Modelling Interconnections in the Global Financial System in the Light of Systemic Risk

Modelování vazeb v globálním finančním systému z pohledu systémového rizika

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Abstract

In this paper, we focus on the link between systemic risk and sovereign crises. We model how state support may influence a distressed financial system on an agent-based network model calibrated to 4Q 2011 data collected from several sources. Our model contributes methodologically to agent-based modelling of banking networks' systemic stability by adding the sovereign sector and the mechanisms of risk transfer between the banks and the sovereigns when state aid is initiated. The model implements two types of state support to banks, bailouts and asset relief. We show that these two have different effect on systemic stability, but both mitigate the systemic crisis in the short run. How the state aid measures are efficient in the long run depends on the model's parameterization.

Keywords

agent-based models, bailout, contagion, financial crises, financial stability, liquidity risk, network models, systemic risk

JEL Codes

C63, D85, G01, G21, G28

Abstrakt

Tento článek se zaměřuje na propojenost finančního systému s krizí státních financí. Za pomoci multiagentního síťového modelu zkoumáme, jak státní pomoc bankám ovlivňuje finanční systém v krizi. Model je následně kalibrován na dataset za 4Q 2011, poskládaný z různých zdrojů. Hlavním přínosem našeho modelu pro metodologii multiagentního modelování finanční stability je přidání sektoru jednotlivých států a mechanizmu přenosu rizika mezi bankami a státy v případě státní pomoci. Model implementuje dva základní typy státní pomoci, rekapitalizaci a odkup aktiv. Ukazujeme, že tyto dva typy mají různý efekt na stabilitu finančního systému, ale oba v krátkém období tlumí systémovou krizi. Účinek těchto opatření v dlouhém období pak závisí na parametrizaci modelu.

Introduction

The recent global crisis started as a crisis of the credit system, continued as a crisis of liquidity and with negative sentiment and overall market slowdown, it finally transformed into economic crisis. In the earlier stages, the sovereigns took an active role, supporting the economic system by bank aid, deposit guarantees, quantitative easing and economic stimuli packages. However, large state support for the financial system as well as for the economy represents a huge burden on government finances and in some cases, mainly in Europe, it has already resulted in sovereign debt crises. Moreover, losing their status of risk-free borrowers and facing increasing prices for credit, the sovereigns too are now significantly weakened and some are in threat of default. Since a large portion of sovereign debt is held by the banking system, there is a danger of the crisis feeding back to where it began in a vicious circle of transferring the toxic debt back and forth between the sovereign and the financial sector.

The overall aim of this paper is to contribute to the discussion on sovereign debt crises and bank crises, which has been recently going on both on the EU and the international level. The main research question is how the stability of the financial system is affected by state aid, how and when a systemic crisis can translate into sovereign crisis and how and when a sovereign crisis can feed back into the system through sovereign debt exposures. The main idea is that banks represented by their balance sheets form nodes in a financial network. Using a computational model, we simulate progression of shocks in the network given various types and levels of state aid. Our approach stems from the recent advances in agent-based network modelling of financial systems, mostly from Nier, et al. (2007).

The following second section will focus on the description of the link between the financial institutions and the sovereigns, mostly in regard to the recent financial crisis. The third section will present the used concepts, presenting a literature review of the modelling techniques that form the grounds for our analysis. In the fourth section, we construct an original model of a financial system which will be used for testing the impact of the sovereign assistance to banks and researching the feedback loops that may arise when such assistance weakens the sovereigns. In the sixth section, we calibrate it to a unique dataset collected from various sources in order to gain more insight into the current situation and outline some practical implications for setting new policies in case of a systemic banking crisis. Finally, we close the paper with a conclusion summarizing our research and findings.

1   The Current Financial Crisis

The true mark of the systemic crisis outbreak was the failure of Lehman Brothers on 15 September, 2008. Even though its bankruptcy meant a very significant shock to the interbank system, the other reason for the crisis to finally break out was psychological. Understanding that state aid is no longer guaranteed even for large, systemically important banks, the share prices of the banking sector plummeted as the investors were no longer

willing to consider financial institutions as an investment opportunity. Moreover, the market of bank debt funding froze and liquidity evaporated from the interbank market. The banking system thus found itself in a deadlock where it was not able to roll over the short-term debt it used to finance most of its operations, but at the same time, the individual institutions held unsettled overdue claims against each other. Moreover, due to the increased cost of lending and severe credit shocks, the banks' capital buffers did not suffice to prevent the system from collapse. Had they not been replenished, a large portion of the banking system would have failed.

Figure 1: Financial sector support in selected advanced economies, 2008 – Jul 2012

Panel A: Total direct support

Panel B: Unrecovered support – impact on public debt
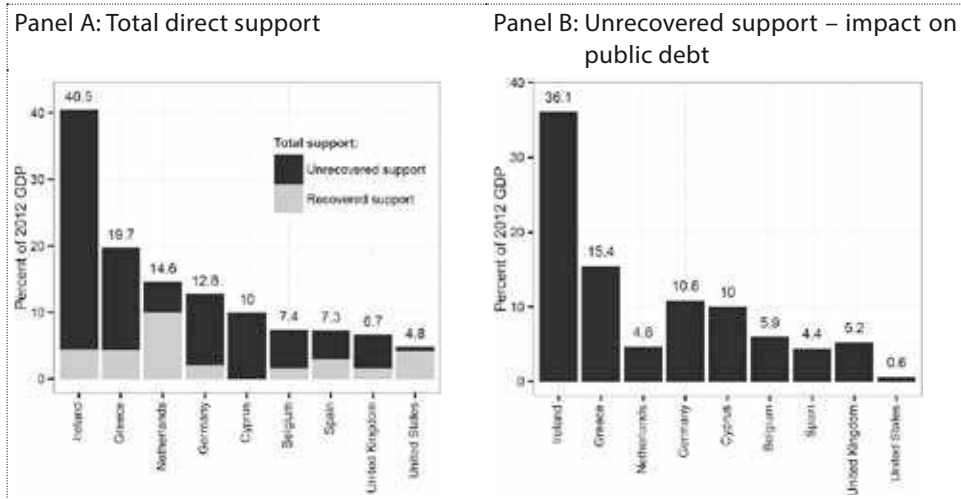
Source: IMF (2013a)

At this point, the states started playing an active role, introducing a number of measures to support the troubled financial institutions. Amongst these measures were strengthening of the deposit insurance, state guarantee schemes, outright bail-outs for bank recapitalisation or loans to alleviate the severe lack of liquidity (Liikanen, 2012). Mostly in Europe, several states introduced bad loan buy-outs or complete bank nationalizations (Petrovic & Tutsch, 2009).

Figure 1 shows the financial sector support in advanced countries as a fraction of the 2012 GDP along with its recovery values. The top rank in terms of GDP fraction belongs to Ireland followed by Greece. In March 2013, Cyprus bailed out its banks using the EUR 10 billion in funds provided by the European Central Bank and International Monetary Fund as the fifth European country to receive such assistance (ECB, 2013). In the short run, the support measures had a positive impact on systemic stability. Panetta, et al. (2009) states that the government support managed to lower the banks' credit default swap (CDS) premiums, which is the main indicator of failure risk. The first drop came when a support measure was announced and subsequently, the premiums fell even further when each of the measures was implemented. Moreover, the larger the amount of funds employed in a support measure, the sharper was the decrease of CDS premiums. Finally, there were

positive spill-over effects of these measures illustrated by falls of CDS premiums in countries other than the one deploying the measure.

However, the above-mentioned support actions proved to be very expensive and progressively, the situation started deteriorating for the sovereigns. As the balance sheet weaknesses moved from the banks to the sovereigns and the tax revenues dropped, the fiscal deficits began to surface. As the individual countries' creditworthiness crumbled and the rating agencies pointed out the associated risks, the investors began panicking and losing confidence even in the sovereign states. As a result, sovereign bond yields and CDS spreads rose and the access to new funding became increasingly more expensive. In a situation like this, when a sovereign guarantee is exercised or a large bank needs to be fully or partially bailed out and on top of that a country finds itself in an economic downturn, the public accounts are in serious trouble.

Unfortunately, the sovereigns did not prove to be anything else than other type of agents in the same financial system and thus by taking the risk on themselves, it did not vanish. Instead, it returned in form of feedback loops from the sovereigns back to the banks later when the sovereigns found themselves in crisis and their own balance sheets were deteriorating. In this manner, the risk and the losses oscillated between the privately-held banks and "publicly-held" sovereigns.

2   Modelling Approach

The modelling framework is based on two central concepts, network theory and agent-based modelling. Network theory is particularly useful for description of connected structures and the pattern of their relationships. A network is a set of nodes connected with edges.[10] Nodes may represent individual agents, for example servers and websites when we study computer networks or people in case of social networks. In the framework of finance, they may represent banks, sovereigns, depositors, companies or other entities in a financial system. Edges contain data on connection of any two particular nodes in the network, determining whether there is a link between two nodes and what is its value and direction. When the network theory is applied to modelling of financial systems, such properties allow us to define the creditor/debtor relationships as well as the size of the mutual claims of individual banks (Klinger, 2011). Network theory proved to be a particularly interesting means of studying impulse transmissions, which includes transmission of negative shocks. We use this methodology for simulating credit shocks in banking systems since when one bank fails and there are no supporting mechanisms such as bail-outs or state guarantees, the losses are transmitted to its creditor banks.

Agent-based modelling is a bottom-up approach that examines how numerous subjects that are each equipped with basic set of data and behavioural rules are interacting in a virtual environment. According to Tesfatsion (2006, p. 835), "[an agent] refers broadly to bundled data and behavioural methods representing an entity constituting part of a computationally constructed world". The individual agent's actions finally lead to certain ag-

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10 More rigorously, network is a graph defined as , where is a set of nodes, is a set of edges and is the mapping function which plots the edges onto individual pairs of nodes (Lewis, 2009).

gregate behavioural patterns on the systemic level. Probably the most well-known paper describing macro-level effects stemming from micro-level behaviour is the one by Schelling (1969), who described how a simple set of individuals' preference of the composition of their neighbourhood may lead to a pattern of segregation on a systemic scale. In our model, the agents represent individual financial institutions or sovereigns, the basic data they hold are their balance sheets and a set of behavioural rules such as when to default, when to sell of a particular amount of assets or when to bail out a certain institution.

Current research applying the previously mentioned methods to the field of financial or banking system stability divides into two main streams: empirical research and theoretical models. Several studies concentrate on the real-world interbank exposure modelling. For example Boss, et al. (2004), Upper & Worms (2004), Wells (2004), Van Lelyveld & Liedorp (2006) or Muller (2006) analyse the banking systems of Austria, Germany, the United Kingdom, the Netherlands and Switzerland respectively. Recently, Halaj and Sorensen (2013) tried to approximate a network of the banks who reported during the 2010 and 2011 EBA stress tests. However, most of the researchers face the problem of virtually non-existent reliable data on individual interbank exposures.

Theoretical models examine how system behaviour is influenced by its general characteristics. The first such model was constructed by Allen & Gale (2000) who studied contagion of funding liquidity shocks. Another early analysis was carried out by Freixas, et al. (2000), who studied contagion in systems where some banks were systemically important. Cifuentes, et al. (2005) and Shin (2008), add a market liquidity contagion channel decreasing the price of illiquid assets. Finally, there are studies that analyse systemic stability by simulation experiments on random networks such as Gai & Kapadia (2010), or Nier, et al. (2007). Finally, Klinger & Teply (2014) add regulatory aspects into this framework. This paper combines theory and empirics as the model is calibrated to the real-world data.

3   The Model

For each individual simulation, our model is defined in several steps. First, the network of banks and sovereigns is initialized together with the balance sheet data of individual agents. Second, the system is stressed by a credit shock, which may originate from a particular bank in the network. Following the initial shock, the stress propagates through the network and may trigger actions of the particular agents such as bank or sovereign defaults, asset fire-sales or state assistance to troubled banks. The simulation continues in several laps until the initial shocks completely dissolve and are no more transmitted further onto other agents.

First, the network is built from the calibration dataset. The total value of all assets in the system upon initialization is a sum of:
a) interbank assets, constituted by all the loans represented by the edges of the interbank network,
b) sovereign debt, constituted by individual banks' exposures towards their domestic sovereigns,
c) external assets, constituted by individual banks' exposures outside the network, e.g. loans to other entities (e.g. households, businesses or foreign sovereigns) or derivatives.

The final setting of banks' balance sheets is depicted in Table 1.

Table 1: Balance sheet variables of a modelled bank

...TOTAL ASSETS	... TOTAL LIABILITIES
...sovereign debt	...interbank liabilities
...interbank assets	...external liabilities (deposits)
...external assets	...equity (capital buffer)

Source: Authors

When the network is prepared, the system is inactive until we impose a shock event initiating the first simulation lap. Similarly, at the beginning of each next lap, each bank may receive a total asset-side shock of , where
- represents losses that banks incur due to default of another bank in the network to which they hold an exposure.
- represents losses that banks incur due to overall drop in asset prices caused by market liquidity effects.
- represents losses that banks incur due to default of a sovereign in the network to which they hold an exposure.

These individual components are described in detail on the following pages.

4   Shock Reaction and Contagion

If the banks affected by the primary shock do not have sufficient capital buffers, a process of cascade contagion effects may unfold, where in each lap of the simulation, the banks that default transmit the shock further onto other banks in the system. Figure 2 depicts the mechanism of shock propagation; the shock-transmitting banks are coloured grey whereas the failed banks are depicted in black.

Figure 2: Scheme of banking system contagion
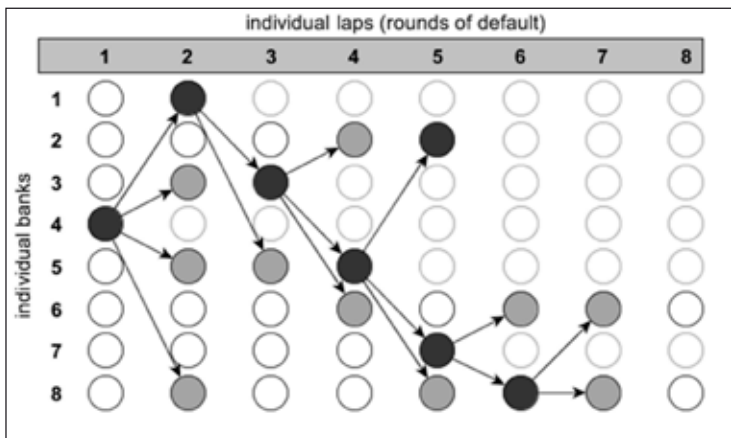
Source: Klinger (2011) inspired by Sell (2001)

Let us consider a bank that receives a shock. Whatever the shock type, it is reflected in the balance sheet and the bank loses a certain part of its assets. Since the sum of assets must

equal the sum of liabilities, the bank has to write off an equal value of liabilities. Firstly, the shocks are absorbed by owners' equity but if the capital buffers are not large enough, the banks default on claims of other creditors. If in lap the -th bank suffers an initial shock, its external behaviour depends on the shock size relative to its balance sheet structure:

a) At first, the shock hits the bank's capital buffer. If the shock is smaller than the bank's capital reserve which means that the bank is able to cover the losses by its own equity, then the capital buffer absorbs the shock completely and the bank does not send it further to other agents in the system.
b) If the capital reserve is not large enough, the residual shock overflows to the interbank liabilities, in which case its value up to the value of the interbank liabilities is uniformly divided into losses of all creditor banks which receive a CreditShock proportional to the size of their exposure to the failing bank. As the failing bank defaults, in the next lap it is removed from the system. Also, in the next lap of the simulation the creditor banks evaluate the received shock. The simulation finishes when there is a lap when no bank propagates the shock further.
c) Additionally, it holds that:
    i. If the shock is smaller than the sum of the bank's capital reserve and its interbank liabilities, it is absorbed completely by these two balance sheet items
    ii. If the shock is larger than the sum of the bank's capital reserve and its interbank liabilities, the shock overflows to external liabilities, meaning that the residual loss is covered by the depositors.

4.1 Market Liquidity Risk Modelling

Market illiquidity, described firstly by Kyle (1985), represents a situation when transactions in which the assets are sold have a negative impact on the asset prices.[11] Along with Gai & Kapadia (2010), we assume that in case a bank is in default, it has to liquidate all of its assets before it is removed from the system. While the sovereign debt is assumed to be more liquid and hence is liquidated in full value, the low market depth may limit the capacity to absorb the external and interbank assets. As a result, these cannot be sold for the price for which they are kept in the bank's books. Following Cifuentes, et al. (2005), we assume an inverse demand function for the external assets, which takes the form of

$$P(\boldsymbol{x})_t = \exp\left(-\frac{\alpha}{E}\sum_{i=1}^{N^b} x_{i,t}\right),$$

Where is the number of banks in the system, is the total value of assets (external and interbank) sold by the -th bank in the system in the current lap, represents the market illiquidity (i.e. the speed at which the asset price declines) and is the new discounted price

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11 *Market liquidity is usually measured by indicators such as market depth, resiliency, tightness, and volatility. These indicators may be aggregated into liquidity indices, which then can be used to quickly compare markets in time and cross-sectionally. Examples of market liquidity indices are found e.g. in Gersl & Komarkova, (2009) or Teply, et al. (2012).*

of external assets calculated in each lap.[12] The additional losses caused by the asset sales are then added to the initial shock on -th bank in the current lap and transmitted accordingly. Furthermore, assuming marking to market accounting, at the end of each lap the external assets of each bank are revalued such that

$$e_{i+1} = e_{i,t} P(\boldsymbol{x})_t.$$

Hence, the losses stemming from such price adjustment result in a price shock of to all banks.

4.2 The Role of Sovereigns

As a means of a sovereign to support its domestic banks, we introduce two possibilities of sovereign assistance. These include:

a) Bailouts and recapitalization (BR) – the sovereigns may pay for losses incurred by the banks to replenish their capital buffers and keep them in business. In this case when a bank receives a shock of , the sovereign covers , adding this value to the bank's external assets. Again, the amount of is then added to the external debt of the -th banks' domestic sovereign as the domestic government needs to find external financing for this rescue measure.

b) Asset relief (AR) – the sovereigns may buy what assets their domestic banks need to sell in fire sales. In this case, in each round every bank sells assets as described in the basic model definition, but only is sold on the market since is bought-out by the bank's domestic government. Assuming fixed across all banks and all sovereigns, Equation 1 is replaced by:

$$P(\boldsymbol{x})_t = \exp\left(-\alpha(1 - k^{AR}) \sum_{i=1}^{N^b} x_{i,t}\right),$$

The amount of is then added to the external debt of the -th banks' domestic sovereign as the domestic government needs to find external financing for this rescue measure.

As we mentioned previously, sovereign assistance may work very well for short-term banking system stabilization, but it puts significant pressure on the intervening sovereigns. According to Acharya, et al. (2012), state assistance to banks requires that the sovereigns immediately issue new debt to finance such measures, which results in immediate increase in the sovereigns' credit risk through the liability side of their balance sheets. In the model, any type of sovereign assistance to the banks results in an increase of the debt of the domestic sovereign. The extra budget deficit resulting from the aid measures is the main driver of a credit risk increase in the model.

The sovereign credit risk in the model is represented by probability of default, which under a certain assumed recovery rate may be roughly approximated from the CDS spreads.

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12 *Upon the system's initialization, the price is set to*

Credit default swaps are contracts insuring against credit events on bonds in case the counterparty defaults. The buyer pays periodically to the seller until either the CDS matures or until a credit event occurs, in which case the buyer of the insurance is entitled to sell to the seller of the insurance the insured bonds for their face value (Hull, 2008). As our model is of short-term character and later on, we calibrate it to yearly data, we chose to implement the probability that a given sovereign defaults in one year. Although strictly speaking, the extraction of this probability from the available 5-year CDS spreads would require diligent modelling of both the default state and the no-default state cash flows, we can simplify the calculation by assuming a flat CDS spread curve and implement the widely used approximation according to J.P. Morgan and Company & RiskMetrics Group (1999):

$$p_{k,t}^{default} = \zeta \left(1 - \frac{1}{\left(1 + \frac{CDS_{k,t}}{1 - RR}\right)^{\tau}} \right),$$

Where is the probability that a given sovereign defaults in one year, is the annual CDS spread, is the recovery rate and is the number of years for the cumulative default probability calculation (in our case, and in line with common practice,).

The link between sovereign deficits and credit risk is documented by econometric studies such as Attinasi, et al. (2009) or Cottarelli & Jaramillo (2012). We use the following equation to update the sovereign CDS spreads at the end of each simulation lap (parameter is later on referred to as the CDS sensitivity):

$$CDS_{k,t+1} = CDS_{k,t} + \beta \frac{deficit_{k,t}}{GDP_k}.$$

Putting the previous points together, at the end of each lap the model collects the total amount of each sovereign's deficit and feeds it into Equation 3 which is then plugged into Equation 4. At the beginning of each simulation lap, a sovereign may default with probability . In that case, each creditor bank receives a equal to the size of exposure to the defaulting sovereign multiplied by . The sovereign debt on its balance sheet is then revalued accordingly.

5   Empirical Analysis

In the following chapter, we calibrate our model to the real-world banking data in order to contribute to the current debate on systemic stability and the link between banks and sovereigns. As documented by many authors (e.g. Mistrulli, (2011)), the data on individual banks' mutual exposures is not available. Therefore, we resort to proxy data inferred from available sources to build the interbank network. Instead of individual banks, the agents in our study represent banking systems of countries which report their banking positions to BIS (referred to as subsystems since they are all part of the global banking system) and these agents' balance sheets are composed of aggregated figures of all banks reporting in

their domestic countries. The "interbank" exposure data are complemented with banking system data collected from several sources to provide a complete picture of the global banking system.

5.1 Data Definition

To calibrate the model to the real-world figures, we collected data from several sources. Table 2 shows the main items which we describe further in greater detail.

Table 2: Banking system balance sheet with data sources

TOTAL ASSETS (EBF Database, Central banks)	
Government debt (Arslanalp & Tsuda (2012), IMF IFS Database)	External liabilities (Calculated)
Interbank assets (BIS International Statistics)	Interbank liabilities (BIS International Statistics)
External assets (Calculated)	Equity (BankScope)

+GDP (World Bank), CDS Spreads for the individual countries (Bloomberg)

Source: Authors

5.1.1 Interbank Assets and Liabilities

The interbank exposure dataset describes the interlinkages in the global banking system. These are collected from the banking section of BIS International Financial Statistics (BCBS, 2013), where the central banks report compiled national aggregates calculated from data on individual banks' in their jurisdiction. To form the interbank exposure matrix, we employ data from the consolidated statistics of foreign claims on immediate borrower basis. The consolidated data provides information on exposures of domestically-owned parent banks on the highest consolidation level and hence they include external exposures of own foreign offices and exclude all internal inter-office positions in the consolidation group (BCBS, 2009). The selection of countries whose banking sectors we included in the analysis was based on data availability and includes Australia, Austria, Belgium, Brazil, Canada, Denmark, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.[13]

Nevertheless, it is not possible to obtain directly the pure bank-to-bank exposures between the individual countries' banking sectors, and some level of approximation is inevitable. To estimate the bank-to-bank exposures from the reporting banking sectors' pool of total claims, we employ another dataset of the BIS statistics, which is the total claims on each country's banking sector by all the reporting sectors, grouped by the type of the debtor institution (i.e. whether it is a bank, public sector or a non-bank private sector). By taking a fraction of bank debt on the total debt, we obtain proxy variables for individual counterparties. Finally, we multiply the whole column of the exposure matrix representing the given counterparty's debts by this variable to calculate the estimated interbank network.

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13 *Czech Republic was not included in the analysis as it does not report its international banking exposures to BIS.*

When the network is created, it can be plotted as in Figure 3. For better readability, we provide two different views for the same dataset. In Panel A, we show the edges of the network (interbank exposures) coloured according to the source of the funds (i.e. the creditor, the bearer of the risk). These visualizations provide an efficient overview of the situation and a quick grasp of the basic relationships. For example, in the centre of the network, we see the "core" sectors, (highly interlinked nodes such as the United States, the United Kingdom, Japan, France, Germany or Switzerland) and around them there are more "peripheral" banking systems. Also, as the visualization algorithm[14] takes into account the relationships in the network and places the nodes accordingly, we can see patterns that are in line with our anticipation based on the individual countries' location or cultural relationships. Note for example the pairs of countries being placed together, such as Sweden and Denmark or Turkey and Greece. Also, the clusters of related countries are placed logically together, such as Italy, Spain and Portugal forming the Southern Europe cluster with proximity to Brazil. Also note that after its default, Greece is placed on the edge of the network with very low connection to other banking systems.

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14 *The visualizations were prepared in Gephi software. For the calculation of the node layout, we used the Force Atlas algorithm, which places the nodes in the graph according to the values of edges in the network matrix. While the scientific article on Force Atlas algorithm is still awaiting acceptance and publication, more information on graph clustering and layouting may be found in Noack (2007).*

Figure 3: Interbank network of the selected countries as of Q4 2011
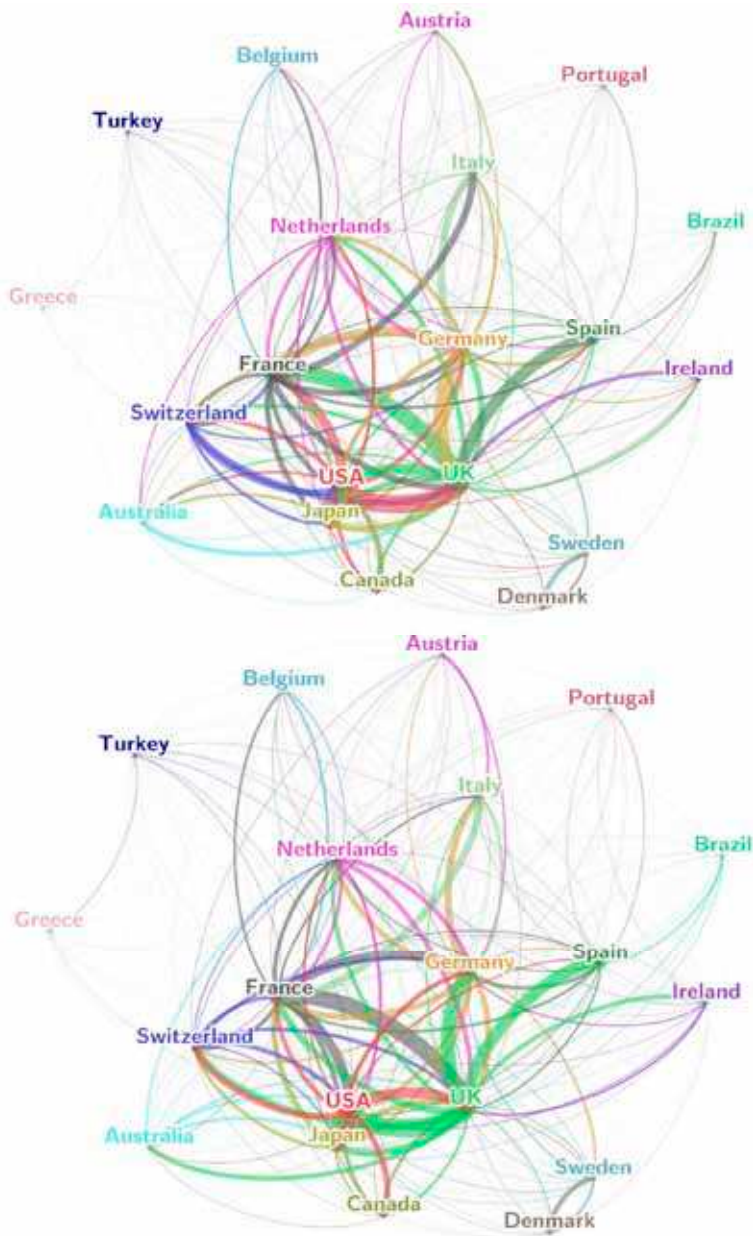
Note: Panel A shows the edges shaded by the creditor node (e.g. exposure of Switzerland against the United States has the same shade as Switzerland on the chart) whereas in Panel B, they are shaded according to the debtor node (e.g. exposure of Germany against the United Kingdom has the same shade as the UK node)

It is necessary to mention that this dataset provides information only on interbank lending and not on external financing of banks by sovereigns or central banks, which may be quite significant, especially in the Eurosystem. On the same note, these data do not provide information on balances in the TARGET2 system, which has been lately discussed in Cecchetti, et al. (2012) and which now form a significant part in the mutual exposures of the Eurosystem banks. The above-mentioned facts mean that Figure 3 does not provide the entirely complete picture of the global banking system. However, in our model, bank financing of these different types is captured in the external assets part of the bank's balance sheet.

5.1.2   Sovereign Debt to Banks

To introduce the link between banks and sovereigns into the banks' balance sheets, we collected two sovereign debt datasets which were then added together. These are exposures to the domestic banking system, collected mainly from Arslanalp & Tsuda (2012) and supplemented by data from the IMF IFS database (IMF, 2012), and exposures to other banking systems, collected from the BIS International Financial Statistics (BCBS, 2013).

While the first dataset collection is straightforward, in case of the second one we have to employ a similar calculation as in the case of interbank assets. Again, the data is taken from the consolidated statistics of foreign claims on immediate borrower basis. To estimate the banks' exposures to sovereigns from the reporting banking sectors' pool of total claims, we multiply the whole column of the exposure matrix representing the given state's debts by the fraction of its sovereign debt on the total debt. The same approach was used in Arslanalp & Tsuda (2012) for the calculation of foreign banking sector holdings of sovereign debt. However, we must note that this data provide information only on the individual sovereigns' debt towards the banking sectors in our sample. Thus it does not describe the countries' total debt positions.

Figure 4 visualizes the figures for each sovereign's debt to the foreign as well as to the domestic banks. We see that for all banking systems except of the United Kingdom and the Netherlands, there is a relatively strong bias towards the domestic banks (note the logarithmic scale of the chart). This phenomenon already documented in Pisani-Ferry (2012), Merler & Pisani-Ferry (2012) or Acharya, et al. (2012), results in a strong link between sovereigns and their domestic banks through balance sheet exposures and is one of the reasons why sovereign risk translates through feedback loops into the domestic banks' risk.
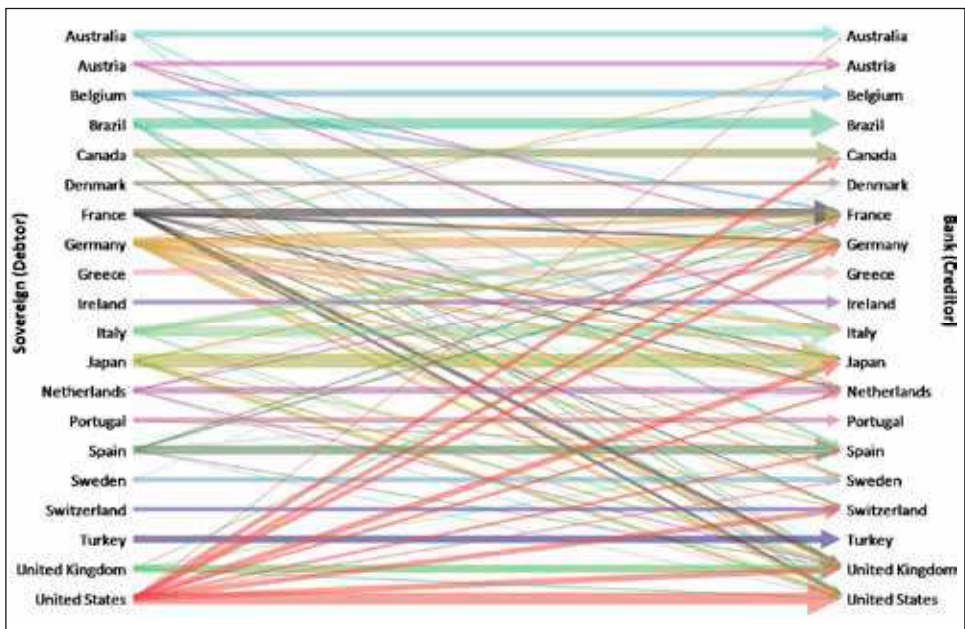
Figure 4: Selected banking systems' exposures to sovereign debt as of Q4 2011
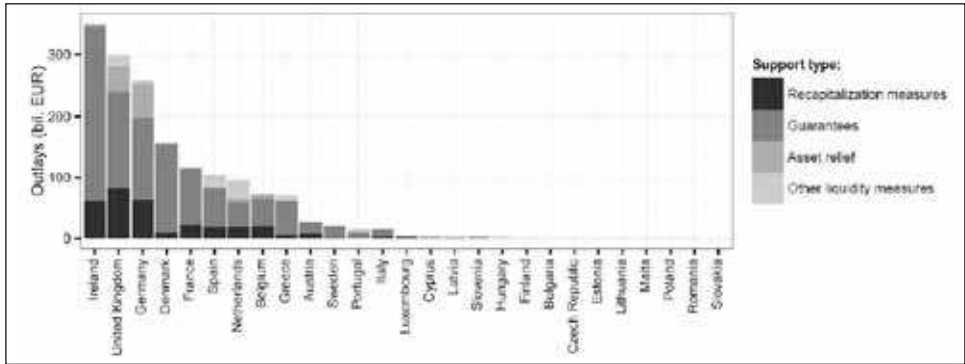
Source: Authors' calculations based on data from Arslanalp & Tsuda (2012), IMF International Financial Statistics and BIS International Financial Statistics

For better insight into the interlinkages between banks and sovereigns, one has to study also the individual exposures. Figure 5 presents this data as a plot of the bipartite network of sovereigns and banking systems in our sample. Similar to Figure 3, the edges represent the sovereign debt towards the individual banking system. Here we see the home bias phenomenon as the largest links are always to the domestic banking system. Also for the individual countries, interesting patterns emerge where the debt to foreign banks is determined largely by geographical or cultural proximity of the individual countries.

Figure 5: Detailed banking systems' exposures to sovereign debt as of Q4 2011

Source: Authors' calculations based on data from Arslanalp & Tsuda (2012), IMF International Financial Statistics and BIS International Financial Statistics

5.1.3   Other Data

The banking systems' total assets represent another important input into the model as it is used for calculation of capital, external assets and external liabilities of the individual banking sectors. Despite it being an important variable for comparison of banking systems in time as well as in cross-section, the data on sums of total assets is not readily available and vary significantly across data sources.[15] To keep our dataset as consistent as possible, the main source we used is the Banking Sector Statistics database of the European Banking Federation (EBF, 2013), which provides data on all European countries in the sample. The data on countries not represented in this primary source were taken from the databases of the individual central banks.

The size of the capital buffers is the main determinant of the stability of the individual banks as well as the whole system. In contrast to the total assets data, in case of banking sector capitalization, we are interested in the proportion of capital to total assets rather than the total sum and hence, the capital ratios were taken from the BankScope database.

Besides balance sheet data for the individual countries' banking systems, the model requires two more datasets for a complete calibration: GDP and CDS spreads of the individual sovereigns. The gross domestic product data was collected from the World Bank database (World Bank, 2013), data on 5-year credit default swap spreads were obtained from Bloomberg.

5.2 Model Calibration

Put all together, the collected data provide a complex picture of the modelled global banking system according to Table 2. The internal assets of individual subsystems are calculated as the sum of their exposures to other subsystems; the sovereign assets as the sum of their exposures to sovereigns and the external assets as the total assets minus the internal and the sovereign assets. Similarly, capital is calculated as the collected capital ratios times the total assets of the individual subsystems; their internal liabilities are sums of their debt towards other subsystems, and the external liabilities are total assets minus capital and the internal liabilities.

Figure 6 provides the final overview of the calibrated balance sheets which are loaded into the model. As we can see on Figure 6A, the external assets constitute the majority of the bank's balance sheets, in fact around 80%, while the sovereign assets account for 12% and the interbank assets only for 8%. Similarly on the liability side depicted in Figure

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15 *E.g. taking the same data from BankScope, the differences in some cases were significant. We explain this by the fact that BankScope is not the best source for total sums of variables for individual banking sectors (Bhattacharya 2003), and resort to the aggregated data from EBF and the central banks.*

6B, external liabilities form an overwhelming 86% of the total liabilities while the banks' equity accounts for 6% and the interbank liabilities for 8%. The fact that the interbank network forms only a small portion of the total banking assets value is the main shortcoming of the pure credit contagion approach. It points at the fact that without oversimplified extrapolation of the interbank network to the rest of the banking system, it is difficult to draw any conclusions from works such as Chan-Lau (2010) that study only the effects of the direct contagion and funding shocks and relies solely on the BIS interbank network data. In fact, our finding stresses the significant gap in the knowledge of banking exposures and demands further data collection which would enable us to break the external assets into more detail.

Figure 6: Balance sheets of the calibrated model as of Q4 2011

Panel A: Banks' assets   Panel B: Banks' liabilities
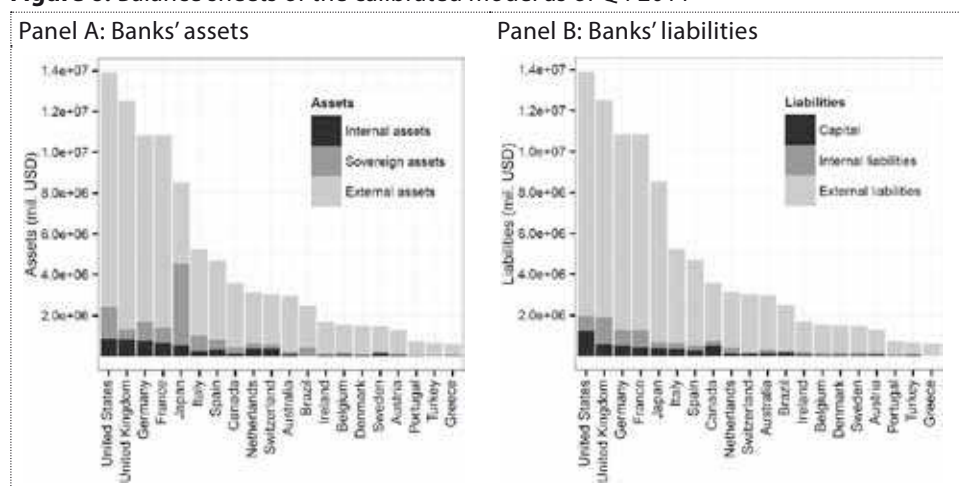

Source: Authors' calculations

As opposed to Chan-Lau (2010), we incorporate the full size of the banking system and the indirect channel of contagion through market liquidity as described by Brunnermeier, et al. (2009) and Cifuentes, et al. (2005). Given the amount of external assets, we expect that the liquidity channel will play a significant role for systemic stability. This channel is recognized also by authors focusing on the direct credit contagion, as documented by Upper (2011).

5.3 Effects of Sovereign Assistance

In this section, we will explore the effects of sovereign assistance on the calibrated global banking system. We will describe the impact and costs of the two support measures. Please note that in this phase the mechanism of risk transmission from the sovereigns back to the financial system (feedback loops) is not yet implemented.

Figure 7: Bailouts and recapitalization effects
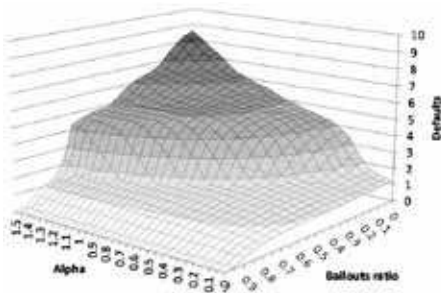
| Panel A: Total defaults - Alpha vs. Bailouts ratio	Panel B: Total cost – Alpha vs. Bailouts ratio
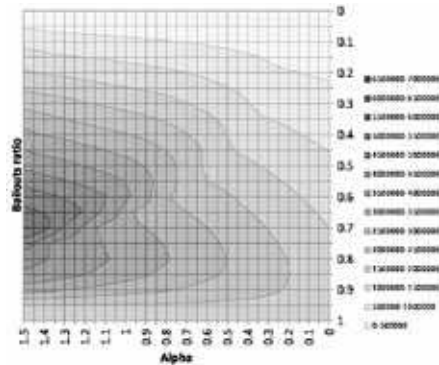
Source: Authors

We first look at the bailouts support measure. Figure 7A depicts the number of bankrupt banking subsystems given various levels of market illiquidity (, referred to as alpha) and various intensities of state support (, referred to as bailouts ratio). The positive effects of this measure are clearly visible and with maximum bailout support, no bank defaults as the shock is captured right at its origin. We see that at low values of alpha, the effect of state aid is very low and almost linear. However, with growing illiquidity, the state support is increasingly important and at maximum alpha, we see a "step-like" dependence where a very small increase in state support may prevent default of three banking subsystems. As to the sovereign deficits caused by this measure, Figure 7B demonstrates that at very low levels of alpha, the costs increase almost linearly with the support intensity. However, for low capitalized systems, under high levels of alpha, the costs rise only until some level of support intensity beyond which they fall sharply. This is caused by the support measure effectively blocking the contagion through market liquidity channel and corresponds to the sharp drop of defaults in Figure 7A.

Figure 8: Asset relief effects

Panel A: Total defaults
- Alpha vs. Bailouts ratio
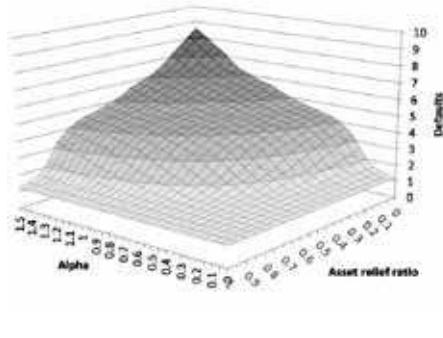
Panel B: Total cost
- Alpha vs. Bailouts ratio
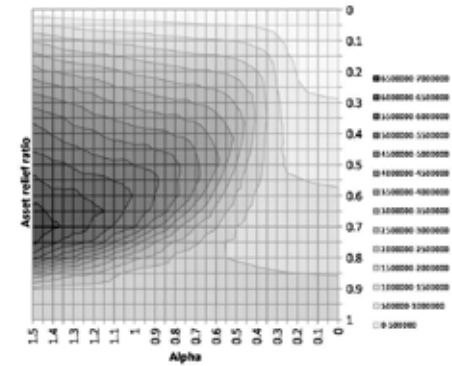
Source: Authors

Secondly, looking at the effects of asset relief programmes as depicted in Figure 8A, we see that they do not cause such sharp drops in numbers of failed banks as those of outright bailouts, but still are very significant. Because asset relief is tied to the liquidity channel, we see that the shape of the dependence of systemic stability on the support intensity () is similar to the shape of its dependence on . Also, in contrast to outright bailouts which may be targeted to the initial propagator, in case of asset relief, the banks which are hit by the primary shock always fail. Looking at the costs of this measure, Figure 8B shows that at the peak they are higher than those of the bailouts. Also, except for the area of support intensity of 0.8 to 0.9 where they are smoother, they have very similar shape as the costs of bailouts. The reason for asset relief to prove such efficiency is that external assets form a large portion of total assets of the system and hence the liquidity effects are very strong.

5.4 Effect of Feedback Loops

Finally, we implement the feedback loops of risk transmission back from the sovereigns to the banking system and study the effects of state aid on the complete model. The figures showing results of this analysis (in the appendix) depict the number of failed banking subsystems in dependence on state aid intensity and accounting for different levels of CDS sensitivity.

First, Figure 9 demonstrates the effects of bailouts and recapitalization. We see that the measure has large impact on the banking system stability, which may be both positive and negative depending on the initially shocked bank and CDS sensitivity setting. Generally, setting CDS sensitivity equal to zero represents a situation in which the sovereigns are not negatively affected by the state aid as increases in their deficits do not result in growth of their CDS spreads and hence also growth of their implied probabilities of default. With

non-zero CDS sensitivities,[16] the feedback loops are in their full function as higher deficit resulting from the state aid increases the default probabilities of sovereigns. In case of bailouts and recapitalization, when the CDS sensitivity is set to zero, the count of failed banking subsystems is a decreasing function of the support intensity.

When large subsystems having high systemic importance (France, Germany, the United States and the United Kingdom) are initially shocked, the effects of support come only at relatively high support intensity as the systemic break-down is prevented only at bailouts ratio exceeding 50%. Moreover, for these countries' subsystems, the number of defaults is never significantly higher with the state support than without it, even though at CDS sensitivities of 1.5 and 3 the positive effects come much later at higher support intensity levels. If other banking subsystems are targets of the initial shock, we see that at non-zero CDS sensitivities, the default count usually increases in the middle of the support intensity interval as the state aid is still insufficient to significantly support the banks but already weakens the sovereigns. This pattern is visible throughout the majority of the initially-hit banking systems. Also, even at non-zero CDS sensitivity levels, in case of almost all initial propagators, the system is better off with full state support than without it. The only exception is Belgium, Brazil and Greece, where state support clearly worsens the systemic crisis. The reason is that they are neither too large nor too interconnected systems and supporting them after they are initially hit only adds another channel of contagion through a sovereign crisis.

Third, Figure 10 shows the effect of asset relief. In case of zero CDS sensitivity, the positive effects of this measure are less significant than in the case of bailouts. On the other hand, as the CDS sensitivity progresses to higher values, the situation stays very similar and thus for high CDS sensitivity cases, this measure would seem as the most fitting one. However, we suppose that this result is somewhat biased because of the dataset employed. First, high portion of external assets in the system results in overestimating the measure's effectiveness. Moreover, the linkages between sovereigns and their non-domestic banks form a minor portion of the total sovereign assets and each country's banking system is aggregated into a single agent. As a result, even though the sovereign which is performing the asset relief programme is severely weakened, its default affects mainly its already failed domestic banking system. If an interbank dataset that more precisely captures the reality was available, we expect this measure to perform significantly worse than bailouts and recapitalization.

Conclusions

In this paper, we focused on the link between systemic risk and sovereign crises. We modelled how state support may influence a distressed financial system on a model calibrated to 4Q 2011 data collected from several sources. Our model contributes methodologically to agent-based modelling of systemic stability by adding the sovereign sector and the mechanisms of risk transfer between the banks and the sovereigns.

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16 *Our choice of CDS sensitivity values of 1.5 and 3 in the figures is in line with econometric studies such as Sand (2012) or Cottarelli & Jaramillo (2012).*

The model implements two types of state support to banks: bailout and asset relief. In the short run when the feedback loops are not yet implemented, the effects of both measure types are positive. In the longer run after implementation of the feedback loops through sovereign defaults on bonds held by the banks, we found that a support measure's real efficiency depends on the measure intensity and CDS sensitivity, i.e. the market perception of the increase in sovereign risk. These effects were the most pronounced in case of bailouts and recapitalization, which according to our simulations may significantly improve the systemic stability. However, with higher CDS sensitivity, it depends on which country is initially hit: in case of banking systems that are systemically important, bailouts are effective throughout the whole support intensity interval, whereas for the banks with lower systemic importance, the support may actually worsen the situation. Table 3 provides the complete overview of the feedback loops analysis.

In general, the model proves that in the short run without the feedback loops, state aid may significantly support the system and in the longer run with the feedback loop effects, it may be effective or harmful depending on the system's parameters. Moreover, the results are indeed different for each individual type of state aid.

Table 3: Impact of individual support measures on a calibrated model

Measure	Description

Bailouts and recapitalization	• At zero CDS sensitivity, the count of failed banks is a decreasing function of support intensity on its whole interval
	• For systemically important subsystems, state support always improves systemic stability, even though it is effective only at relatively high support intensity.
	• At higher CDS sensitivities and in the middle of the support intensity interval, the effects are:
	  - Negative when the initially failed subsystem has lower systemic importance
	  - Neutral when the initially shocked subsystem is systemically important, the effects come in the second half of the support intensity interval
	• At full support intensity, the measure has a positive effect for all countries except for Belgium, Brazil and Greece

Asset relief	• Efficient at the whole support intensity interval • At zero CDS sensitivity the effects are less pronounced than in case of bailouts but still significant • At non-zero CDS sensitivity levels, the positive effects stay significant • The model is likely to overestimate this measure's efficiency due to the dataset employed. However, currently there is no better data on interbank exposures available

Source: Authors

Also, we found that majority of the total assets in our system are constituted by external assets. This points out the shortcomings of studies that examine the systemic stability only on the BIS interbank network data such as Chan-Lau (2010), as this dataset amounts only to a small fraction of the total banking assets. It stressed the need for deeper analysis and more data availability on the structure of the interbank and state-bank exposures.

Finally, because of the agent-based modelling approach, we may extend our model in the future with other types of financial market agents such as large multinational institutions, pension funds, insurance companies or even individual depositors. Moreover, we may add

the real economy along with its input/output flows and observe the effects on individual sectors when one sector is hit by a credit crunch or a drop in output. The flexibility and extensibility of our modelling approach is another strong benefit, which may lead to many more conclusions in the future research.

Acknowledgment

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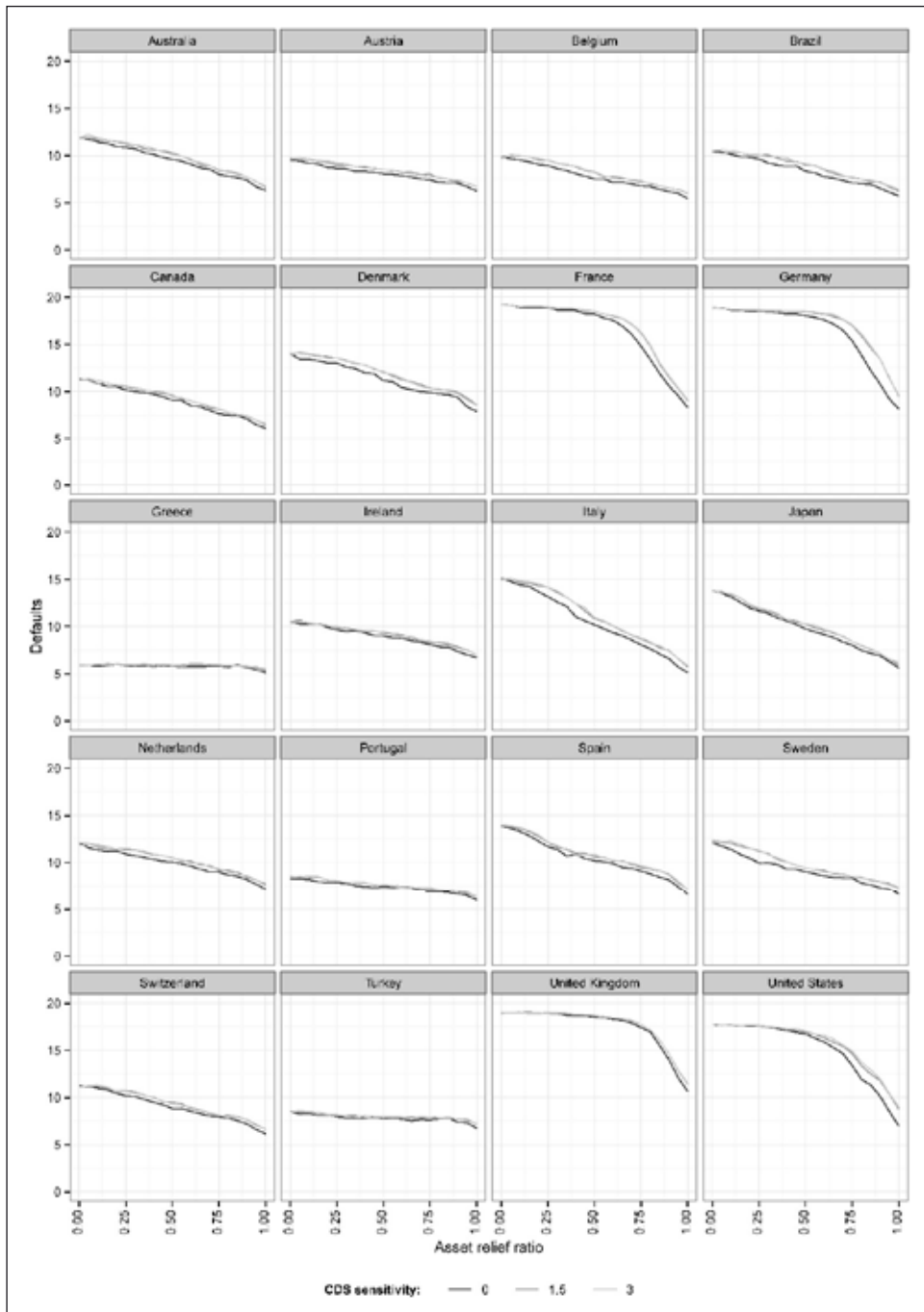
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Appendix

Figure 9: Bailouts and recapitalization with feedback loops
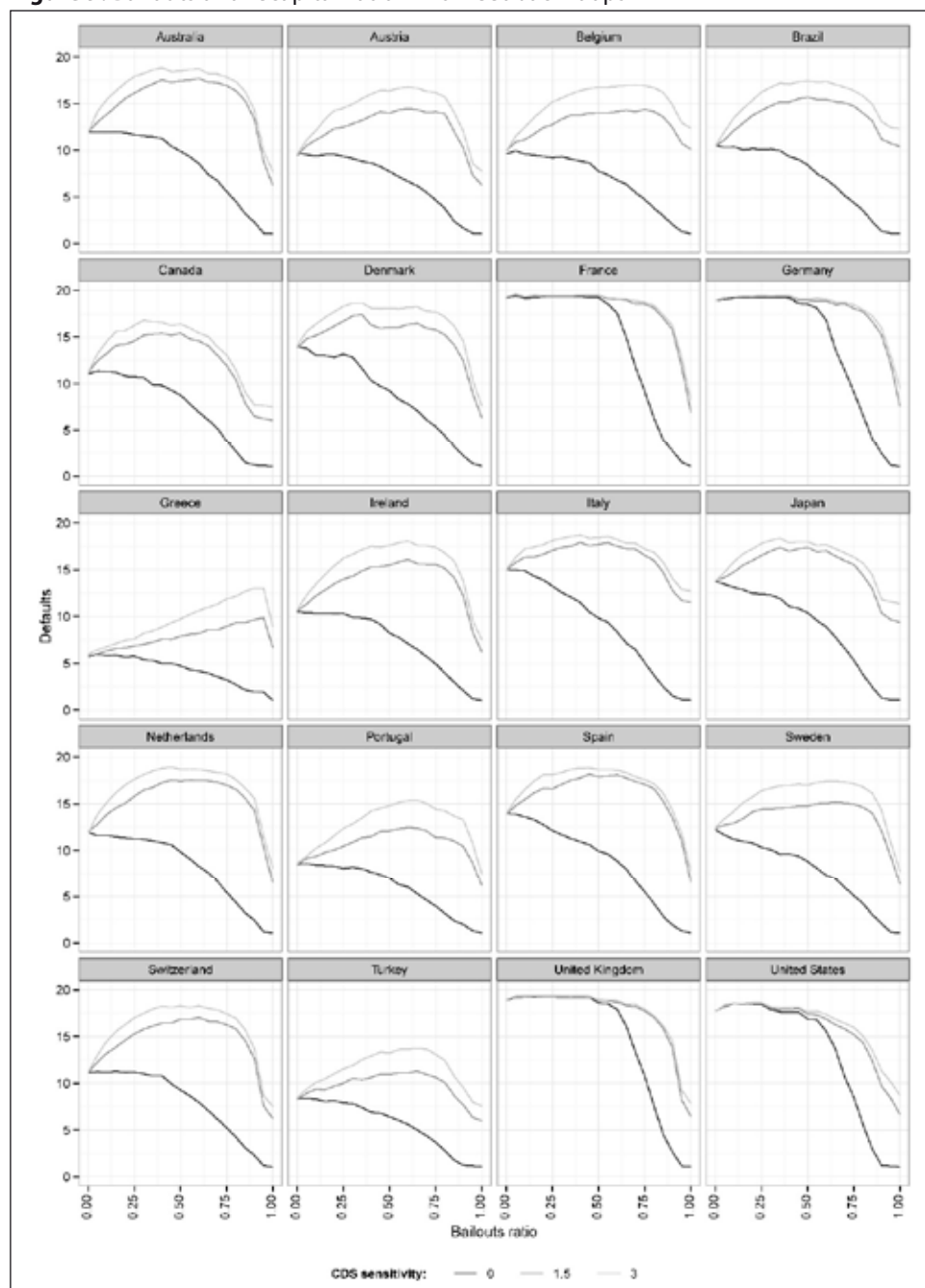
Source: Authors

Figure 10: Asset relief with feedback loops on the calibrated model

Source: Authors