SYSTEMIC RISK AND FINANCIAL STABILITY: ANALYZING THE EFFECTS OF BANK AID

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Abstract

This paper focuses on the link between financial system and sovereign debt crises through sovereign support to banks on one hand and banks' exposures to weak sovereigns on the other. We construct an agent-based network model of an artificial financial system allowing us to analyse the effects of state support on systemic stability and feedback loops of risk transfer back into the system. The model is calibrated to the real-world data using a unique dataset put together from various sources and tested with various parameter settings in Monte Carlo simulations. Our analyses yield the following key results: Firstly, in the short term, all support measures improve systemic stability. Secondly, in the longer run, the effects of state support depend on several parameters but still there are settings in which it significantly mitigates the systemic crisis. Finally, there are differences among the effects of different types of support measures.

Keywords

Agent-based models, financial stability, liquidity risk, network models, systemic risk.

1 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.

2 The Current Financial Crisis

The true mark of the systemic crisis outbreak was the failure of Lehman Brothers on 15 September, 2008. 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.

At this point, the states started playing an active role, introducing a number of measures to support the troubled financial institutions. In the short run, the support measures had a positive impact on systemic stability. However, the 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. As a result, sovereign bond yields and CDS spreads rose and the access to new funding became increasingly more expensive.

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.

3 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.[1] Nodes may represent individual agents, for example servers and websites when we study computer networks or people in case of social networks. 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.

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.

[1] More rigorously, network is a graph defined as $G = (N, E, f)$, where N is a set of nodes, E is a set of edges and $f: E \rightarrow N \times N$ is the mapping function which plots the edges onto individual pairs of nodes (Lewis, 2009).

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). 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 (2013) add regulatory aspects into this framework. This paper combines theory and empirics as the model is calibrated to the real-world data.

4 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

$\boldsymbol{a_i}$...TOTAL ASSETS	$\boldsymbol{l_i}$... TOTAL LIABILITIES
s_i...sovereign debt	b_i...interbank liabilities
q_i...interbank assets	d_i...external liabilities (deposits)
e_i...external assets	c_i...equity (capital buffer)

Source: Author

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 $\Delta = CreditShock + PriceShock + GovtShock$, where

- $CreditShock$ represents losses that banks incur due to default of another bank in the network to which they hold an exposure.
- $PriceShock$ represents losses that banks incur due to overall drop in asset prices caused by market liquidity effects.
- $GovtShock$ represents losses that banks incur due to default of a sovereign in the network to which they hold an exposure.

4.1 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

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 t the i-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.

4.2 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.[2] 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.

4.3 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.

b. *Asset relief* (AR) – the sovereigns may buy what assets their domestic banks need to sell in fire sales.

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

[2] 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).

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.

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).

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)

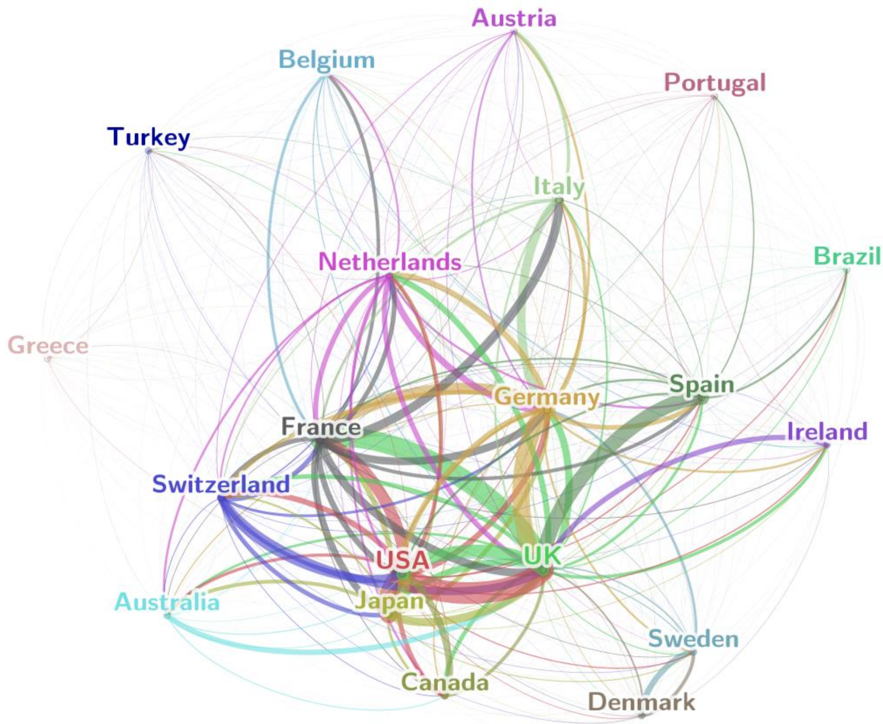
Source: Author

5.1.1 Interbank Assets and Liabilities

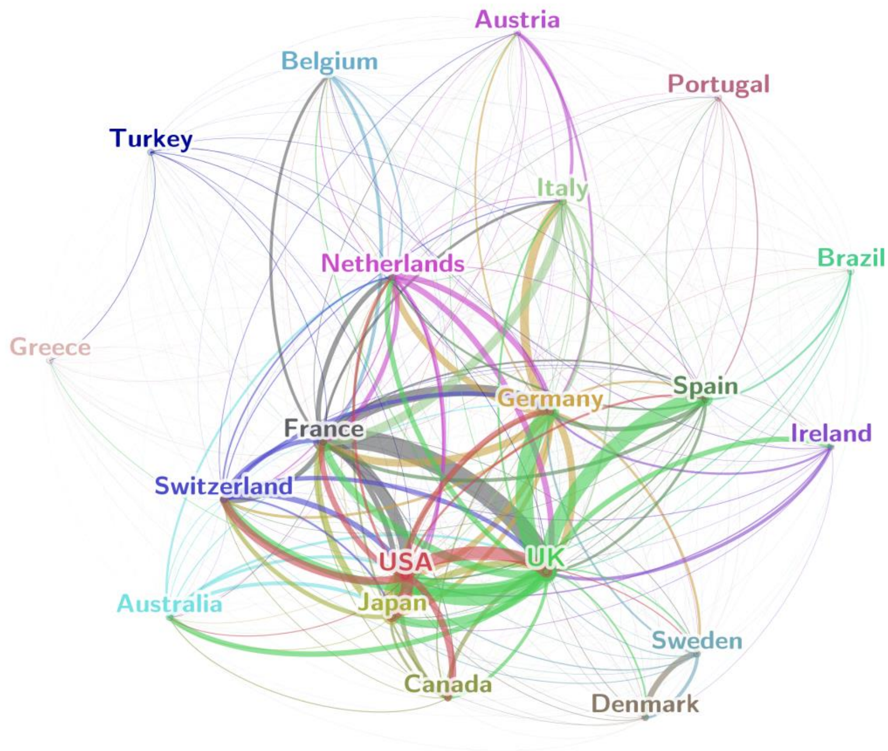
The interbank exposure dataset describes the interlinkages in the global banking system. These are collected from BIS International Financial Statistics (BCBS, 2013).

Figure 1: Interbank network of the selected countries as of Q4 2011

Panel A:



Panel B:



Source: Author based on data from BIS International Financial Statistics

Note: Panel A shows the edges coloured by the creditor node (e.g. exposure of Switzerland against the United States is coloured in blue, which is the colour of Switzerland on the chart) whereas in Panel B, they are coloured according to the debtor node (e.g. exposure of Germany against the United Kingdom is coloured in green as well as the UK node)

To form the interbank exposure matrix, we employ data from the consolidated statistics of foreign claims on immediate borrower basis. 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.[3]

When the network is created, it can be plotted as in Figure 1. 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, 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.

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).

For better insight into the interlinkages between banks and sovereigns, one has to study also the individual exposures. Figure 2 presents this data as a plot of the bipartite network of sovereigns and banking systems in our sample. Here we see the home bias phenomenon as the largest links are always to the domestic banking system.

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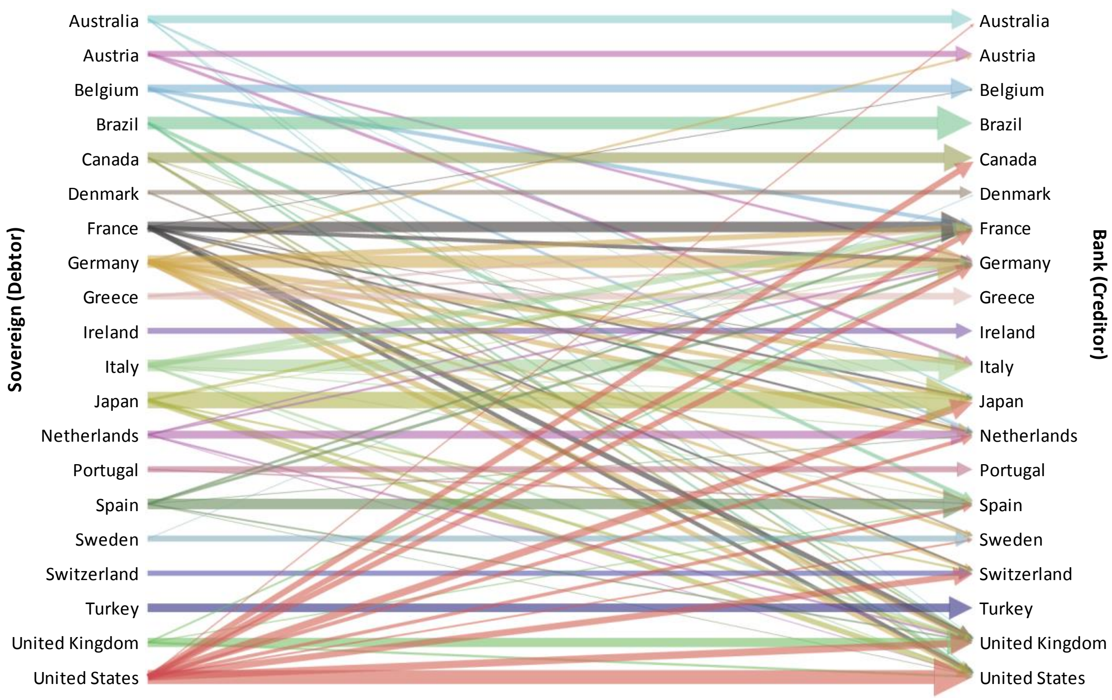
[3] Czech Republic was not included in the analysis as it does not report its international banking exposures to BIS.

Figure 2: Detailed banking systems' exposures to sovereign debt as of Q4 2011



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

Note: The edges are coloured by the debtor node (e.g. exposure of Canadian banking system to the US sovereign is coloured in red). The edges' thickness represents the exposure size on a natural log scale and all exposures amounting to less than USD 5 billion were filtered out for better readability.

5.1.3 Results

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.

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.

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: Author

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.

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