{A}_\beta\right)_{1,s}$.

W_β — Sum of risk-weighted assets (RWA).

C_β — tier 1 capital.

R_β — tier 1 capital ratio, $R_\beta = C_\beta / W_\beta$.

The RWA of a bank β in the data are calculated according to Basel III. We instead make use of a weighted sum as our definition of RWA:

$$W_\beta = W_\beta^{\mathrm{SD}} + W_\beta^{\mathrm{other}} = \sum_{s=1}^{N_{SD}} r_s S_{\beta,s} + \sum_{s=1}^{N_{SD}} \sum_{a=2}^{N_A} w_{a,s} \left(\mathbf{A}_\beta\right)_{a,s}, \tag{2}$$

where r_s denotes the risk factor (weight) of the SD s and $w_{a,s}$ for $a \geq 2$ are the risk factors of other assets from different countries. Cash is an important part of any bank's assets. However, it presents no risk and is therefore absent in this summation. The weights for the RWA are estimated using an optimization procedure against the reported aggregated holdings of risk-weighted assets. While debt with longer maturity poses less immediate risk, in this study we use a simple sum of all holdings, regardless of their maturity.

4.2. Modeling sovereign debts and other assets

The EBA data details the country of origin of the sovereign debt. We assign the following variables for sovereign debt s, where s is again the indicator for the country of origin:

S_s — Total exposure, owned by all the banks in our database, $S_s = \Sigma_{\beta=1}^{N_B} S_{\beta,s}$.

r_s — Risk factor, $r_s = w_{1,s}$. Before shock, $r_1 = r_2 = \cdots = r$

D_s — Yearly average of the CDS spread.

$Q(D_s)$ — Spreading Parameter; $Q(D_s) = 1 - 2^{-D_s/100}$, so that $Q(0) = 0$, $Q(100) = 0.5$, as shown in Fig. 4.

We use the following variables for assets from the other subcategories:

$A_{a,s}$ Total exposure to all assets from asset category a from country s, owned by the all banks in our database, $A_{a,s} = \Sigma_{\beta=1}^{N_B} \left(\mathbf{A}_\beta\right)_{a,s}$.
$w_{a,s}$ Risk factor. Before shock, $w_{a,1} = w_{a,2} = \cdots = w_a$
Q_a Spreading Parameter for a given asset class; constant across all countries.

As pointed out before, the data regarding the exposure to other asset classes than sovereign debt come in aggregate form. In other words, while we know $\left(\mathbf{A}_\beta\right)_a$, we infer $\left(\mathbf{A}_\beta\right)_{a,s}$ from the sovereign debt holdings. This is an assumption which we find supported by the regional bias in the sovereign debt holdings we discovered through a network analysis in Fig. 2. The regional bias suggests a tendency of banks to be active mostly in domestic and familiar markets. Furthermore we posit that a portfolio of one asset class in one country exhibits similar risk as a portfolio of the same asset class in another country, e.g. corporate lending in Italy is similar to corporate lending in Spain, while lending across different asset classes has a different risk profile.

4.3. Iteration model

We run simulations for different crisis scenarios. One, we shock the sovereign debts of a given country by increasing their risk factors. The only interaction occurs between banks and sovereign debts; the other asset categories are unaffected. Two, we shock any sector of a given country by increasing its risk factor, and we include the possibility of spillover to other asset classes. The sector suffering the initial shock can be any of the seven asset categories, from sovereign debt to commercial real estate. Three, we shock the banks in a given country by decreasing their capital by a certain percentage.

4.3.1. Shocking sovereign debts

We simulate a crisis scenario which starts with sovereign debts. We consider ten different shock origins:

(1) GIIPS (Greece, Italy, Ireland, Portugal, Spain)
(2) Eastern Europe (Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, Slovakia, Slovenia)
(3) Benelux (Belgium, Netherlands, Luxembourg)
(4) Greece
(5) Italy
(6) France
(7) Germany
(8) Spain
(9) US
(10) Japan

The simulation process is as follows: Upon initialization, an SD or a set of SDs from the countries of origin above has their risk factor increased at $t = 0$.

1. At $t = 1$, these shocks on SDs are propagated to the banks who own those SDs. As a result of the increased risk factors, the RWA of the affected banks is increased and their tier 1 capital ratio decreased.
2. At $t = 2$, those shocks on the banks are propagated back to SDs. A bank that is affected by the shock in the previous step might be forced to take action, putting pressure on the SDs in its portfolio. The risk factors of all SDs owned by affected banks are therefore increased, depending on the decrease in the tier 1 capital ratio of those banks.
3. At $t = 3$, shocks on SDs are propagated to banks, in a manner much like the step $t = 1$. The propagation continues back and forth between SDs and banks for $t = 4, 5, \ldots$.

The capital C_β of bank β remains constant throughout the simulation run. Therefore the change tier 1 capital ratio is entirely determined by the change in the RWA.

As described above, we model the risk propagation from the banks to the SD s (at $t = 2, 4, 6, \ldots$) through the increase in risk factors. Each SD s contributes to the risk-weighted assets W_β^{SD} of bank β, and thus each bank holding an affected SD will see an increase in their RWA proportional to its exposure to this SD. The exposures from other sectors also contribute to the risk-weighted assets W_β^{other} of each bank. These, however, will remain unchanged:

$$r_s(t+1) = r_s(t)/\Omega_s(t), \tag{3}$$

$$w_{a,s}(t+1) = w_{a,s}(t), \tag{4}$$

where

$$\Omega_s(t) = 1 - Q(D_s)\left(1 - \frac{\sum_{\beta=1}^{N_B} S_{\beta,s}\, P\left(\frac{R_\beta(t)}{R_\beta(t-1)}\right)}{\sum_{\beta=1}^{N_B} S_{\beta,s}}\right) \tag{5}$$

with no changes on the bank side, that is, in C_β. The value for the risk weights is capped at $r_{\max} = 2$.

$P(x)$ is a function which allows us to model the bank response to distress. The argument x is the fraction of capital tier 1 ratio left after a shock with respect to the tier 1 capital ratio in the previous time step; accordingly $1 - x$ is the relative loss in one time step. Our analysis considers two broad cases: banks that are risk averse and react to a deterioration of their tier 1 capital ratio accordingly on one hand, and banks that are risk neutral on the other.

Risk attitudes correspond to different curvatures of the utility function. For payoffs, a concave utility function describes the risk aversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985); for losses, the utility function of a risk averse agent therefore is convex. Functions of the form Max $\left[1 - (1-x)^\alpha,\ 0\right]$ are convex, linear, or concave on the interval 0 to 1 depending on the choice of α. For simplicity, we consider a linear approximation,

$$P_\alpha(x) = \mathrm{Max}\left[1 - \alpha(1-x),\quad 0\right] \tag{6}$$

for $0 \le x \le 1$ as the possible bank response functions to a decrease in tier 1 capital ratio. In this case Eq. (5) simplifies to

$$\Omega_s(t) = 1 - \alpha\, Q(D_s)\left(1 - \frac{\sum_{\beta=1}^{N_B} S_{\beta,s}\, \frac{R_\beta(t)}{R_\beta(t-1)}}{\sum_{\beta=1}^{N_B} S_{\beta,s}}\right) \tag{7}$$

In our analysis we focus on the cases $\alpha = 1$ which we call the linear case (risk neutral attitude) and $\alpha = 2$ which we call the steep case (risk averse attitude) as shown in Fig. 5. The linear case implies that a bank will find a 20% drop in tier 1 capital ratio twice as bad as a 10% drop in tier 1 capital ratio. In the steep case, losses would be perceived much more negatively, modeling a larger sensitivity to losses. Therefore the steep function causes a more drastic effect given the same decrease in tier 1 capital ratio. Alternatively, the impact of the parameter α can be interpreted as follows: α determines for which value x the function $P(x)$ reaches the minimum value of zero, the worst case scenario. The larger α, the smaller the decline in tier 1 capital ratio that corresponds to the worst case scenario.

Eqs. (5) and (7) incorporate the CDS spread in basis points D_s. As a bank suffers from an increase in their RWA and a decrease in tier 1 capital ratio, it is reasonable to assume that this will affect debts of different quality differently. The higher the spread is for a sovereign debt, the more its risk weight will increase for the next simulation step. If the SD has a low spreading parameter, it will not be very affected by the banks' financial condition. With this, we model that Greek debt, for example, will deteriorate more given

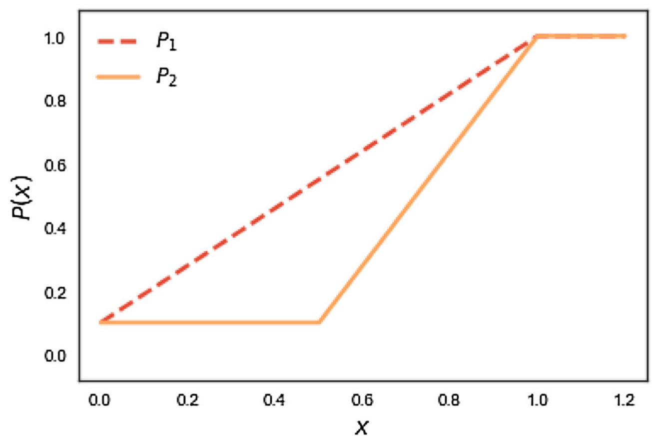

Fig. 5. The reduction factor $P(x)$ in Eq. (5). The dotted curve shows the linear case, and the solid curve shows the steep case.

additional market stress than German debt. We refer to $Q(D_s)$ as the spreading parameter.

The change in risk factors in Eq. (4) changes the RWA as follows:

$$W_\beta^{\mathrm{SD}}(t+1) = \sum_{s=1}^{N_{\mathrm{SD}}} S_{\beta,s} r_s(t)/\Omega_s(t), \tag{8}$$

$$W_\beta^{\mathrm{other}}(t+1) = W_\beta^{\mathrm{other}}(t). \tag{9}$$

4.3.2. Shocking other asset categories

In this crisis scenario, an asset category is being shocked, and there will be spill-over to other asset categories. The simulation process can then be described as follows. We initialize an asset categories in a country or a set of countries to have its risk factor increased at $t = 0$. We consider the same 10 scenarios as in the previous case.

1. At $t = 1$, these shocks on assets are propagated to the banks who own those assets. As a result of the increased risk factors, the RWA of the affected banks is increased and their tier 1 capital ratio decreased.
2. At $t = 2$, those shocks on the banks are propagated back to assets. A bank that is affected by the shock in the previous step might be forced to take action, putting pressure on all their assets in its portfolio. We emulate this by increasing the risk factors of the assets that the affected bank holds, depending on how many of these assets the bank holds and how much its tier 1 capital ratio has decreased. Unlike in the previous scenario where the increase in risk factor was limited to sovereign debts, that is, the asset class in which the shock started, in this scenario the risk weights of all assets of affected banks will increase.
3. At $t = 3$, the increased risk factors across all asset classes lead to a new, higher value for the risk-weighted assets of the banks. Just like in step $t = 1$, this causes a further decrease in tier 1 capital ratio. The propagation continues back and forth until the system saturates.

The capital C_β of bank β remains constant throughout the simulation run.

As pointed out before, it is likely that a stress to a bank's portfolio originating from some of its exposures will lead to adjustments across all asset classes. In that case the shock propagation will not only change the risk factors for sovereign debts, but it will also affect the risk factors for the remaining asset classes. Again, we allow a maximum value of 2 for the risk weights. Extending the shock propagation, we rewrite Eq. (4) as follows:

$$\begin{aligned} r_s(t+1) &= r_s(t)/\Omega_s(t), \\ w_{a,s}(t+1) &= w_{a,s}(t)/\Omega_a(t), \end{aligned} \tag{10}$$

where $\Omega_a(t)$ is extended to the case of non-SDs:

$$\Omega_a(t) = 1 - \alpha\, Q_a \left(1 - \frac{\sum_{\beta=1}^{N_\mathrm{B}} A_{\beta,a} \frac{R_\beta(t)}{R_\beta(t-1)}}{\sum_{\beta=1}^{N_\mathrm{B}} A_{\beta,a}} \right). \tag{11}$$

Like its counterpart for sovereign debts, the shock parameter will depend on the other asset classes through the asset-specific holdings of a bank $A_{\beta,a}$ and the equivalent of a spreading parameter, Q_a. Recall that we have chosen to set Q_a to be the same for all countries.

In the same way as $Q(D_s)$ models the susceptibility of sovereign debt s to deteriorating market conditions, Q_a describes how strongly asset class a is affected by a reduction in tier 1 Capital of banks exposed to it. If we set $Q_a = 0$, we recover Eq. (4) and we prohibit any spillover into other asset classes. For any other value $0 < Q_a \le 1$, banks affected by an initial shock in the SD sector will cause an increase in risk factor for other asset classes, proportionally to their exposures.

4.3.3. Shocking the capital of banks

Previously we have kept the capital C_β of all banks constant. However, we can well imagine a scenario in which a shock to a bank or to a couple of banks stems from a sudden drop in equity. Such a sudden drop would leave a bank potentially over-leveraged, that is, their tier 1 capital ratio becomes too small. Our model allows us to study the effect of such a shock as well. We do this as follows, considering the same 10 scenarios as in the previous case.

1. At $t = 1$, the capital of a bank or a group of banks is reduced by a certain percentage. As a result of that, their tier 1 capital ratio decreases.
2. At $t = 2$, those shocks on the banks are propagated to assets, like in the previous scenarios, the only difference being that all assets start out with their original risk weights. The risk weights of all assets that are held by affected banks will increase.
3. At $t = 3$, the increased risk factors across all asset classes lead to a new, higher value for the risk-weighted assets for all banks holding them. In this step, the crisis originating in a subset of banks spreads to other banks. Again this propagation continues back and forth until the system saturates.

The iteration process follows the same dynamics as in the scenarios in which we shocked sovereign debt and other asset classes, using Eqs. (10) and (11).

5. Simulation results

Using our model, we obtain simulation results for the three different scenarios described in the previous section, (a) shocking sovereign debt, (b) shocking any asset category allowing for spillover, and (c) shocking bank capital. We characterize the initial shock, market conditions, and the behavior of market participants by two parameters and a response function. As the *shock origin* we consider the ten scenarios as described in Section 4.3. The *shocked sector* refers to the part of the financial network in which the shock starts; this may be an asset class or the equity of a bank. When shocking assets, we increase their risk weights, increasing the risk-weighted assets and thus reducing banks' tier 1 capital ratio. The *shock size* ranges from increasing the risk weights by a factor of one-

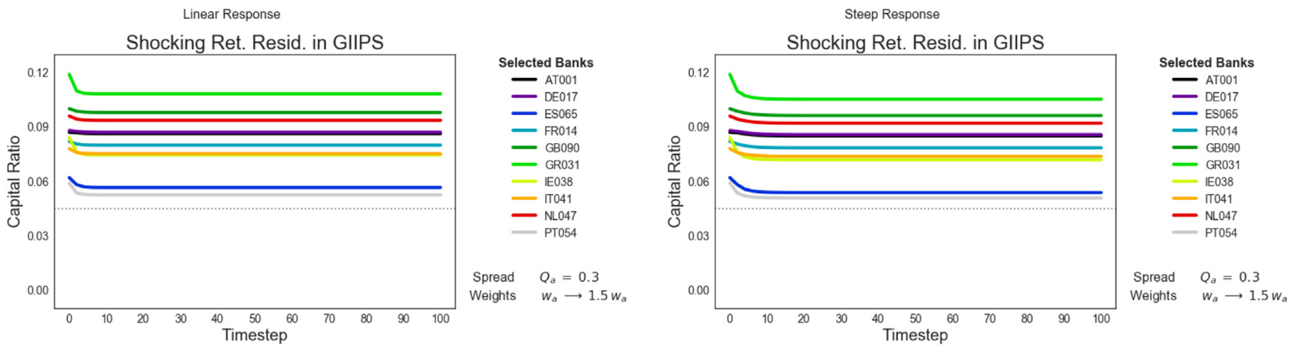

Fig. 6. Tier 1 capital ratios over time after a shock to the retail residential sector in GIIPS countries, given different bank response functions and both a small shock size and a small spreading parameter.

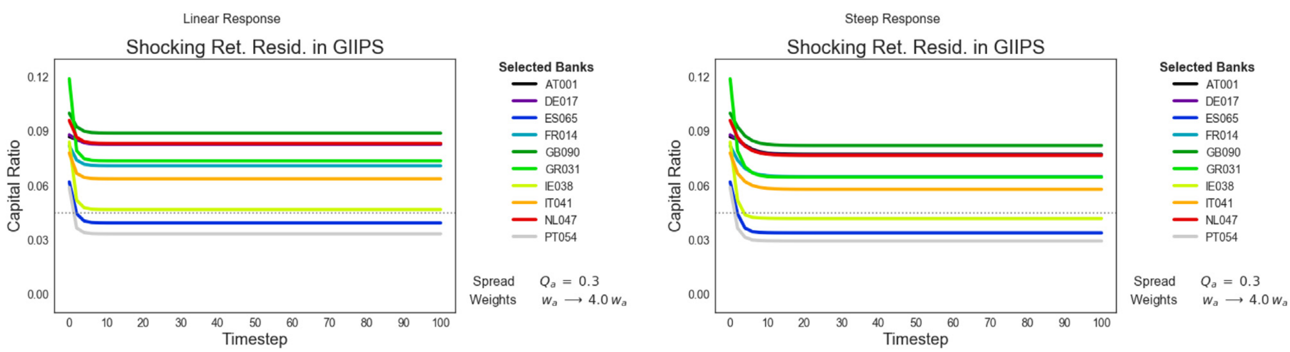

Fig. 7. Tier 1 capital ratios over time after a shock to the retail residential sector in GIIPS countries, given different bank response functions and a large size and a small spreading parameter.

and-a-half to four.[3] We perturb the banks by simulating a sudden decrease of their equity and thus reducing the tier 1 capital ratio; this *shock size* ranges from a reduction by 10 to 90 percent. The *spreading parameter* describes the market conditions for sovereign debt Q_s and for other asset classes Q_a. The spreading parameter Q_s for the sovereign debt is a function of the CDS spread as shown in Fig. 4. The spreading parameters for the other asset classes is a free parameter where for simplicity we set $Q_1 = Q_2 = \cdots = Q_a$ for all asset classes. The *bank response function* $P(x)$ describes the behavior of market participants. We distinguish between the linear and the steep bank response function $P(x)$ as put forth in Eq. (6).

5.1. Shocking sovereign debt only

The first scenario in our simulation considers a shock to sovereign debt without any spillover to the other asset classes. Sovereign debt usually makes up a small fraction of a bank's assets, with exposure of most banks of about one tenth of the total as shown in Fig. 1 in the data section.

If we use risk weights (r_s) for sovereign debt at the lower end of the range described in Table 1, the impact of sovereign debt on a bank's risk-weighted assets becomes all but negligible. Therefore, even a major shock in any of the ten different shock origins will not have any significant effect on banks' risk-weighted assets for initial risk weights $r_s = 0.002$. In turn, the tier 1 capital ratio decrease is so minor that any shock propagation is stalled right away. This finding holds for both the linear and the steep bank response function. Therefore, the value we initially assume for the risk weights r_s becomes crucial.

If we use the risk weights at the upper end of the range in Table 1, $r_s = 0.1$, a major shock such as a fourfold increase in those risk weights for an affected country will have a measurable impact on banks holding a large chunk of this sovereign debt. However, the shock propagation stalls after at most a couple of steps for both the linear and the steep bank response function. If we consider a shock originating in a country or region with very low sovereign debt CDS spread, such as Germany or the Benelux countries, the increase in risk weights diminishes already in the step right after the initial shock. Considering the GIIPS countries, which exhibit the largest CDS spreads in our data set, the shock propagates for two steps; however it does not noticeably impact banks any more than the original shock.

5.2. Allowing for spillover between asset classes

We have observed that shocks to sovereign debt alone do not become systemic events within the framework of our model. This is mainly due to three reasons:

(i) Many banks hold only a low amount of sovereign debt.
(ii) The risks weights of sovereign debt are very low, signifying that it is considered practically riskless. The European sovereign debt crisis at least raises doubts regarding the risk-free nature of sovereign debt.
(iii) We do not consider a spillover between asset classes, that is, a shock to sovereign debt will remain contained within the sovereign debt sector.

We therefore proceed to analyze the results when we include other asset classes with their larger risk weights as the source of shocks as well as when we allow for a spillover from one asset class to another, according to Eqs. (5) and (11).

[3] Recall that we limit the magnitude of a risk weight to $w_{max} = 2$, which shall not be exceeded through the initial shock.

Table 1
Weighted average model for risk-weighted assets. The values for the exposure to different asset classes are for bank AT001. We present an example calculation for risk weights at the lower end of the range determined by our optimization procedure.

a	Item		w_a range	A_a	w_a	w_aA_a
1	Sovereign Debt		[0.002, 0.1]	27,267	0.002	55
2	Financial institutions		[0.5, 1.0]	25,044	0.5	12,522
3	Corporate		[0.5, 1.3]	61,237	0.5	42,866
4	Retail:	Residential Mortgages	[0.5, 0.8]	36,663	0.5	14,665
5		Revolving	[0.8, 1.2]	23,153	0.8	18,522
6		SME	[1.0, 1.3]	3,467	1.0	3,467
7	Commercial real estate		[1, 2]	22,228	1.0	22,228
Total RWA W, according to Eq. (2)						114,325

We take 10 of the 90 banks as a sample to illustrate the dynamics and the outcome of a shock from various origins. The banks are Erste Bank Group (AT001), Deutsche Bank (DE017), Banco de Sabadell (ES065), Credit Agricole (FR014), Barclays (GB090), National Bank of Greece (GR031), Bank of Ireland (IE038), Unicredit (IT041), ING Bank (NL047), and Banco Comercial Portugues (PT054). This selection aims to represent a good cross section of all European banks and to demonstrate one or more banks very vulnerable to the scenarios we consider. For example, we can expect Deutsche Bank to be initially more strongly effected by a crisis that originates in Germany, scenario (7).

The first scenario we consider is a shock which originates in the GIIPS countries, Greece, Italy, Ireland, Portugal and Spain. Figs. 6–8 show the dynamics for the banks given an increase of the risk weights associated with residential mortgages from these countries. For most banks, retail residential mortgages are the most important or second most important asset class by exposure. We present results for different shock sizes, spreading parameters, and bank response function. If we consider a spreading parameter of $Q_a = 0.3$, the system is stable for both a linear and a steep bank response function, as Fig. 6 indicates As a matter of fact, a fourfold increase of the risk weights does not cause a systemic event either, see Fig. 7. The sudden large increase in risk weights, however, causes a tremendous decline in the tier 1 capital ratio for banks heavily involved in mortgages in this region. Banks from other than GIIPS countries see an obvious downtick in their tier 1 capital ratios as well. As a consequence, a couple of banks fall below the Basel III threshold.

If we increase the spreading parameter to $Q_a = 0.6$ while still considering a linear bank response function, the system remains in the stable regime, and the initial shock does not cause a spillover. If we consider a spreading parameter of $Q_a = 0.6$ and assume a steep bank response function, however, the system exhibits instability. This can be seen in Fig. 8, and it holds true for any shock size. While an increase of risk weights increase of $w_a \to 4w_a$ could not cause a systemic event for a lower spreading parameter or a linear bank response function, even the smallest increase of w_a will trigger a systemic event if the spreading parameter is sufficiently large and we use the steep bank response function. As an example, Fig. 8 shows how $w_a \to 1.5w_a$ causes all banks to eventually fall below the Basel III threshold in our simulations.

Fig. 8 has demonstrated that even small shocks may eventually cause a systemic event, given an adverse set of parameters. While we concluded that sovereign debt in isolation cannot trigger a systemic event, we revisit this problem, now allowing for spillover to other asset classes. Specifically, we focus on the conditions that have facilitated a systemic event after an initial shock to residential mortgages. Fig. 9 shows the dynamics for the banks given an increase of risk weights for sovereign debt from GIIPS countries from 0.002 to 0.008. We use a spreading parameter of $Q_a = 0.6$ and the steep bank response function. While the slope of the tier 1 capital ratio decline is much less than in Fig. 8 and therefore the development of the systemic event is considerably slower, the dynamics become equivalent. Indeed, the final tier 1 capital values for the banks are very similar for both cases, not shown in the figure.

Our observations for these two cases hold for a shock origin in other asset classes from the GIIPS countries as well. In absence of a systemic event, the final tier 1 capital ratio of a bank can be well approximated by the impact of the initial shock on its tier 1 capital ratio. In other words, the exposure to a specific asset class from a specific country determines the magnitude of tier 1 capital losses. If we observe a systemic event, however, banks start deteriorating uniformly as the initial shock has spread to all asset classes. In this case, the initial exposure to a specific asset class from a specific country influences only the initial rate of decline, but it does not affect the outcome.

Table 2 indicates how many banks would be distressed in the ten scenarios we have proposed. Since only the steep bank response function and a high enough spreading parameter can trigger a systemic event, we consider shocks to all seven sectors given $P_{steep}(x)$ and $Q_a = 0.6$. We report how many banks fall below the Basel III threshold after 50 time steps and after 100 time steps. As we can see by comparing Figs. 8 and 9, shocks to different sectors and with different shock sizes permeate the system at different speeds.

In many cases, two thirds or more of the 90 banks can be considered distressed in our simulation after 100 time steps. This is true regardless of shock origin and the asset class which is initially shocked. The largest average distress across all asset classes can be found when shocking the GIIPS countries; 65.6 percent of all banks have fallen below the Basel III threshold after 100 time steps. Even after only 50 time steps, shocks to assets from the GIIPS country have large destructive capacity, distressing nearly half of all banks. A shock to assets from Spain leads to the second largest number of distressed banks across all sectors, with 64.9 percent of all banks having a tier 1 capital ratio of less than 4.5% after 100 time steps. As compared to a shock to the GIIPS countries of which Spain is a part, a shock to assets from Spain tends to spread more slowly, leaving only about a quarter of banks distressed after 50 time steps. We observe that, while most shocks have large negative impacts, a shock to corporate loans damages the system very quickly. In contrast, shocks to retail SME loans or commercial real estate tend to spread out more slowly, allowing for more time to intervene. We report these results in more detail in the appendix in Table 12, 13, 14, 15, 16, 17, 18 and 19.

5.3. Shocking the equity of banks

So far we have only shocked the risk-weighted assets of the banks. Subsequently, we simulate the reduction of equity in a subset of banks. Since in this study we analyze the European banking system, we focus on scenarios (1) through (8). We report both the average loss in tier 1 capital ratio as well as the number of banks which fall below the Basel III threshold of 4.5 percent. The results are presented in Tables 3–10.

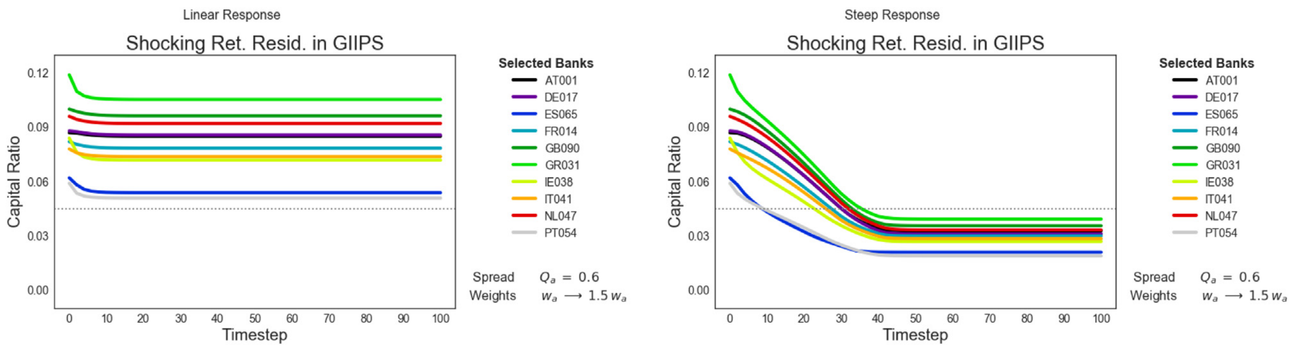

Fig. 8. Tier 1 capital ratios over time after a shock to the retail residential sector in GIIPS countries, given different bank response functions and a small shock size and a larger spreading parameter.

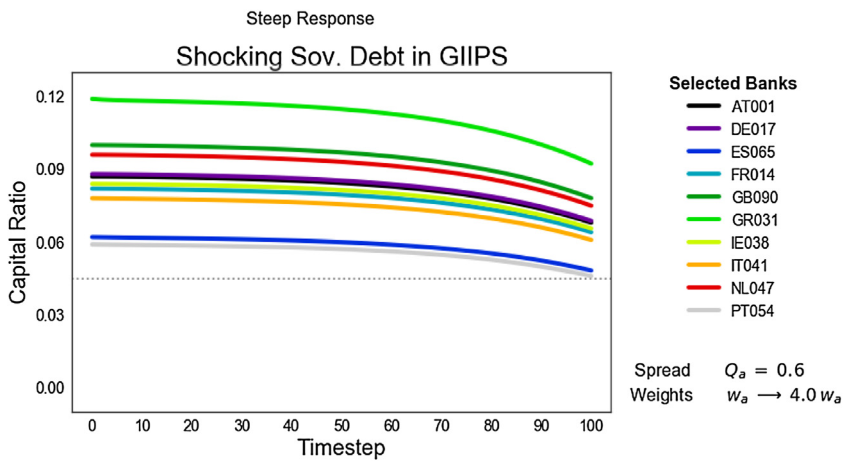

Fig. 9. Tier 1 capital ratios over time after a shock to sovereign debt in GIIPS countries, given different bank response functions and spreading parameters. Note that only the first 100 time steps of the simulation are shown, and after roughly 100 time steps more the system reaches a stationary state like in Fig. 8.

Table 2
Number of banks that would fall below the Basel III threshold of 4.5% tier 1 capital ratio given a shock to different sectors in each of our ten scenarios. We list the number of distressed banks after 50 simulation time steps (D_{50}) and after 100 simulation time steps (D_{100}). The initial shock is a sudden increase of the risk weights of the shocked sector of a particular country or region by 50%, causing an increase of the risk-weighted assets of banks. The numbers include the two banks which are below the threshold originally.

Sector	Financial		Corporate		Ret. Resid.		Ret. Rev.		Ret. SME		Comm. RE		Average	
Origin	D_{50}	D_{100}	D_{50}	D_{100}	D_{50}	D_{100}	D_{50}	D_{100}	D_{50}	D_{100}	D_{50}	D_{100}	D_{50}	D_{100}
(1) GIIPS	72	77	71	72	78	81	12	75	48	76	55	76	48.6	65.6
(2) EE	5	75	35	76	5	74	3	27	4	56	5	67	8.4	53.9
(3) Benelux	7	75	57	76	19	76	3	8	5	69	5	69	14.0	53.6
(4) Greece	3	56	15	76	4	59	3	15	3	18	3	48	4.7	39.1
(5) Italy	27	77	69	75	20	76	3	20	16	76	17	76	22.0	57.4
(6) France	8	76	68	75	22	76	3	44	8	75	5	71	16.6	59.9
(7) Germany	72	77	71	75	21	78	3	22	5	69	25	76	28.4	57.0
(8) Spain	19	78	68	75	60	80	5	69	12	75	12	75	25.7	64.9
(9) US	12	77	69	75	25	76	5	69	4	64	10	75	18.3	62.6
(10) Japan	3	62	22	76	5	69	3	15	3	53	3	55	5.6	47.6
Average	22.9	73.1	54.5	75.1	25.9	74.5	4.4	36.4	11.0	63.1	14.1	68.8	19.3	56.1

Table 3
Effect of an equity shock that originates in the GIIPS countries. There are a total of 43 banks from these countries. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in GIIPS countries (Loss GIIPS) as well as the average loss in tier 1 capital ratio for banks in other than GIIPS countries (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for the GIIPS countries (D_{100} GIIPS) and for other than GIIPS countries (D_{100} Other).

Origin	Shock size	Q_A	$P(x)$	Loss Avg	Loss GIIPS	Loss other	D_{100} Total	D_{100} GIIPS	D_{100} Other
GIIPS	20%	0.3	lin	12.1	24.0	1.2	5	5	0
			steep	16.1	29.5	3.8	11	10	1
		0.9	lin	31.9	46.9	18.2	27	25	2
			steep	72.0	75.2	69.1	88	42	46
	50%	0.3	lin	28.4	56.1	3.0	35	34	1
			steep	33.7	61.8	7.9	38	37	1
		0.9	lin	57.6	79.4	37.7	47	42	5
			steep	76.4	84.5	69.1	89	43	46

Table 4
Effect of an equity shock that originates in the Eastern European countries. There are a total of 4 banks from these countries. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Eastern Europe (Loss EE) as well as the average loss in tier 1 capital ratio for banks in other than Eastern European countries (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for the Eastern Europe (D_{100} EE) and for other than Eastern European countries (D_{100} Other).

Origin	Shock size	Q_A	$P(x)$	Loss Avg	Loss EE	Loss other	D_{100} Total	D_{100} EE	D_{100} Other
Eastern Europe	20%	0.3	lin	1.0	21.2	0.0	3	1	2
			steep	1.1	22.5	0.1	3	1	2
		0.9	lin	1.4	24.8	0.3	3	1	2
			steep	69.3	74.3	69.1	87	4	83
	50%	0.3	lin	2.4	52.0	0.0	4	2	2
			steep	2.5	53.2	0.1	4	2	2
		0.9	lin	3.4	57.7	0.9	4	2	2
			steep	69.7	84.0	69.1	87	4	83

Table 5
Effect of an equity shock that originates in the Benelux countries. There are a total of 7 banks from these countries. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Benelux countries (Loss Benelux) as well as the average loss in tier 1 capital ratio for banks in other than Benelux countries (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for the Benelux countries (D_{100} Benelux) and for other than Benelux countries (D_{100} Other).

Origin	Shock size	Q_A	$P(x)$	Loss Avg	Loss Benelux	Loss other	D_{100} Total	D_{100} Benelux	D_{100} Other
Benelux	20%	0.3	lin	2.2	21.8	0.6	2	0	2
			steep	3.5	24.1	1.8	3	0	3
		0.9	lin	10.1	31.4	8.3	3	0	3
			steep	69.5	77.5	68.8	87	7	80
	50%	0.3	lin	5.4	52.8	1.4	3	1	2
			steep	7.8	55.3	3.8	6	3	3
		0.9	lin	24.3	67.3	20.7	14	7	7
			steep	70.1	85.9	68.8	87	7	80

Table 6
Effect of an equity shock that originates in Greece. There are a total of 6 banks in Greece. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Greece (Loss Greece) as well as the average loss in tier 1 capital ratio for banks in other than Greece (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Greece (D_{100} Greece) and for other than Greece (D_{100} Other).

Origin	Shock Size	Q_A	$P(x)$	Loss Avg	Loss Greece	Loss Other	D_{100} Total	D_{100} Greece	D_{100} Other
Greece	20%	0.3	lin	1.6	22.5	0.1	2	0	2
			steep	2.0	25.3	0.3	2	0	2
		0.9	lin	3.2	31.2	1.2	3	1	2
			steep	69.4	75.0	69.0	88	6	82
	50%	0.3	lin	3.8	53.8	0.2	5	3	2
			steep	4.3	56.8	0.6	5	3	2
		0.9	lin	7.6	67.1	3.4	8	5	3
			steep	70.1	84.4	69.0	88	6	82

Table 7
Effect of an equity shock that originates in Italy. There are a total of 6 banks in Italy. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Italy (Loss Italy) as well as the average loss in tier 1 capital ratio for banks in other than Italy (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Italy (D_{100} Italy) and for other than Italy (D_{100} Other).

Origin	Shock Size	Q_A	$P(x)$	Loss Avg	Loss Italy	Loss Other	D_{100} Total	D_{100} Italy	D_{100} Other
Italy	20%	0.3	lin	1.6	22.7	0.4	4	2	2
			steep	2.7	26.0	1.4	4	2	2
		0.9	lin	8.3	34.9	6.8	6	3	3
			steep	69.4	72.9	69.2	87	5	82
	50%	0.3	lin	4.0	54.2	1.1	7	5	2
			steep	5.9	57.7	2.9	8	5	3
		0.9	lin	20.9	71.7	18.0	10	5	5
			steep	70.0	83.1	69.2	87	5	82

It comes as no surprise that a shock to banks in the GIIPS countries would have the largest effect on the entire system. Almost half of the banks in our data set are based in one of these five countries, and therefore the size of the initial shock would be quite significant. Furthermore, we recognize that a linear bank response function effectively stops spillover of the crisis. For example, in scenario (i), even given the largest shock size of 50 percent and a large spreading parameter of $Q_a = 0.9$, only five banks from other countries would fall below the Basel III requirements. The importance of the spreading parameter is again amplified in case of the steep response function: If the spreading parameter is large and we assume a steep bank response function, the initial shock size matters very little. Almost all banks would fall below the Basel III tier 1 capital ratio threshold given these parameters, regardless of where the shock originated.

Table 8
Effect of an equity shock that originates in France. There are a total of 4 banks in France. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in France (Loss France) as well as the average loss in tier 1 capital ratio for banks in other than France (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for France (D_{100} France) and for other than France (D_{100} Other).

Origin	Shock Size	Q_A	$P(x)$	Loss Avg	Loss France	Loss Other	D_{100} Total	D_{100} France	D_{100} Other
France	20%	0.3	lin	1.7	21.7	0.8	2	0	2
			steep	3.4	24.1	2.4	3	0	3
		0.9	lin	12.0	32.8	11.0	4	0	4
			steep	69.3	74.5	69.1	87	4	83
	50%	0.3	lin	4.2	52.6	1.9	6	4	2
			steep	7.3	55.3	5.0	7	4	3
		0.9	lin	28.3	68.6	26.4	12	4	8
			steep	69.7	84.0	69.1	87	4	83

Table 9
Effect of an equity shock that originates in Germany. There are a total of 12 banks in Germany. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Germany (Loss Germany) as well as the average loss in tier 1 capital ratio for banks in other than Germany (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Germany (D_{100} Germany) and for other than Germany (D_{100} Other).

Origin	Shock Size	Q_A	$P(x)$	Loss Avg	Loss Germany	Loss Other	D_{100} Total	D_{100} Germany	D_{100} Other
Germany	20%	0.3	lin	3.6	22.5	0.6	3	1	2
			steep	5.3	25.8	2.1	3	1	2
		0.9	lin	13.6	35.8	10.2	3	1	2
			steep	69.9	75.2	69.0	87	11	76
	50%	0.3	lin	8.6	53.9	1.6	8	6	2
			steep	11.5	57.4	4.4	9	7	2
		0.9	lin	31.8	72.8	25.5	18	11	7
			steep	71.1	84.5	69.0	87	11	76

Table 10
Effect of an equity shock that originates in Spain. There are a total of 25 banks in Spain. We simulate a sudden drop of bank equity by 20% and by 50%. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Spain (Loss Spain) as well as the average loss in tier 1 capital ratio for banks in other than Spain (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Spain (D_{100} Spain) and for other than Spain (D_{100} Other).

Origin	Shock Size	Q_A	$P(x)$	Loss Avg	Loss Spain	Loss Other	D_{100} Total	D_{100} Spain	D_{100} Other
Spain	20%	0.3	lin	7.0	24.3	0.4	3	2	1
			steep	9.3	30.0	1.4	7	6	1
		0.9	lin	18.8	45.7	8.4	17	15	2
			steep	70.7	75.4	68.9	87	24	63
	50%	0.3	lin	16.4	56.7	0.9	21	20	1
			steep	19.5	62.5	3.0	23	21	2
		0.9	lin	37.4	80.2	21.0	29	24	5
			steep	73.3	84.6	68.9	88	25	63

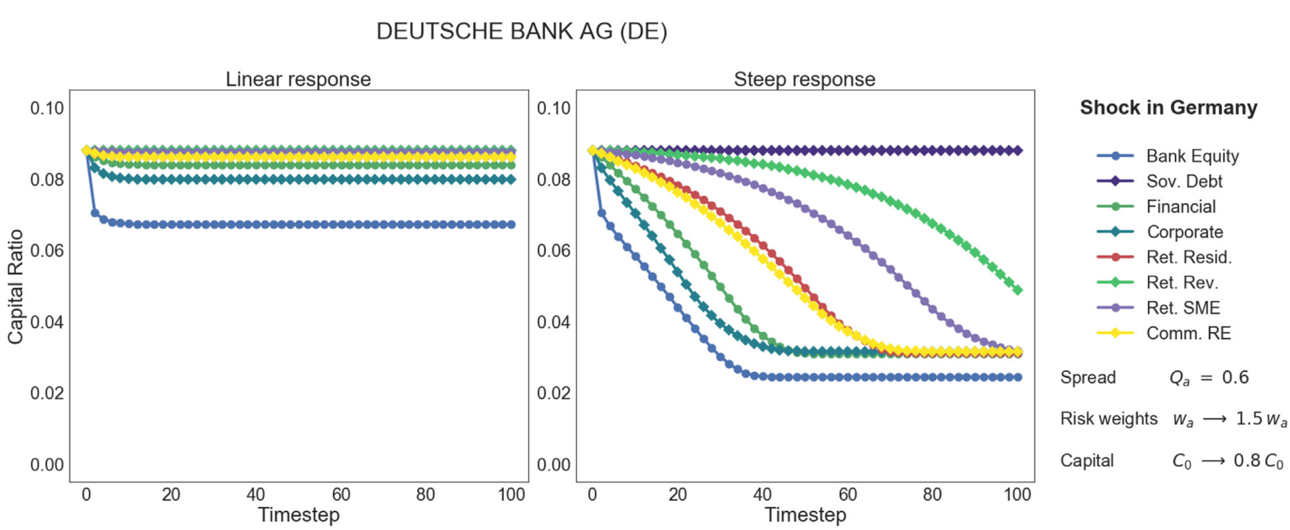

Fig. 10. Evolution of the tier 1 capital ratio of Deutsche Bank (DE017) for a shock to various sectors in Germany, given a linear response function and a steep response function.

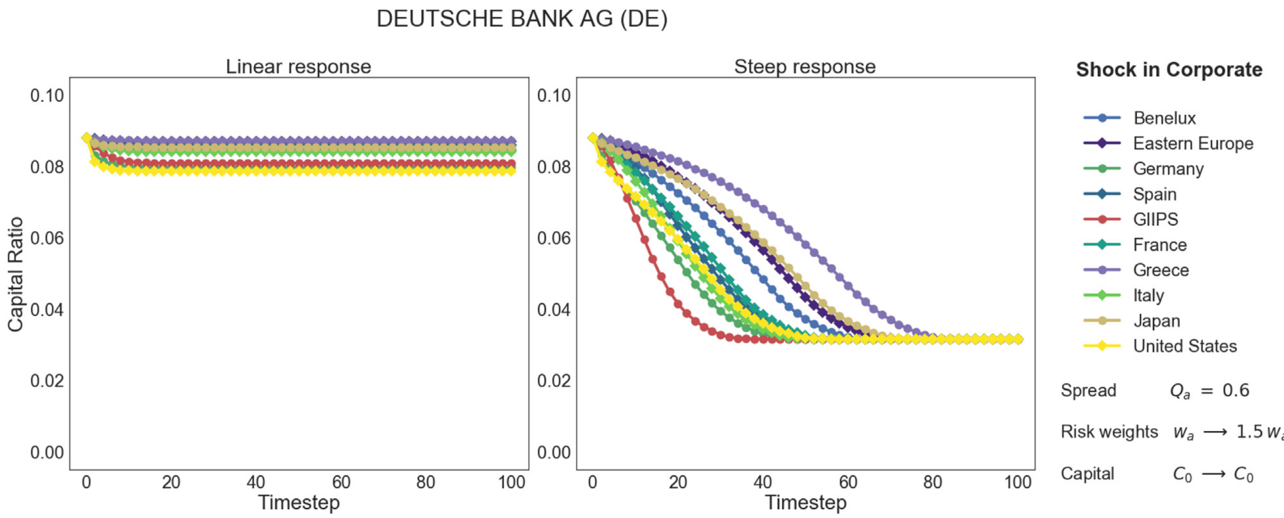

Fig. 11. Evolution of the tier 1 capital ratio of Deutsche Bank (DE017) for a shock to corporate loans in various countries or regions, given a linear response function and a steep response function.

In order to compare the dynamics of a shock to a bank's equity, that is, a direct shock, to the dynamics after an indirect shock through an asset class, we consider in more detail the outcomes for Deutsche Bank (DE017) as an example. Fig. 10 illustrates the development of the tier 1 capital ratio of Deutsche Bank for a shock to asset classes from Germany as well as the equity of all German banks. We initialize the shock by an increase of risk weights of the shocked asset class by 50 percent or decreasing the equity of German banks by 20 percent, respectively. We let the simulation run until a stationary state is reached; for better comparability we only show the results of the first 100 time steps, though.

We confirm that the linear response triggers now systemic event and we focus on the results for the steep response function. A shock to the equity of all German banks has both the largest initial impact on Deutsche Bank and leads to the lowest tier 1 capital ratio at the end of the simulation. In fact, the final tier 1 capital ratio is about one fifth lower than for shock to other asset classes. A shock to corporate loans or financial loans from Germany causes the fastest deterioration of the tier 1 capital ratio of Deutsche Bank, as this bank is strongly invested in these two asset classes. Shocks to other asset classes lead to slightly different dynamics: While the tier 1 capital ratio in the cases of initial shocks to corporate and financial loans is practically linear, a shock to other asset classes starts slowly, with a low downward slope, but picks up pace as time goes by. Apparently, an initial shock in these asset classes builds up slowly and it is not until other, more important asset classes to the bank become affected that the propagation causes bigger losses. Interestingly, for this reason, the shock that originates in the corporate loan sector and causes a tier 1 capital ratio decline the fastest leaves the bank at a slightly higher tier 1 capital ratio at the end of the simulation. The shock spreads at such a high rate that the maximum risk weight of $w_a = 2$ is achieved very quickly for this asset class, stalling the propagation before "infecting" other asset classes. It needs to be pointed out, though, that this difference is minor, and in all cases Deutsche Bank falls below the Basel III threshold in our simulations.

In Fig. 10, we only consider shocks that originate in Germany, affecting German assets and German banks' equity initially. Fig. 11 focusses on the asset class of corporate loans, which we have identified as the shock affecting the bank the fastest, and we differentiate now by origin of shock. The shock size and spreading parameter are the same as in the previous discussion. Since we have used the sovereign debt holdings of Deutsche Bank to approximate its holdings in other classes, Fig. 11 is an approximation to how affected the bank will be due to its holdings as well as the potential of a shock to spread throughout the market. Again, we only observe a decrease in tier 1 capital ratio through the initial shock using the linear bank response function, and we observe a systemic event using the steep bank response function. As we have seen before, a shock to assets from GIIPS countries leads to the fastest decline in tier 1 capital ratio for Deutsche Bank, which reflects the size of the original shock, followed by a shock to German assets which reflects the domestic bias of Deutsche Bank. Interestingly, a shock to US exhibits a very quick decline in tier 1 capital ratio as well. This is not too surprising however, because we would expect an global player like Deutsche Bank to be very active on the US market. It takes the longest time for shocks from Greece (due to the comparably low amount of Greek assets on the market), Japan and Eastern Europe (due to the limited amount of holdings in these regions) to put Deutsche Bank below the Basel III threshold. However, as before the initial shocks all converge to roughly the same final value of tier 1 capital ratio for Deutsche Bank.

5.4. Phase space analysis

In our exploration of specific parameters, we have recognized that there appears to be a phase transition for the steep bank response function, depending on the value for the spreading parameter. In the following we expand our analysis to a wide range of parameters for both, a linear and a steep response function. We use a shock originating in the Benelux countries as an example to discuss the outcome for the banks in our sample given. We choose the Benelux countries because unlike a shock to the GIIPS countries which involves a very large amount of assets and banks or to Eastern Europe, for example, which involves much fewer assets and banks, this scenario corresponds to a mid-sized shock with respect to assets and number of initially affected banks. We want to point out that the following analysis and its findings are applicable to shocks from different origins.

Fig. 12 show the phase diagrams for a shock originating in the Benelux countries, using a linear bank response function. Each of the subplots captures a different crisis origin and explores the outcome for a wide range of parameters of shock size and spreading. We consider a crisis onset due to a sudden loss in tier 1 equity for all banks in the Benelux countries as well as crisis onsets due to a sudden increase in risk weights for assets from a given asset class in Portugal, Italy, Ireland, Greece, and Spain. We allow the shock between banks and assets to propagate back and forth for 200 time steps, that is, 100 propagations from assets to banks and

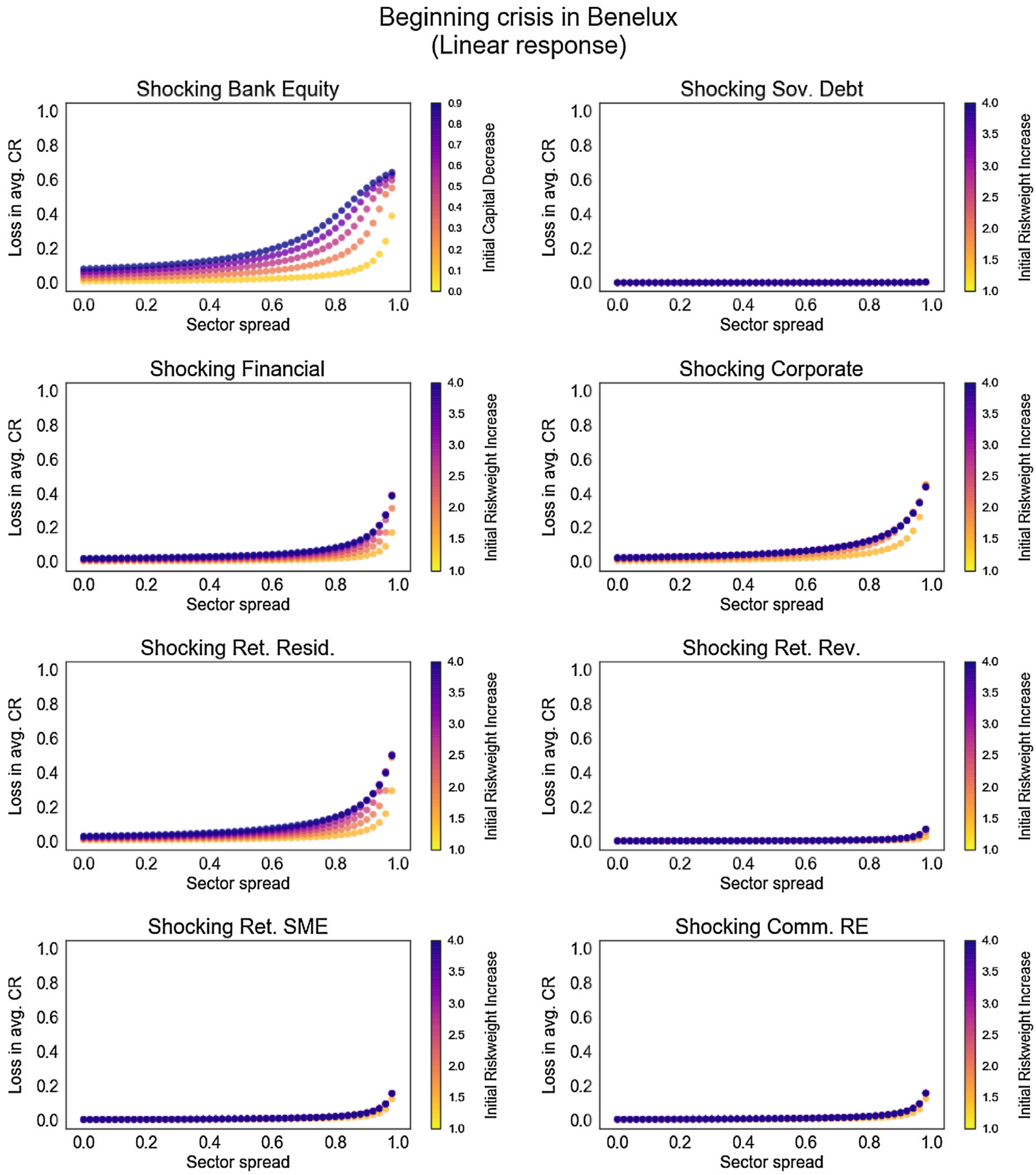

Fig. 12. Phase space for different scenarios given a linear bank response function: We consider a variety of initial shock sizes to banks and asset classes as well as a variety of values for the spreading parameter. We observe no amplification of shocks. The size of the initial shock is indicated by the color, where from yellow (small shock) to dark purple (very large shock). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

100 propagations back from banks to assets. On the y-axis we show the average decrease in tier 1 capital ratio of all banks. On the x-axis we show the sector spread, that is, the value of the parameter Q_a, which indicates how affected an asset from a given asset class is when banks holding it experience distress. For the presentation of these results, we set $Q_2 = \ldots = Q_a$ for all asset classes except the sovereign debt where we use the idiosyncratic values from the CDS swaps. Indicated by colors is the size of the original shock. We consider the following range of shock sizes: In the case of banks, we reduce the capital by 10 to 90 percent. In the case of the other assets, the shock is initiated by an increase of risk weights by 50 percent up to a fourfold increase.

Our main observation in Fig. 12 is that, as expected, the impact on banks grows with the size of the spillover Q between sectors grows as well as with the size of the original shock. A shock scenario which begins with a sudden reduction in capital for banks in our data set appears to have the largest negative effect on the system. Let us first consider the scenario in which all banks in the Benelux countries were to suffer from an abrupt loss of 10 percent of their equity and therefore suffer from a reduction of their tier 1 capital ratio by 10 percent. The systemic consequences then depend on the size of the spreading parameter, Q_a. In the case of weak spreading, $Q_a = 0.3$, banks from Benelux countries see a total reduction of their tier 1 capital ratio R of 11.0 percent, barely more than through the initial shock alone. Banks from all other countries will see a reduction in their R of 0.3 percent. This comes out to an average reduction in R of 1.1 percent, reflecting that there are far fewer banks in the Benelux countries than in the rest of Europe. In

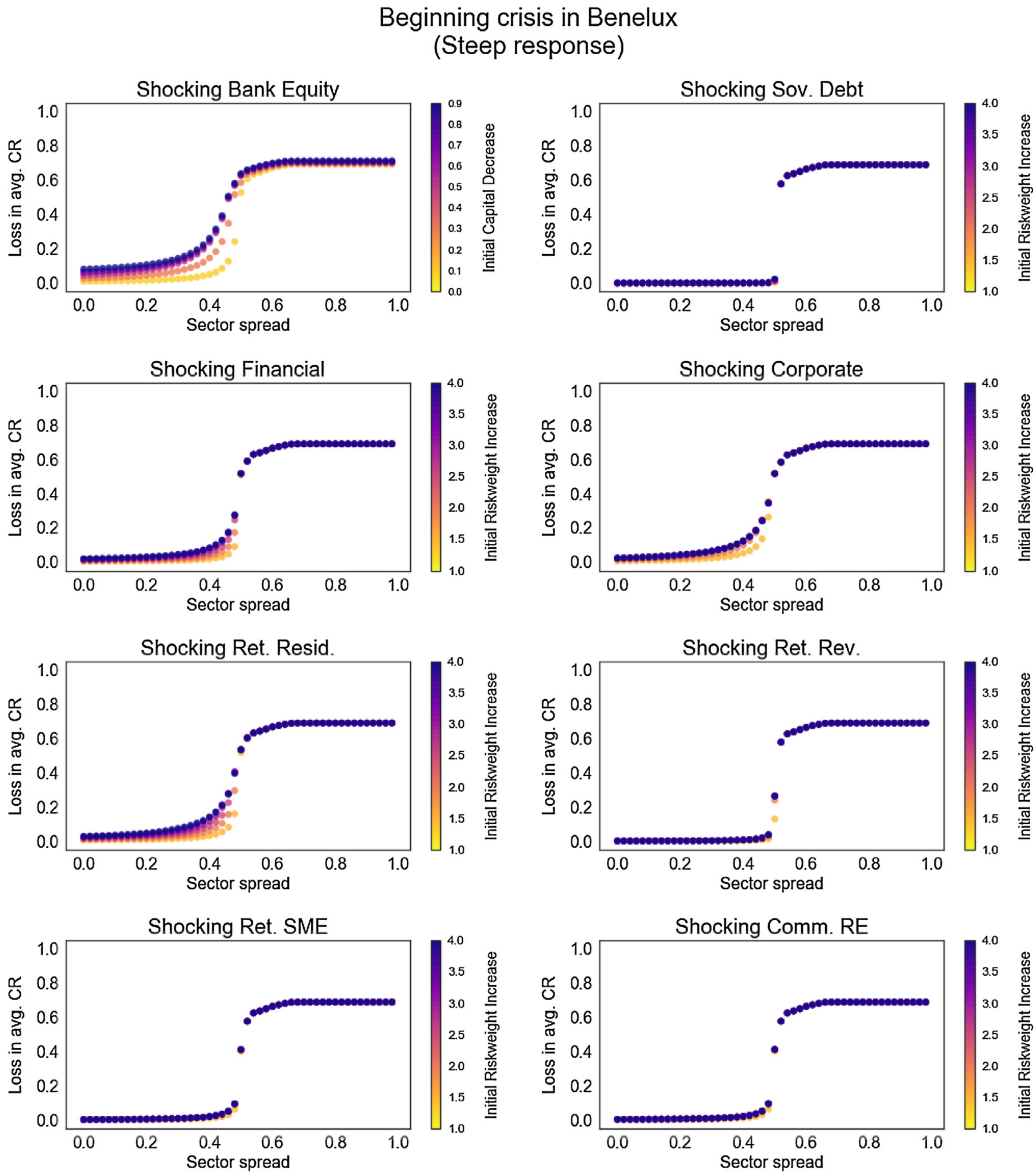

Fig. 13. Phase space for different scenarios given a steep bank response function: We consider a variety of initial shock sizes to banks and asset classes as well as a variety of values for the spreading parameter. The size of the initial shock is indicated by the color, where from yellow (small shock) to dark purple (very large shock). We observe behavior reminiscent of a second order phase transition, where the critical parameter is the magnitude of the sector spread Q_a. The tipping point of the system appears to be around $Q_a = 0.55$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the case of strong spreading, $Q_a = 0.9$, the reduction in tier 1 capital ratio for banks from Benelux countries is more drastic, amounting to a total of 16.5 percent. We also observe a noticeable effect on banks from other European countries which see their R reduced by 4.1 percent. With larger initial shock size, these numbers become bigger, but not systemically. This is quite analogous to our previous discussion in Section 5.3 and reflected in Table 5.

The results are very different, as we have discussed before, if we consider a steep bank response function. We recognize two distinct regimes of the system in Fig. 13, depending on the size of the spreading parameter. If $Q_a \leq 0.5$, then the loss in the tier 1 capital ratios of banks grows, but it grows slowly and steadily with increasing Q_a and with increasing initial shock size, very much in the same fashion as it has in Fig. 12 for the linear bank response function. However, if $Q_a \geq 0.6$, banks lose, on average, about 75% of their tier 1 capital ratio. In other words, all banks with less than 18 percent tier 1 capital ratio at the onset of the simulation are in acute danger of falling the stress test in this scenario. Remarkably, this behavior is true for all asset classes and bank equity, with the exception of sovereign debt which we will discuss later. Furthermore, regardless of the asset class in which the shock originated and regardless of the size of the initial shock size, the final tier 1 capital ratio of banks will be the same.

We speculate that the system exhibits a phase transition around $Q_a = 0.55$, and as a consequence the banking network can be extremely fragile. Below this parameter, an initial shock can be

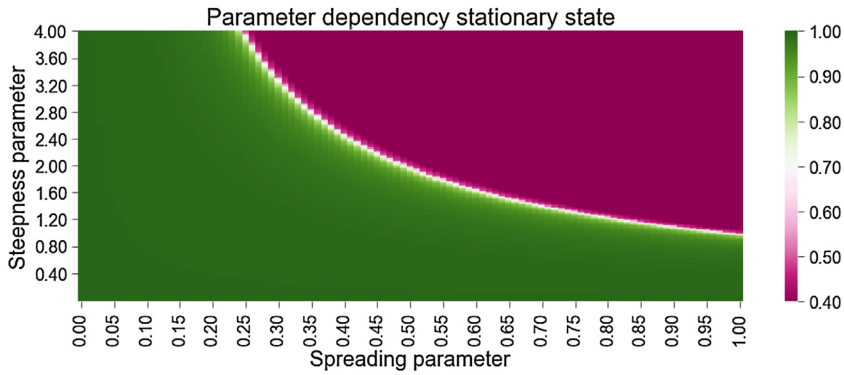

Fig. 14. Stationary state that the system reaches in the simulation depending on the spreading parameter Q_a and the steepness parameter α. Green colors indicate a very small average deterioration of the tier 1 capital ratios of the banks in the system, whereas purple indicates the worst attainable stationary state. The bright line separating the two regimes indicates the point of the phase transition. The plot corresponds to a shock to loans in the French financial sector. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

quite damaging to banks, however it diminishes over time. Above this parameter, an initial shock does not diminish as quickly as it spreads to other sectors of the system. Instead it has the potency to affect all asset classes and thus all banks.

This sudden switching behavior can be better understood when considering the slope at the transition as well as the dependence on the initial shock size leading up to the transition point. We observe that the transition is smoothest for a shock to bank equity, followed by a shock to corporate loans and loans to financial institutions. Since corporate loans and loans to financial institutions tend to make up a very large part of the balance sheets of banks, especially larger banks, a shock to these asset classes is more impactful than a shock to other asset classes. Likewise, a shock to bank equity of 10 or 20 percent or more is a significant shock. In contrast, a shock to revolving retail or SME has only a minor initial impact on many banks. For the sake of the argument, let's consider a fairly small shock to the risk weights of a given asset class. Obviously, no disruption to a specific asset class by itself by themselves cause a systemic event because banks are diversified across asset classes and countries, and therefore a small change to one risk weight will be a very small change to a bank's overall risk-weighted assets – and, in turn, to its tier 1 capital ratio. A systemic event gets underway if the initial shock can fester for long enough and spread to other countries and asset classes, increasing the associated risk weights. In the case of the bigger asset classes (corporate and financial) as well as equity, the initial shock will have had a measurable impact already, such that the transition looks less sharp. In the case of the smaller asset classes (ret. revolving and SME), however, the transition is very sudden: Below a certain spreading parameter, the shock remains contained and the possible damage to tier 1 capital ratios is bounded by the volume of these asset classes; but beyond that spreading parameter, the shock spreads to all parts of the system.

A notable exception is sovereign debt. Due the low risk weights and also the idiosyncratic spreading parameters derived from the CDS swaps, an initial shock within the scope of current risk weights is often just too small to cause a systemic event. Given a very large initial shock or very many time steps, a systemic event can, nevertheless, be triggered by a shock to sovereign debt. The value of Q_a for the phase transition, however, may be very different than that for the other asset classes. This again reflects the idiosyncratic spreading parameters.

Fig. 14 shows the dependency of the outcome of the simulation with respect to the parameters Q_a and α which we had identified as critical parameters of the phase transition. We observe that there is a sharp boundary between two regimes, one corresponding to the resilient and one corresponding to the fragile phase. If we increase Q_a, the steepness parameter α necessary for a regime switch decreases accordingly. Interpreting the steepness parameter as an indicator of risk aversion, this implies that if the market is fragile, small amounts of risk aversion among the banks may be sufficient to topple the system. Conversely, if Q_a, a measure related to the probability of default of the assets, is small, the banking system is particularly robust, even if banks are very risk averse. Fig. 14 illustrates one specific shock scenario, that of a shock to financial institutions in France; other scenarios yield a similar result with a small shift to the regime boundary.

6. Discussion and conclusion

In this paper we have analyzed the European Banking Authority stress test results. We have created a bipartite network with banks on one side and assets on the other, based on European banks' holdings of sovereign debt from 30 European nations, the United States, and Japan. We have proposed a systemic risk propagation in which we take into consideration the interconnectivity between banks based on the overlap of their asset portfolios. We have analyzed the systemic impact of shocks to bank assets by increasing the risk weight of these assets as well as of shocks to the equity of banks. Both types of shocks lead to an initial decrease in the tier 1 capital ratio of the affected banks. In our propagation model a deterioration of the tier 1 capital ratio prompts a reaction of the banks, putting stress on assets in their portfolio and further enhancing the crisis. We have considered a linear response of banks to the shock and we confirm that banks are more affected by the initial shock than by subsequent spillovers. In accordance with Glasserman and Young (2015), we find no significant contagion, hence the effect of the shock is locally contained and can be explained by portfolio overlap and the size of the initial shock. If, however, the banks' response is described by a steeper function, the stability of the banking network becomes strongly dependent on a spreading parameter. This spreading parameter has a critical value associated with a phase transition. Below the critical value, the system exhibits stability and is comparable to the linear case: We observe no spillover and losses depend on both the size of the initial shock and the origin of the shock. However, above the critical value the system breaks down, and we observe a very large deterioration of the tier 1 capital ratio of all banks; in fact most banks fall below the Basel III threshold. The critical value depends slightly on the origin of the shock and the asset class; however, the outcome for the banks beyond the critical value of the spreading parameter is then independent of the origin of the shock and of the size of the initial shock.

Our results show that even though the systemic risk propagation through the banking network is homogeneous once strong contagion is present, the trajectory of tier 1 capital ratio deterioration for a given bank depends on the origin of the shock, the size of the shock and its balance sheet. We suggest that our model is a good complement to the current stress tests to capture the interconnectivity of banks due to their portfolio similarities, their business models, and their regional biases. Understanding these dynamics can be helpful to regulators as well as policy makers, and it may serve to inform the impact of interventions and the lack thereof in times of crisis.

Acknowledgment

The authors would like to thank J. Detemple, Y. Ikeda, W. Souma, and H. Yoshikawa for their encouraging and helpful comments and discussions. This study was supported in part by the Projects "Large-scale Simulation and Analysis of Economic Network for Macro Prudential Policy" and "Dynamics of Economy and Finance from the Economic Network Point of View" undertaken at Research Institute of Economy, Trade and Industry (RIETI), MEXT, JAPANas Exploratory Challenges on Post-K computer (Studies of Multi-level Spatiotemporal Simulation of Socioeconomic Phenomena, Macroeconomic Simulations), Grant-in-Aid for Scientific Research (KAKENHI) by JSPS Grant Numbers 17H02041, 18K03451, and 20H02391, NSF EAGER-SES Grant1452061, and U.S. DoD, Network Science Division, Army Research Office (ARO), award ID: W911NF2010187.

Appendix A. Additional tables

Table 11
20 largest banks in the data set, sorted by value of assets. The international degree is the number of links indicating a large portfolio overlap a bank has to banks outside of its own country, as shown in Fig. 2. For comparison, the mean and median international degree across all banks in the data set are 2.4 and 1.5, respectively.

Ranking	Bank Code	Bank Name	International degree
1	GB089	HSBC HOLDINGS plc	10
2	FR013	BNP PARIBAS	10
3	GB088	ROYAL BANK OF SCOTLAND GROUP plc	3
4	DE017	DEUTSCHE BANK AG	7
5	FR014	CREDIT AGRICOLE	2
6	NL047	ING BANK NV	6
7	ES059	BANCO SANTANDER S.A.	5
8	GB090	BARCLAYS plc	5
9	GB091	LLOYDS BANKING GROUP plc	1
10	IT041	UNICREDIT S.p.A	3
11	FR016	SOCIETE GENERALE	13
12	NL048	RABOBANK NEDERLAND	5
13	ES060	BANCO BILBAO VIZCAYA ARGENTARIA S.A.	4
14	IT040	INTESA SANPAOLO S.p.A	2
15	DE018	COMMERZBANK AG	2
16	FR015	BPCE	3
17	BE004	DEXIA	10
18	SE084	Nordea Bank AB (publ)	5
19	DK008	DANSKE BANK	5
20	ES061	BFA-BANKIA	0

Table 12
Effect of a shock that originates in the GIIPS countries. There are a total of 43 banks in the GIIPS countries. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in the GIIPS countries (Loss GIIPS) as well as the average loss in tier 1 capital ratio for banks in other than the GIIPS countries (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for the GIIPS countries (D_{100} GIIPS) and for other than the GIIPS countries (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss GIIPS	Loss Other	D_{100} Total	D_{100} GIIPS	D_{100} Other
GIIPS	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	2	0
				steep	0.0	0.0	0.0	2	2	0
			0.9	lin	0.0	0.0	0.0	2	2	0
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	0.1	0.2	0.0	2	2	0
				steep	0.1	0.2	0.1	2	2	0
			0.9	lin	0.2	0.3	0.1	2	2	0
				steep	69.0	69.0	69.1	87	41	46
	Financial	150	0.3	lin	3.3	4.7	2.0	2	2	0
				steep	4.9	6.6	3.2	3	2	1
			0.9	lin	10.5	12.8	8.4	3	2	1
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	14.7	20.9	9.0	5	4	1
				steep	18.5	25.0	12.5	7	6	1
			0.9	lin	30.3	36.4	24.8	20	17	3
				steep	69.0	69.0	69.1	87	41	46
	Corporate	150	0.3	lin	10.1	17.2	3.6	4	3	1
				steep	14.3	22.6	6.8	8	7	1
			0.9	lin	30.3	39.9	21.6	20	17	3
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	23.7	39.0	9.7	21	19	2
				steep	27.2	41.5	14.1	22	19	3
			0.9	lin	38.5	49.5	28.5	33	29	4
				steep	69.0	69.0	69.1	87	41	46

Table 12 (*Continued*)

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss GIIPS	Loss Other	D_{100} Total	D_{100} GIIPS	D_{100} Other
	Ret. Resid.	150	0.3	lin	6.2	11.5	1.3	2	2	0
				steep	8.4	14.7	2.6	3	3	0
			0.9	lin	16.3	24.2	9.0	7	6	1
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	24.1	42.9	6.8	23	23	0
				steep	29.5	48.5	12.1	30	29	1
			0.9	lin	42.0	56.9	28.4	37	34	3
				steep	69.0	69.0	69.1	87	41	46
	Ret. Rev.	150	0.3	lin	1.5	3.0	0.2	2	2	0
				steep	2.1	3.8	0.5	2	2	0
			0.9	lin	3.7	5.9	1.7	2	2	0
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	4.1	7.9	0.7	2	2	0
				steep	5.2	9.4	1.3	2	2	0
			0.9	lin	8.6	13.5	4.2	4	3	1
				steep	69.0	69.0	69.1	87	41	46
	Ret. SME	150	0.3	lin	3.0	5.5	0.7	2	2	0
				steep	4.2	7.1	1.5	2	2	0
			0.9	lin	8.4	12.1	5.0	4	3	1
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	5.4	9.8	1.3	3	3	0
				steep	6.9	11.7	2.5	3	3	0
			0.9	lin	11.8	16.8	7.2	6	5	1
				steep	69.0	69.0	69.1	87	41	46
	Comm. RE	150	0.3	lin	3.8	6.6	1.2	2	2	0
				steep	5.1	8.4	2.1	2	2	0
			0.9	lin	10.0	14.0	6.3	4	3	1
				steep	69.0	69.0	69.1	87	41	46
		400	0.3	lin	6.7	11.7	2.1	2	2	0
				steep	8.4	13.7	3.5	4	3	1
			0.9	lin	13.7	19.0	8.8	6	5	1
				steep	69.0	69.0	69.1	87	41	46

Table 13
Effect of a shock that originates in Eastern Europe. There are a total of 4 banks in Eastern Europe. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Eastern Europe (Loss EE) as well as the average loss in tier 1 capital ratio for banks in other countries than in Eastern Europe (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Eastern Europe (D_{100} EE) and for other than Eastern Europe countries (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss EE	Loss Other	D_{100} Total	D_{100} EE	D_{100} Other
Eastern Europe	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
			0.9	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
		400	0.3	lin	0.0	0.2	0.0	2	0	2
				steep	0.0	0.2	0.0	2	0	2
			0.9	lin	0.0	0.2	0.0	2	0	2
				steep	69.0	67.9	69.1	87	4	83
	Financial	150	0.3	lin	0.6	4.1	0.4	2	0	2
				steep	0.9	4.8	0.7	2	0	2
			0.9	lin	1.9	6.5	1.7	2	0	2
				steep	69.0	67.9	69.1	87	4	83
		400	0.3	lin	3.2	19.3	2.4	3	0	3
				steep	4.4	21.2	3.6	3	0	3
			0.9	lin	8.9	26.0	8.1	4	1	3
				steep	69.0	67.9	69.1	87	4	83
	Corporate	150	0.3	lin	1.8	16.4	1.1	2	0	2
				steep	2.5	18.4	1.8	2	0	2
			0.9	lin	5.4	23.0	4.6	4	1	3
				steep	69.0	67.9	69.1	87	4	83
		400	0.3	lin	5.0	39.5	3.4	5	2	3
				steep	6.6	40.6	5.0	5	2	3
			0.9	lin	12.5	43.8	11.0	6	2	4
				steep	69.0	67.9	69.1	87	4	83
	Ret. Resid.	150	0.3	lin	0.6	7.3	0.3	2	0	2
				steep	0.9	8.1	0.6	2	0	2
			0.9	lin	1.8	9.8	1.5	2	0	2
				steep	69.0	67.9	69.1	87	4	83
		400	0.3	lin	3.1	28.6	1.9	2	0	2
				steep	4.4	31.0	3.1	2	0	2
			0.9	lin	9.7	37.3	8.4	4	1	3
				steep	69.0	67.9	69.1	87	4	83

Table 13 (*Continued*)

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss EE	Loss Other	D_{100} Total	D_{100} EE	D_{100} Other
	Ret. Rev.	150	0.3	lin	0.4	5.0	0.1	2	0	2
				steep	0.5	5.7	0.2	2	0	2
			0.9	lin	0.8	6.7	0.5	2	0	2
				steep	69.0	67.9	69.1	87	4	83
		400	0.3	lin	0.9	12.7	0.4	2	0	2
				steep	1.1	13.4	0.6	2	0	2
			0.9	lin	1.9	14.8	1.3	2	0	2
				steep	69.0	67.9	69.1	87	4	83
	Ret. SME	150	0.3	lin	0.4	5.3	0.2	2	0	2
				steep	0.6	5.9	0.3	2	0	2
			0.9	lin	1.1	7.1	0.8	2	0	2
				steep	69.0	67.9	69.1	87	4	83
		400	0.3	lin	0.8	9.8	0.4	2	0	2
				steep	1.1	10.5	0.6	2	0	2
			0.9	lin	2.0	12.1	1.5	2	0	2
				steep	69.0	67.9	69.1	87	4	83
	Comm. RE	150	0.3	lin	0.3	1.1	0.3	2	0	2
				steep	0.5	1.5	0.5	2	0	2
			0.9	lin	1.2	2.5	1.1	2	0	2
				steep	69.0	67.9	69.1	87	4	83
		400	0.3	lin	0.7	2.1	0.6	2	0	2
				steep	1.0	2.7	0.9	2	0	2
			0.9	lin	2.1	4.4	2.0	2	0	2
				steep	69.0	67.9	69.1	87	4	83

Table 14

Effect of a shock that originates in the Benelux countries. There are a total of 7 banks in the Benelux countries. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in the Benelux countries (Loss Benelux) as well as the average loss in tier 1 capital ratio for banks in other than the Benelux countries (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for the Benelux countries (D_{100} Benelux) and for other than the Benelux countries (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Benelux	Loss Other	D_{100} Total	D_{100} Benelux	D_{100} Other
Benelux	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
			0.9	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
		400	0.3	lin	0.0	0.1	0.0	2	0	2
				steep	0.0	0.1	0.0	2	0	2
			0.9	lin	0.0	0.1	0.0	2	0	2
				steep	69.0	72.0	68.8	87	7	80
	Financial	150	0.3	lin	0.5	3.6	0.2	2	0	2
				steep	0.7	4.1	0.5	2	0	2
			0.9	lin	1.8	5.5	1.5	3	0	3
				steep	69.0	71.9	68.8	87	7	80
		400	0.3	lin	2.3	15.7	1.2	3	0	3
				steep	3.5	17.1	2.4	3	0	3
			0.9	lin	8.3	21.5	7.2	3	0	3
				steep	69.0	71.9	68.8	87	7	80
	Corporate	150	0.3	lin	1.0	5.7	0.6	2	0	2
				steep	1.8	7.0	1.4	2	0	2
			0.9	lin	5.3	11.2	4.8	3	0	3
				steep	69.0	71.9	68.8	87	7	80
		400	0.3	lin	3.2	16.8	2.1	4	0	4
				steep	5.2	19.0	4.0	4	0	4
			0.9	lin	12.7	25.5	11.6	4	0	4
				steep	69.0	71.9	68.8	87	7	80
	Ret. Resid.	150	0.3	lin	0.8	6.8	0.3	2	0	2
				steep	1.2	7.7	0.7	2	0	2
			0.9	lin	3.2	10.3	2.6	3	0	3
				steep	69.0	71.9	68.8	87	7	80
		400	0.3	lin	3.7	28.1	1.7	3	1	2
				steep	5.9	31.5	3.7	4	1	3
			0.9	lin	14.5	38.6	12.5	5	1	4
				steep	69.0	71.9	68.8	87	7	80
	Ret. Rev.	150	0.3	lin	0.0	0.1	0.0	2	0	2
				steep	0.1	0.2	0.1	2	0	2
			0.9	lin	0.2	0.3	0.2	2	0	2
				steep	69.0	71.9	68.8	87	7	80
		400	0.3	lin	0.2	0.4	0.1	2	0	2
				steep	0.3	0.5	0.2	2	0	2
			0.9	lin	0.7	1.0	0.7	2	0	2
				steep	69.0	71.9	68.8	87	7	80

Table 14 (*Continued*)

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Benelux	Loss Other	D_{100} Total	D_{100} Benelux	D_{100} Other
	Ret. SME	150	0.3	lin	0.3	1.9	0.1	2	0	2
				steep	0.4	2.3	0.3	2	0	2
			0.9	lin	1.2	3.3	1.0	2	0	2
				steep	69.0	71.9	68.8	87	7	80
		400	0.3	lin	0.5	3.8	0.3	2	0	2
				steep	0.9	4.3	0.6	2	0	2
			0.9	lin	2.2	5.9	1.9	2	0	2
				steep	69.0	71.9	68.8	87	7	80
	Comm. RE	150	0.3	lin	0.3	2.4	0.1	2	0	2
				steep	0.5	2.7	0.3	2	0	2
			0.9	lin	1.2	3.7	1.0	2	0	2
				steep	69.0	71.9	68.8	87	7	80
		400	0.3	lin	0.6	4.4	0.3	2	0	2
				steep	0.9	4.9	0.6	2	0	2
			0.9	lin	2.3	6.4	1.9	3	0	3
				steep	69.0	71.9	68.8	87	7	80

Table 15
Effect of a shock that originates in Greece. There are a total of 6 banks in Greece. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Greece (Loss Greece) as well as the average loss in tier 1 capital ratio for banks in other than Greece (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Greece (D_{100} Greece) and for other than Greece (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Greece	Loss Other	D_{100} Total	D_{100} Greece	D_{100} Other
Greece	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.1	0.0	2	0	2
			0.9	lin	0.0	0.1	0.0	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	0.0	0.4	0.0	2	0	2
				steep	0.0	0.4	0.0	2	0	2
			0.9	lin	0.0	0.5	0.0	2	0	2
				steep	69.0	69.0	69.0	87	5	82
	Financial	150	0.3	lin	0.5	4.2	0.3	2	0	2
				steep	0.7	5.1	0.4	2	0	2
			0.9	lin	1.3	6.8	0.9	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	2.7	19.8	1.4	2	0	2
				steep	3.3	22.1	2.0	3	1	2
			0.9	lin	5.8	26.9	4.3	4	1	3
				steep	69.0	68.8	69.0	87	5	82
	Corporate	150	0.3	lin	1.7	16.0	0.7	2	0	2
				steep	2.2	19.0	1.0	2	0	2
			0.9	lin	4.1	25.4	2.6	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	4.3	38.1	1.9	5	2	3
				steep	5.1	39.7	2.6	5	2	3
			0.9	lin	8.2	44.1	5.6	6	2	4
				steep	69.0	68.8	69.0	87	5	82
	Ret. Resid.	150	0.3	lin	0.8	10.0	0.2	2	0	2
				steep	1.1	11.4	0.3	2	0	2
			0.9	lin	1.7	14.1	0.8	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	3.5	38.8	1.0	3	1	2
				steep	4.4	42.5	1.7	3	1	2
			0.9	lin	7.4	48.8	4.4	4	1	3
				steep	69.0	68.8	69.0	87	5	82
	Ret. Rev.	150	0.3	lin	0.5	6.4	0.0	2	0	2
				steep	0.6	7.4	0.1	2	0	2
			0.9	lin	0.8	8.9	0.3	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	1.2	15.9	0.1	2	0	2
				steep	1.4	17.1	0.2	2	0	2
			0.9	lin	2.0	19.2	0.7	2	0	2
				steep	69.0	68.8	69.0	87	5	82
	Ret. SME	150	0.3	lin	0.3	2.9	0.1	2	0	2
				steep	0.4	3.6	0.2	2	0	2
			0.9	lin	0.7	5.0	0.4	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	0.5	5.2	0.2	2	0	2
				steep	0.7	6.2	0.3	2	0	2
			0.9	lin	1.2	8.0	0.7	2	0	2
				steep	69.0	68.8	69.0	87	5	82

Table 15 (*Continued*)

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Greece	Loss Other	D_{100} Total	D_{100} Greece	D_{100} Other
	Comm. RE	150	0.3	lin	0.6	6.0	0.2	2	0	2
				steep	0.8	7.1	0.3	2	0	2
			0.9	lin	1.2	9.3	0.7	2	0	2
				steep	69.0	68.8	69.0	87	5	82
		400	0.3	lin	1.0	10.7	0.4	2	0	2
				steep	1.3	12.1	0.5	2	0	2
			0.9	lin	2.0	14.6	1.1	2	0	2
				steep	69.0	68.8	69.0	87	5	82

Table 16
Effect of a shock that originates in Italy. There are a total of 6 banks in Italy. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Italy (Loss Italy) as well as the average loss in tier 1 capital ratio for banks in other than Italy (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Italy (D_{100} Italy) and for other than Italy (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Italy	Loss Other	D_{100} Total	D_{100} Italy	D_{100} Other
Italy	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
			0.9	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
		400	0.3	lin	0.0	0.1	0.0	2	0	2
				steep	0.0	0.1	0.0	2	0	2
			0.9	lin	0.0	0.2	0.0	2	0	2
				steep	69.0	66.1	69.2	87	5	82
	Financial	150	0.3	lin	0.9	5.2	0.7	2	0	2
				steep	1.6	6.7	1.3	2	0	2
			0.9	lin	4.1	10.5	3.8	3	0	3
				steep	69.0	66.1	69.2	87	5	82
		400	0.3	lin	4.4	22.9	3.3	3	0	3
				steep	6.5	25.9	5.3	3	0	3
			0.9	lin	14.7	33.7	13.6	7	3	4
				steep	69.0	66.1	69.2	87	5	82
	Corporate	150	0.3	lin	2.2	18.8	1.2	2	0	2
				steep	3.8	22.4	2.7	5	2	3
			0.9	lin	11.2	32.3	10.0	5	2	3
				steep	69.0	66.1	69.2	87	5	82
		400	0.3	lin	5.9	43.1	3.7	7	4	3
				steep	8.6	44.5	6.5	7	4	3
			0.9	lin	18.7	48.8	16.9	9	4	5
				steep	69.0	66.1	69.2	87	5	82
	Ret. Resid.	150	0.3	lin	0.8	5.3	0.5	2	0	2
				steep	1.3	6.5	1.0	2	0	2
			0.9	lin	3.3	9.5	3.0	3	0	3
				steep	69.0	66.1	69.2	87	5	82
		400	0.3	lin	4.1	25.0	2.9	3	1	2
				steep	6.6	29.2	5.3	5	2	3
			0.9	lin	16.7	39.7	15.3	8	3	5
				steep	69.0	66.1	69.2	87	5	82
	Ret. Rev.	150	0.3	lin	0.1	0.2	0.0	2	0	2
				steep	0.1	0.3	0.1	2	0	2
			0.9	lin	0.4	0.6	0.3	2	0	2
				steep	69.0	66.1	69.2	87	5	82
		400	0.3	lin	0.2	0.7	0.2	2	0	2
				steep	0.4	1.0	0.4	2	0	2
			0.9	lin	1.1	1.9	1.1	2	0	2
				steep	69.0	66.1	69.2	87	5	82
	Ret. SME	150	0.3	lin	0.6	6.7	0.3	2	0	2
				steep	1.1	8.0	0.7	2	0	2
			0.9	lin	2.9	11.2	2.4	3	0	3
				steep	69.0	66.1	69.2	87	5	82
		400	0.3	lin	1.2	12.1	0.5	2	0	2
				steep	1.9	13.5	1.2	2	0	2
			0.9	lin	4.5	16.8	3.8	3	0	3
				steep	69.0	66.1	69.2	87	5	82
	Comm. RE	150	0.3	lin	0.8	7.4	0.4	2	0	2
				steep	1.3	8.7	0.8	2	0	2
			0.9	lin	3.2	12.0	2.7	3	0	3
				steep	69.0	66.1	69.2	87	5	82
		400	0.3	lin	1.5	13.1	0.8	2	0	2
				steep	2.2	14.5	1.4	2	0	2
			0.9	lin	5.0	17.8	4.2	3	0	3
				steep	69.0	66.1	69.2	87	5	82

Table 17
Effect of a shock that originates in France. There are a total of 4 banks in France. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in France (Loss France) as well as the average loss in tier 1 capital ratio for banks in other than France (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for France (D_{100} France) and for other than France (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss France	Loss Other	D_{100} Total	D_{100} France	D_{100} Other
France	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
			0.9	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
		400	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.1	0.0	2	0	2
			0.9	lin	0.0	0.1	0.0	2	0	2
				steep	0.0	0.1	0.0	2	0	2
	Financial	150	0.3	lin	0.3	1.6	0.3	2	0	2
				steep	0.6	2.0	0.6	2	0	2
			0.9	lin	1.8	3.4	1.7	2	0	2
				steep	69.0	68.1	69.1	87	4	83
		400	0.3	lin	1.9	8.8	1.5	2	0	2
				steep	3.3	10.6	3.0	3	0	3
			0.9	lin	8.8	16.1	8.5	3	0	3
				steep	69.0	68.1	69.1	87	4	83
	Corporate	150	0.3	lin	1.2	8.8	0.9	2	0	2
				steep	2.4	10.6	2.0	2	0	2
			0.9	lin	7.6	16.7	7.2	3	0	3
				steep	69.0	68.1	69.1	87	4	83
		400	0.3	lin	3.7	23.8	2.8	2	0	2
				steep	6.2	25.9	5.3	4	0	4
			0.9	lin	15.7	32.3	14.9	5	1	4
				steep	69.0	68.1	69.1	87	4	83
	Ret. Resid.	150	0.3	lin	0.6	3.3	0.5	2	0	2
				steep	1.1	4.1	1.0	2	0	2
			0.9	lin	3.2	6.7	3.1	3	0	3
				steep	69.0	68.1	69.1	87	4	83
		400	0.3	lin	3.3	15.9	2.7	2	0	2
				steep	5.7	19.5	5.1	3	0	3
			0.9	lin	16.1	29.7	15.4	5	1	4
				steep	69.0	68.1	69.1	87	4	83
	Ret. Rev.	150	0.3	lin	0.1	0.5	0.1	2	0	2
				steep	0.2	0.6	0.1	2	0	2
			0.9	lin	0.5	1.0	0.5	2	0	2
				steep	69.0	68.1	69.1	87	4	83
		400	0.3	lin	0.3	1.4	0.2	2	0	2
				steep	0.5	1.8	0.4	2	0	2
			0.9	lin	1.5	3.0	1.5	2	0	2
				steep	69.0	68.1	69.1	87	4	83
	Ret. SME	150	0.3	lin	0.3	2.6	0.2	2	0	2
				steep	0.6	3.2	0.5	2	0	2
			0.9	lin	1.9	4.8	1.8	2	0	2
				steep	69.0	68.1	69.1	87	4	83
		400	0.3	lin	0.6	4.9	0.4	2	0	2
				steep	1.1	5.7	0.9	2	0	2
			0.9	lin	3.2	8.0	3.0	3	0	3
				steep	69.0	68.1	69.1	87	4	83
	Comm. RE	150	0.3	lin	0.3	1.0	0.2	2	0	2
				steep	0.5	1.3	0.4	2	0	2
			0.9	lin	1.4	2.4	1.3	2	0	2
				steep	69.0	68.1	69.1	87	4	83
		400	0.3	lin	0.5	2.0	0.4	2	0	2
				steep	0.9	2.5	0.8	2	0	2
			0.9	lin	2.5	4.4	2.5	3	0	3
				steep	69.0	68.1	69.1	87	4	83

Table 18
Effect of a shock that originates in Germany. There are a total of 12 banks in Germany. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Germany (Loss Germany) as well as the average loss in tier 1 capital ratio for banks in other than Germany (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Germany (D_{100} Germany) and for other than Germany (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Germany	Loss Other	D_{100} Total	D_{100} Germany	D_{100} Other
Germany	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.0	0.0	2	0	2
			0.9	lin	0.0	0.0	0.0	2	0	2
				steep	0.0	0.1	0.0	2	0	2
		400	0.3	lin	0.0	0.2	0.0	2	0	2
				steep	0.0	0.3	0.0	2	0	2
			0.9	lin	0.1	0.3	0.1	2	0	2
				steep	69.0	69.0	69.0	87	11	76
	Financial	150	0.3	lin	2.5	14.0	0.7	3	1	2
				steep	3.7	16.6	1.7	3	1	2
			0.9	lin	9.2	24.0	6.9	3	1	2
				steep	69.0	68.9	69.0	87	11	76
		400	0.3	lin	8.5	44.5	3.0	6	4	2
				steep	10.9	45.8	5.6	6	4	2
			0.9	lin	21.2	50.4	16.7	8	5	3
				steep	69.0	68.9	69.0	87	11	76
	Corporate	150	0.3	lin	3.0	13.5	1.4	3	1	2
				steep	4.9	16.5	3.1	3	1	2
			0.9	lin	12.8	25.8	10.8	3	1	2
				steep	69.0	68.9	69.0	87	11	76
		400	0.3	lin	8.1	33.4	4.3	3	1	2
				steep	11.3	35.7	7.5	3	1	2
			0.9	lin	22.4	42.5	19.3	6	2	4
				steep	69.0	68.9	69.0	87	11	76
	Ret. Resid.	150	0.3	lin	0.8	1.6	0.6	2	0	2
				steep	1.3	2.3	1.1	2	0	2
			0.9	lin	3.5	4.8	3.2	3	1	2
				steep	69.0	68.9	69.0	87	11	76
		400	0.3	lin	4.2	8.6	3.5	3	1	2
				steep	6.9	12.2	6.1	3	1	2
			0.9	lin	18.1	24.4	17.1	4	1	3
				steep	69.0	68.9	69.0	87	11	76
	Ret. Rev.	150	0.3	lin	0.1	0.2	0.1	2	0	2
				steep	0.1	0.3	0.1	2	0	2
			0.9	lin	0.4	0.6	0.4	2	0	2
				steep	69.0	68.9	69.0	87	11	76
		400	0.3	lin	0.3	0.6	0.2	2	0	2
				steep	0.5	0.9	0.4	2	0	2
			0.9	lin	1.3	1.7	1.2	2	0	2
				steep	69.0	68.9	69.0	87	11	76
	Ret. SME	150	0.3	lin	0.2	0.3	0.2	2	0	2
				steep	0.4	0.5	0.4	2	0	2
			0.9	lin	1.2	1.4	1.1	2	0	2
				steep	69.0	68.9	69.0	87	11	76
		400	0.3	lin	0.4	0.5	0.4	2	0	2
				steep	0.8	1.0	0.8	2	0	2
			0.9	lin	2.2	2.6	2.1	3	1	2
				steep	69.0	68.9	69.0	87	11	76
	Comm. RE	150	0.3	lin	1.2	5.7	0.5	3	1	2
				steep	1.8	7.0	1.0	3	1	2
			0.9	lin	4.5	10.5	3.6	3	1	2
				steep	69.0	68.9	69.0	87	11	76
		400	0.3	lin	2.1	10.4	0.9	3	1	2
				steep	3.1	11.8	1.8	3	1	2
			0.9	lin	6.8	15.7	5.5	3	1	2
				steep	69.0	68.9	69.0	87	11	76

Table 19
Effect of a shock that originates in Spain. There are a total of 25 banks in Spain. We simulate a sudden increase of risk weights to 150 percent and to 400 percent of their original value. We show the average loss in tier 1 capital ratio across the entire system (Loss Avg), the average loss in tier 1 capital ratio for banks in Spain (Loss Spain) as well as the average loss in tier 1 capital ratio for banks in other than Spain (Loss Other). We also show the number of banks failing the stress test by having their tier 1 capital ratio drop below 4.5 percent: We again count the total number of distressed banks after 100 time steps for the entire system (D_{100} Total), for Spain (D_{100} Spain) and for other than Spain (D_{100} Other).

Origin	Sector	Shock Size (%)	Q_A	$P(x)$	Loss Avg	Loss Spain	Loss Other	D_{100} Total	D_{100} Spain	D_{100} Other
Spain	Sov. Debt	150	0.3	lin	0.0	0.0	0.0	2	1	1
				steep	0.0	0.0	0.0	2	1	1
			0.9	lin	0.0	0.0	0.0	2	1	1
				steep	0.0	0.0	0.0	2	1	1
		400	0.3	lin	0.0	0.1	0.0	2	1	1
				steep	0.0	0.2	0.0	2	1	1
			0.9	lin	0.1	0.2	0.0	2	1	1
				steep	69.0	69.3	68.9	87	24	63
	Financial	150	0.3	lin	1.4	4.2	0.3	2	1	1
				steep	2.0	5.7	0.6	2	1	1
			0.9	lin	4.2	9.4	2.1	3	1	2
				steep	69.0	69.3	68.9	87	24	63
		400	0.3	lin	6.6	19.3	1.7	3	2	1
				steep	8.5	22.9	2.9	5	3	2
			0.9	lin	15.0	31.7	8.6	9	7	2
				steep	69.0	69.3	68.9	87	24	63
	Corporate	150	0.3	lin	5.2	17.1	0.6	3	2	1
				steep	7.3	22.1	1.6	5	4	1
			0.9	lin	15.4	35.5	7.7	11	9	2
				steep	69.0	69.3	68.9	87	24	63
		400	0.3	lin	12.2	39.0	1.9	11	10	1
				steep	14.1	41.3	3.6	12	10	2
			0.9	lin	21.7	48.1	11.5	17	15	2
				steep	69.0	69.3	68.9	87	24	63
	Ret. Resid.	150	0.3	lin	3.8	12.9	0.3	2	1	1
				steep	5.1	16.2	0.8	3	2	1
			0.9	lin	9.7	24.7	3.9	5	3	2
				steep	69.0	69.3	68.9	87	24	63
		400	0.3	lin	14.0	46.7	1.4	16	15	1
				steep	16.9	52.0	3.5	21	19	2
			0.9	lin	25.3	58.3	12.6	22	20	2
				steep	69.0	69.3	68.9	87	24	63
	Ret. Rev.	150	0.3	lin	0.9	3.2	0.0	2	1	1
				steep	1.2	4.1	0.2	2	1	1
			0.9	lin	2.2	6.0	0.7	2	1	1
				steep	69.0	69.3	68.9	87	24	63
		400	0.3	lin	2.5	8.7	0.1	2	1	1
				steep	3.2	10.4	0.4	2	1	1
			0.9	lin	5.3	14.1	1.9	3	2	1
				steep	69.0	69.3	68.9	87	24	63
	Ret. SME	150	0.3	lin	1.8	6.2	0.1	2	1	1
				steep	2.3	7.6	0.3	2	1	1
			0.9	lin	4.1	11.1	1.4	3	2	1
				steep	69.0	69.3	68.9	87	24	63
		400	0.3	lin	3.2	11.0	0.2	3	2	1
				steep	3.9	12.7	0.5	3	2	1
			0.9	lin	6.1	16.3	2.2	3	2	1
				steep	69.0	69.3	68.9	87	24	63
	Comm. RE	150	0.3	lin	1.9	6.4	0.2	2	1	1
				steep	2.5	7.9	0.4	2	1	1
			0.9	lin	4.3	11.5	1.6	2	1	1
				steep	69.0	69.3	68.9	87	24	63
		400	0.3	lin	3.4	11.5	0.4	2	1	1
				steep	4.2	13.1	0.7	3	2	1
			0.9	lin	6.5	16.8	2.5	4	2	2
				steep	69.0	69.3	68.9	87	24	63

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