Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

DIPLOMA THESIS

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Charles University in Prague

Faculty of Social Sciences

Institute of Economic Studies

DIPLOMA THESIS

Systemic risk and sovereign crises

Modelling interconnections in the financial system

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Academic Year: 2012/2013

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed and properly cited resources and literature. He further declares that the thesis has not been used previously for obtaining a university degree.

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Signature: ....

Acknowledgements

I would like to express my sincere gratitude to PhDr. Petr Teplý Ph.D. for supervising my work on this thesis. All of his insights and suggestions were greatly appreciated. I am also grateful to David Kubásek for valuable consultations regarding the implementation of the model.

Special thanks belong to my parents for kind support during my studies and to Tereza Fišerová for carefully reviewing the thesis and standing by my side.

Master Thesis Proposal

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Proposed Topic: Systemic risk and sovereign crises

Topic Characteristics: 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 itself into economic crisis. In these earlier stages, the sovereign states took an active role, supporting the economic system by bank aid, quantitative easing and economic stimuli packages. However, the 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 sovereign states too are now 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.

Meanwhile, in the new market environment the survivor banks are struggling to drive their profits back up. Despite the pressure for recapitalization and increased systemic safety in form of new regulatory standards, for large financial institutions the perceived way to go is to once again inflate their balance sheets without too much worry about the consequences of their possible failure. On the contrary, the recent history taught them that the larger, more leveraged and thus more systemically important a bank is, the larger the probability of a bailout. The world economy finds itself on the crossroads once again but this time the sovereign states cannot afford to play the guardian role anymore.

The overall aim of this project is to add new contribution in the field of sovereign debt crises and bank crises, which has been broadly discussed both on the EU and international level recently. The role of the sovereign states in the financial system will be examined, be it as regulatory bodies, providers of bank aid or agents of the financial system as such.

Hypotheses: The main research question is how the behaviour of the financial system is affected by its individual parameters, how and when its stress can translate into sovereign crises and on the other hand, how and when a sovereign crisis can feed back into the financial system through sovereign debt exposures. For example, I will be testing hypotheses such as:

I. In the first stage of a financial distress, state aid significantly reduces the extent of a financial crisis, decreases the number of failed banks and mitigates the depositor loses.

II. However, as the states run out of reserve funds, the crisis inevitably returns through sovereign defaults.

III. As the sovereigns send negative shocks back into the financial system through default on sovereign debt, another wave of bank failures begins.

IV. Still, in total, the system would not be better off without the state aid because sudden total failure would cost more than a slower process of regulated deleveraging.

Methodology: In the thesis, I will extend the framework I have introduced in Klinger (2011) and Klinger and Teplý (2012). It is based on two main approaches, network theory and agent-based modelling, and its main idea is the loss transfer in case of a financial system crisis. This approach understands the financial system as a network of banks and sovereigns represented by their balance sheets and linked together by mutual claims. When a subject finds itself in a severe financial distress and is incapable of honouring its obligations, it sends a negative shock through the network which depending on the financial soundness of the shock-receiving creditors can result in another wave of defaults. Furthermore, to model all aspects of the mutual interlinkages of the banking and the sovereign sector, I will incorporate banking regulation, state aid in form of bailouts and deposit guarantees, and liquidity modelling. Some parameters of the model will be calibrated according to available data collected from BankScope, Bank for International Settlements database or databases of national central banks, the impact of other parameters on the system will be examined in simulations.

Outline:

1. Introduction:
    a. *Research motivation*
    b. *Structure outline*
2. Theoretical part:
    a. *Description of the current situation*
    b. *Literature review*
    c. *Identification of the key drivers to be incorporated into the model*
3. The model:
    a. *Model construction*
    b. *Calibration*
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4. Conclusion:
    a. *Results summary*
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Core Bibliography:

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Author

Supervisor

Abstract

This thesis 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. After illustrating the main relationships on the recent financial crisis, 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 the feedback loops of risk transfer back into the financial system. First, the model is tested with various parameter settings in Monte Carlo simulations and second, it is calibrated to the real world data using a unique dataset put together from various sources. Our analyses yield the following key results: Firstly, in the short term, all the support measures improve the 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 the different types of support measures.

JEL Classification: C63, C90, D85, E61, G01, G15, G18, G21, G28, H60

Keywords: agent-based models, bailout, contagion, financial crises, financial stability, liquidity risk, network models, state support, systemic risk

Abstrakt

Tato práce se zaměřuje na vazby mezi krizemi finančního systému a dluhovými krizemi jednotlivých států skrze státní pomoc na jedné straně a expozice bank vůči státnímu dluhu na straně druhé. Po ilustraci hlavních vztahů na nedávné finanční krizi zkonstruujeme multiagentní síťový model finančního systému, který nám umožní analyzovat efekty státní podpory na systémovou stabilitu a efekty zpětné vazby, při kterých se riziko přenáší ze států zpět na bankovní systém. Nejprve testujeme různé parametrizace modelu pomocí Monte Carlo simulací. Následně je model zkalibrován pomocí jedinečné sady dat složené z různých zdrojů. Klíčové výsledky naší analýzy jsou následující: Zaprvé, v krátkodobém horizontu veškerá opatření na podporu bank zlepšují systémovou stabilitu. Za druhé, v delším časovém horizontu závisí účinky státní podpory na parametrizaci modelu, ale stále existují nastavení, za kterých státní pomoc výrazně zmírňuje systémovou krizi. A konečně, existují rozdíly mezi účinky různých typů podpůrných opatření.

Klasifikace JEL: C63, C90, D85, E61, G01, G15, G18, G21, G28, H60

Klíčová slova: finanční krize, finanční nákaza, finanční podpora, finanční stabilita, multiagentní modely, riziko likvidity, síťové modely, státní podpora, systémové riziko

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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.

Meanwhile, in the new market environment, the survivor banks are struggling to restore their profits. Despite the pressure for recapitalization and increased systemic safety in form of new regulatory standards, large financial institutions start a regulatory race again, as for them the perceived way to advance is to once again inflate their balance sheets without worrying about the consequences of their possible failure. On the contrary, the recent history taught them that the larger, more leveraged and thus more systemically important a bank is, the larger the probability of a bailout. Again, the world economy finds itself on the crossroads but this time the sovereign states cannot afford to play the guardian role anymore.

The overall aim of this thesis 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. It examines the role of the sovereigns, be it as regulatory bodies, providers of bank aid or members of the financial network as such. The main research question is how the stability of the financial system is affected by its individual parameters, mostly those associated with the link between the banks and the sovereigns, how and when its stress can translate into sovereign crises and on the other hand, how and when a sovereign crisis can feed back into the system through sovereign debt exposures. The research hypotheses are the following:

i. *In the short term, state aid significantly reduces the extent of a financial crisis and decreases the number of failed banks.*

ii. *In the longer term, as the sovereigns are weakened by the support provided to the banks, they may send negative shocks back to the system. Still, in total, the system would not be better off without the state aid.*

iii. *There are differences among the types of state aid. The direct support is more efficient as opposed to the liquidity measures which are only prolonging the resolution of the debt crises.*

The thesis is a logical follow-up of our previous research, Klinger (2011) and Klinger & Teply (2013), where we used agent-based network simulations to assess the impact of various settings of banking regulation on systemic stability. The main idea which we employed successfully in our previous research is that the banks may be represented by their balance sheets and they form nodes in a network, connected with mutual claims. It stems from the recent advances in network modelling of financial systems, which are described in more detail later in the following chapters, mostly from Nier, et al. (2007).

The following second chapter 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 chapter will present the used concepts more rigorously, presenting a literature review of the theories behind the main mechanics of our research question as well as of the models and modelling techniques that form the grounds and inspiration for our analysis. In the fourth chapter, 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 fifth chapter, we test the model thoroughly in Monte Carlo simulations to get better understanding of its inner processes and its results. In the sixth chapter 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 happening later in the future. Finally, we close the thesis with a conclusion summarizing our research and findings.

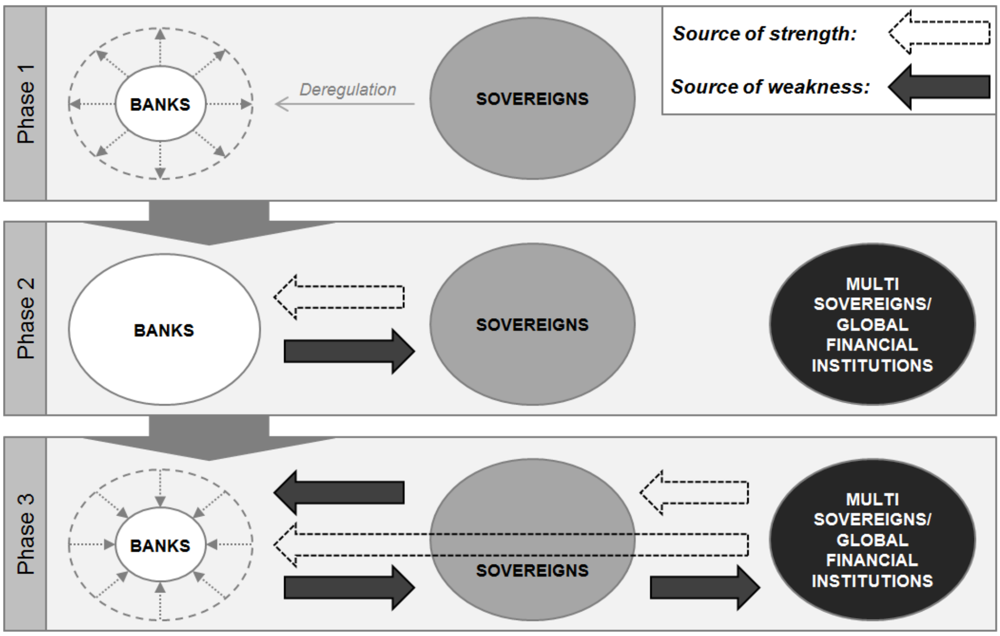
2 The Context of State Aid

To set the issue of sovereign aid into the current context, the following chapter provides a short outline of the recent financial crisis and its individual phases as it progressed from its beginning in 2007/2008.

2.1 The Current Financial Crisis

The High-level Expert Group on reforming the structure of the EU banking sector classifies the development of the recent financial crisis into five phases: "Subprime crisis" phase, "Systemic crisis" phase, "Economic crisis" phase, "Sovereign crisis" phase and a "Crisis of confidence in Europe phase" (Liikanen, 2012). However, for the purpose of describing the interlinkages between the financial system and state sector, we identify three main phases of the crisis as presented in Figure 1.

Figure 1: The interconnections among sovereigns and banks



Source: Author based on Caruana (2012)

2.1.1 Phase One: Subprime Crisis and Before

This phase is characteristic with risk build-up and successive rapid deterioration of market conditions which stood at the beginning of the recent crisis. It is well known that the first shockwaves came from the U.S. subprime mortgage market. However, what really can be considered as the cause of the crisis is the development which preceded it, and which stretches back to the collapse of the Bretton-Woods system. In the times of the Bretton-Woods, the banking practice was heavily regulated. With strict controls of cross-border capital flows, the banks operated mostly on the local basis and the financial system formed much less complex structure than the one of 2007. The deposit rates as well as the lending rates were set by strict government rules with margins that gave the bankers a solid space for profit and ensured systemic stability (Schooner & Taylor, 2009). Moreover, in the reminiscence of the Great Depression, there was the Glass-Steagall act that put a Chinese wall between commercial and investment banking and several similar legislative acts outside the United States.

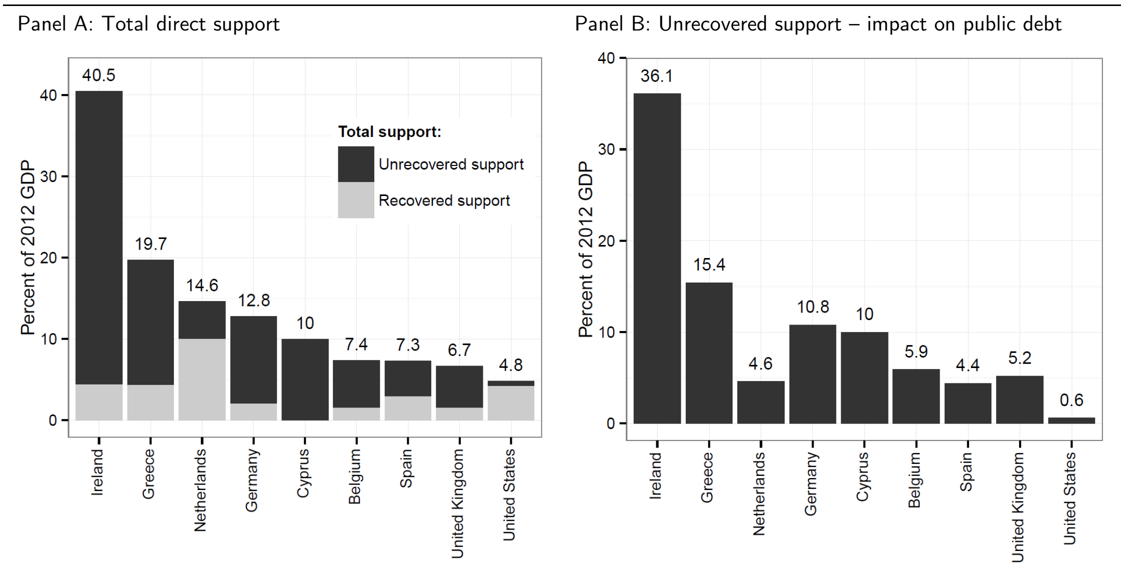
However, when the Bretton Woods system fell, apart the environment experienced transformation from heavily regulated to highly competitive. Without the heavy regulation, competitive pressures were squeezing the interest rate spreads and the resulting sharp decline in profit margins caused that the only way for the financial institutions to maintain their profit levels was through increasing the scale of operations by heavily leveraging their balance sheets (Klinger, 2011). As banks went to race for leverage, the credit market completely changed its character and started bringing cheap funds to households who begun taking mortgages on a massive scale. The steady growth in investment was driving the asset prices upwards and soon it resulted in a *"Ponzi scheme"* where credit could have been granted even to people with no income. Meanwhile, to be able to further increase the leverage, the banks and mortgage companies started repackaging the loans, slicing and selling them across the financial system to other banks and investors in the form of an opportunity of a low-risk, high-return investment. Although the role of the sovereigns and their governments may not be obvious at the first sight, due to the insufficient regulation of the financial institutions and allowing these profound changes to happen, these subjects in fact were the crucial part of this development.

The first signs of problems appeared in 2007 when the unsustainability began to surface and the banks began writing off subprime mortgage securities. However, as the banks' situation gradually deteriorated, so did the trust of their investors and lenders. In connection to the need of short-term financing on which the banks laid out the foundations of their business models for the last three decades, this provided a deadly mix which prepared ground for a much more severe and far-reaching systemic crisis.

2.1.2 Phase Two: Systemic Crisis and State Aid

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 shares of the banking sector dropped 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 2: Financial sector support in selected advanced economies, 2008 – Jul 2012

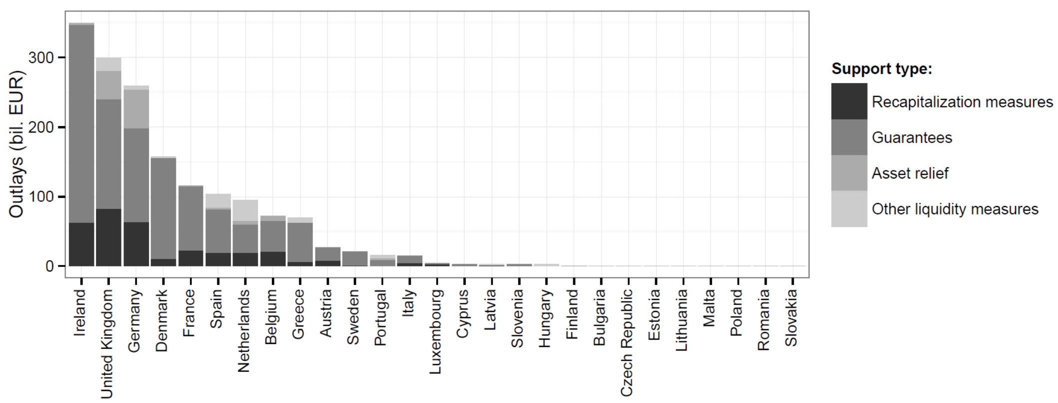


Source: IMF (2013a)

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). According to Panetta, et al. (2009, p. 1), "*...the magnitude of the action taken to support the banking system has been unprecedented.*"

Figure 2 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). The United Stated managed to recover almost 90% of the provided funds. Moreover, Figure 3 providing the detailed break-down of support to the financial sector for the EU27 countries shows that in absolute terms, Ireland and the United Kingdom invested the largest amounts in their financial systems.

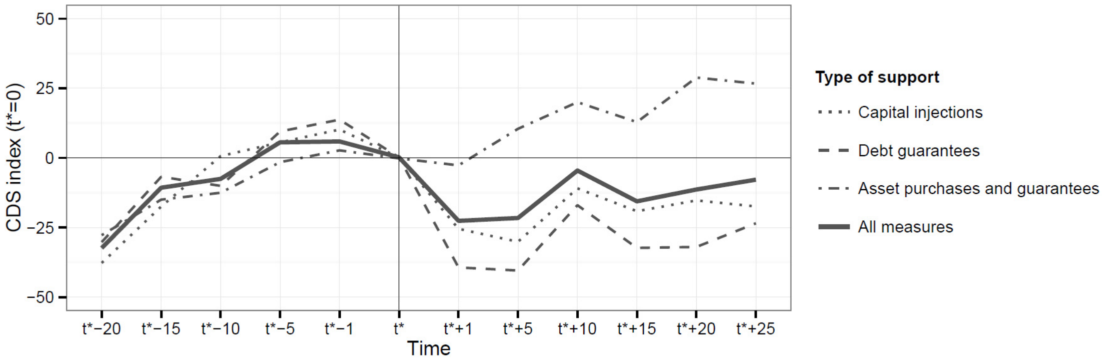
Figure 3: Used amounts of aid to financial institutions, 1 Oct 2008 – 1 Dec 2011



Source: Author based on data from EC (2012)

As to the effects of the state aid, in the short run, the support measures definitely 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. Figure 4 presents the effects of different measures on the CDS premiums of 11 selected countries. [1]

Figure 4: Effects of state support measures on bank CDS premiums



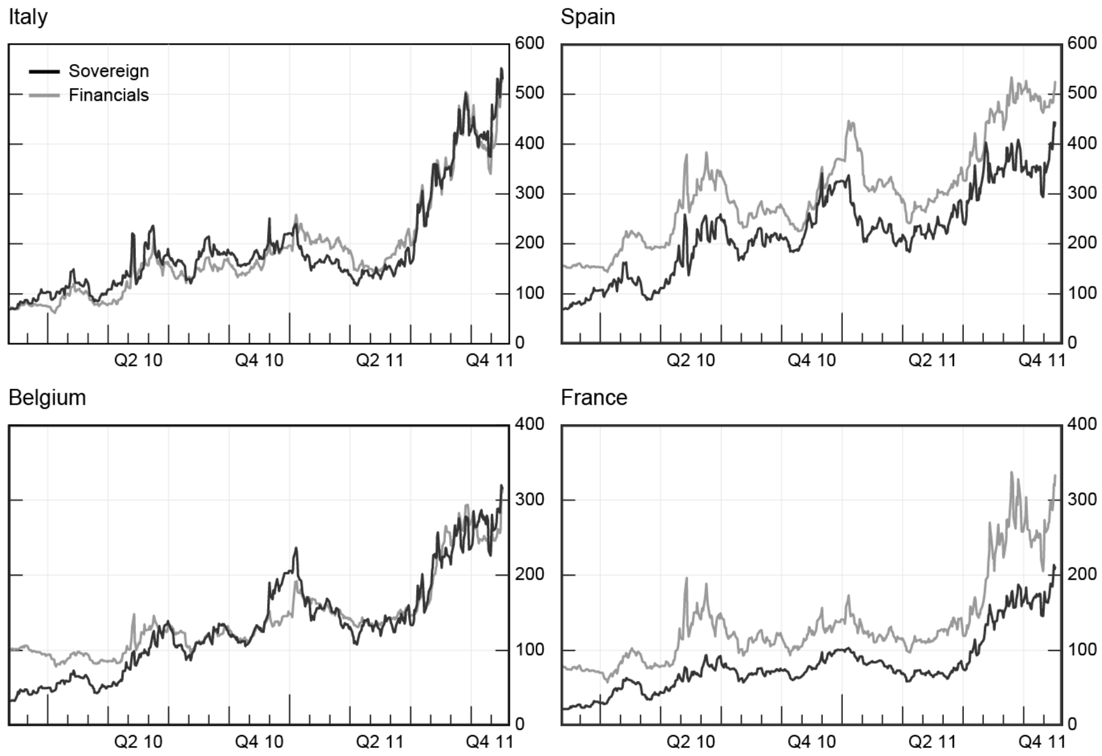
Source: Author according to Panetta, et al. (2009)

2.1.3 Phase Three: Sovereign Crisis and the Feedback Loops

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.

[1] Australia, France, Germany, Italy, Japan, the Netherlands, Spain, Switzerland, the United Kingdom and the United States

Figure 5: CDS spreads of selected countries and their respective financial systems



Source: Author based on Caruana (2012)
Note: CDS for financials are simple averages over a sample of domestic financial institutions

Unfortunately, the sovereigns did not prove to be anything else than other type of agents in the same financial system and thus by transferring 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. Illustration of impact of such feedback loops is provided in Figure 5, where we can observe the CDS spreads of selected sovereigns and how they affect CDS spreads of domestic financial systems. According to Caruana (2012), these loops may be divided into four key channels:

i) As a large portion of sovereign debt was held by the same banks that were receiving the support, the losses on banks' sovereign portfolios weakened the banks' balance sheets and led to capital losses. Moreover, due to increased counterparty risk, the funding decreased in availability and increased in cost;

ii) Deterioration in sovereign creditworthiness reduces the value of the collateral that banks were able to use for wholesale funding and to obtain liquidity from the central bank;

iii) Rating agencies as well as investors are aware of the impact of the public sector on a country's financial system. Hence, sovereign rating downgrades almost always flow through to domestic banks downgrades, further worsening their status a borrowers.

iv) Deterioration in the creditworthiness of the sovereigns also reduces the benefits of government guarantees to the banks as these lose value and market credibility.

In this manner, the risk and the losses oscillate between the privately-held banks and "publicly-held" sovereigns. However, we argue that from the systemic point of view, the state aid plays important positive role during the crisis because it manages to dilute the shocks and spread them in time. Finally, it is clear that most of the losses were finally paid by the general public in role of depositors or taxpayers.

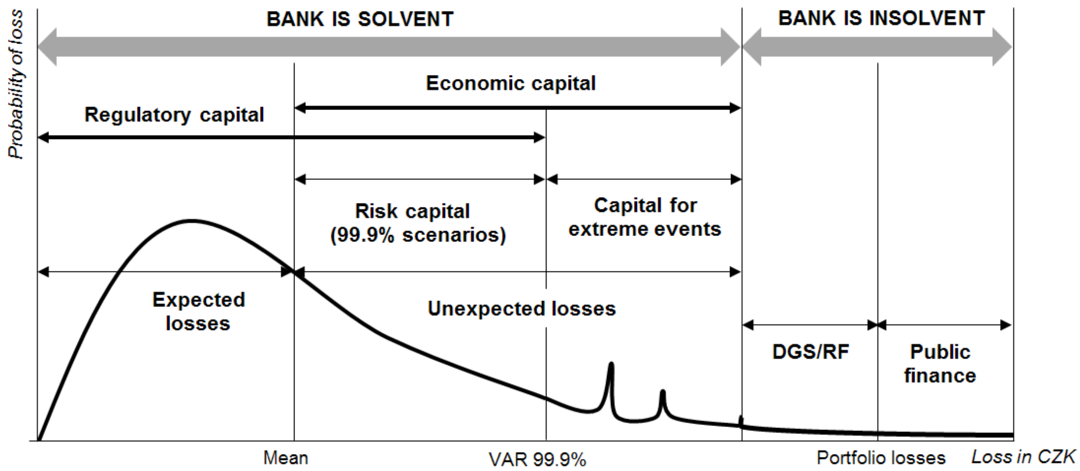
3 Theoretical Background

The following chapter provides a literature review of both the main concepts of state help in case of a systemic financial crisis, studies associated with the recent financial crisis and the modelling framework which we use further to construct the model of the financial system.

3.1 Sovereign Debt Crises and State Aid

The current international economic turmoil has highlighted the strong interconnection among sovereign debt and bank crises, which came into interest of the researchers only very recently, when the sovereign crisis and the crisis of Europe started to unfold. Figure 6 demonstrates the part played by public interventions in rescuing troubled banks, indicating key implications for public finance.

Figure 6: Bank's insolvency and public finance involvement



Source: Author based on Campolongo, et al. (2011) and Teply (2009)
Note: DGS = Deposit Guarantee Schemes, RF = Resolution Funds

A bank is insolvent when its capital does not cover incurred losses. In this case two main kinds of public support are possible: Deposit Guarantee Schemes (DGS) and Resolution Funds (RF), and government support such as capital injections, liquidity interventions, asset purchases or guarantees. On the other hand, banks are linked with governments in three main ways: sovereign bonds in their portfolios, sovereign bonds used as collateral for operations with central banks and other counterparties, and finally through guarantees issued by sovereigns on banks' liabilities.

From the onset of the current financial crisis, the topic of sovereign crises came into interest of many researchers and numerous publications were written on this topic including Manasse & Roubini (2009) who provide an empirical study of the conditions leading to a sovereign crisis, Reinhart & Rogoff (2009) who explore the history of sovereign countries in individual case studies, Enderlein, et al. (2012) who investigate behaviour of governments which find themselves on the verge of default, Borensztein & Panizza (2009) who examine possible costs to the defaulting sovereign arising from its failure or Dias (2012) who investigates the asynchronization between PIIGS countries (Portugal, Ireland, Italy, Greece and Spain) and other resilient countries in the Eurozone through the minimum spanning tree and the associated hierarchical tree analyses. On a related note, Estrella & Schich (2011), develop a valuation method of bank debt insurance by troubled sovereigns, Pisani-Ferry (2012) describes problems that arise from this linkage to the Euro area, Campolongo, et al. (2011) build a model estimating the probability and magnitude of economic losses and liquidity shortfalls occurring in the banking sector.

However, the literature on sovereign debt crises is not only a matter of the current "post-crisis" age as documented by classic works of Bulow & Rogoff (1989b) who explore how heavily indebted sovereigns can perform a partial restructuring of their debt, Bulow & Rogoff (1989a), who study the contracting issues of lending to small countries, Eichengreen & Portes (1995), who draw implications from the Mexican crisis or Cantor & Packer (1996), who investigate the what determines sovereign rating and what impact the ratings have. Finally, Laeven & Valencia (2008), recently updated by Laeven & Valencia (2012), provide a detailed catalogue of systemic banking crises along with description of the links they had to the sovereign sector.

3.2 Used Methodology

For better understanding of the impact of the link of sovereigns and banking institutions on financial system stability, in the rest of the thesis we will be constructing, testing and calibrating a model of a virtual financial system. Here, we will briefly introduce the basic modelling framework, which is based on two central concepts, both of them relatively new and associated with computational economics and study of complex systems. These two are network theory and agent-based modelling. Since the core idea of the model presented in this thesis is similar to Klinger & Teply (2013) and Klinger (2011), this chapter draws from the description of the main concepts which we laid out in these works.

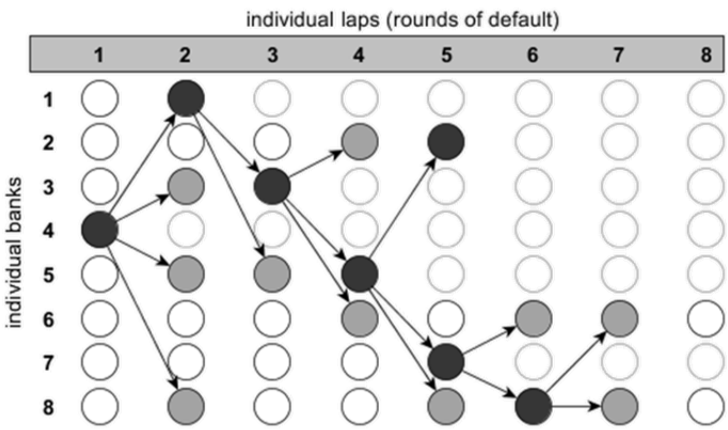
3.2.1 Network Modelling

The network theory is particularly useful for description of connected structures and the pattern of their relationships, whether these are social networks, the Internet, networks of citations of scientific papers, or complex financial systems. We state already in Klinger (2011) that a network is a set of nodes connected with edges. Defined more rigorously, it is a graph defined as $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{E}, \boldsymbol{f})$, where $\boldsymbol{N}$ is a set of nodes (also called vertices), $\boldsymbol{E}$ is a set of edges (also called links) and $\boldsymbol{f}: \boldsymbol{E} \rightarrow \boldsymbol{N} \times \boldsymbol{N}$ is the mapping function which plots the edges onto individual pairs of nodes (Lewis, 2009).

Nodes may represent individual agents, depending on the field we use the network approach in. Among others, these are servers and websites when we study computer networks or people in case of social networks. In the framework of finance, they may represent banks, traders, depositors, companies or whatever else entity which constitutes a part of a financial system. Edges may contain more data than just the false/true property describing the (non)connection of any two particular nodes in the network. What may also matter is the orientation of an edge, defining whether it points from node A to node B, from node B to node A or both ways at the same time. Also the edges may have different weights, which is a property representing the strength of their mutual connections. When, as in our case, 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). Finally, arrangement of the edges is defined by various mapping functions, which leads to different network shapes (or topologies), such as "random network" where it is decided randomly according to certain predefined probability whether an edge will be formed between two nodes or not, "star" where all other nodes are connected to one central node or "ring" where each node has exactly two edges and there are all the edges are connected into one cluster. Comprehensive description of individual topologies and other network properties and references to the original research on network theory are provided among others in Wilhite (2006) or Lewis (2009).

Network theory proved to be a particularly interesting means of studying impulse transmissions, which includes transmission of negative shocks. The most illustrative example of utilization of this methodology is the advancement of contagion through a network of subjects where a small collection of infected nodes may result into epidemics.[2] Obviously, we can use this methodology also 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. If these creditors' capital buffers do not suffice to cover the incurred losses, in the next lap some of these also default on their obligations while sending the shock even further into the system (Klinger, 2011). In Figure 7 depicting the mechanism of shock propagation, the propagating banks are coloured grey whereas the failed banks are depicted in black.

Figure 7: Scheme of banking system contagion



Source: Klinger (2011) inspired by Sell (2001)

3.2.2 Agent-Based Modelling

Generally, agent based modelling is a bottom-up approach that examines how numerous subjects that are each equipped with basic set of behavioural rules are interacting in a virtual environment. According to Tesfatsion (2006a, 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 aggregate behavioural patterns on the systemic level. Probably the most well-known paper 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. On a related note, much

[2] For information about the field of epidemiology research, see e.g. Meyers (2007).

space was given to agent-based models of financial markets which use simple sets of instructions for the individual trading agents, which on a macro level lead to patterns that replicate the stylized facts of financial markets (e.g. Lux & Marchesi, (2000)). A thorough guidebook to agent-based economics was published by Tesfatsion & Judd (2006b) and recently, this approach is being recognized and implemented also in the field of systemic stability research. For a demonstration of how well this framework is suited for modelling of financial systems, see e.g. Farmer & Foley (2009), or an FSI Award winning paper of Jo (2012), in which he analysed contagion risk with an agent-based network model. In such models, 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.

3.2.3 Applications for Modelling Banking Systems

As mentioned in Klinger (2011), the 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.

3.2.3.1 Empirical Research

There are several studies that concentrate on the real-world interbank exposure modelling, analysing especially the proneness of banking systems to systemic distress that results from the effects of contagion. Such studies usually focus on local banking networks, 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.

Most of the researchers face the problem of virtually non-existent reliable data on individual interbank exposures. To address this issue, they commonly turn to the use of aggregate banks' balance sheets and employ the assumption of maximum entropy based on the supposition that the individual banks distribute their exposures as evenly as possible (Upper, 2011). However, this simplification is unrealistic and underestimates the potential of contagion and systemic distress (Mistrulli, 2011).

3.2.3.2 Theoretical Models

The theoretical models examine how system behaviour is influenced by its general characteristics. The first such model was constructed by Allen & Gale (2000) who showed that the structures with more interbank links are more resilient in case of a distress situation. Another early analysis was carried out by Freixas, et al. (2000), who studied contagion in systems where some banks were systemically important. The simple framework of pure credit shock contagion is extended in Cifuentes, et al. (2005) and Shin (2008), who 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), who find that the linkages among banks are absorb the shocks initially but when the severity of systemic distress exceeds a certain threshold, they may cause greater instability. Our approach will build on such theoretical models and mostly on a paper by Nier, et al. (2007), who constructed a simulation model on which they examine how different parameters of a banking system affects its resilience. Moreover, we will build on Klinger & Teply (2013), who add regulatory aspects into this framework.

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 several types of balance sheet shocks, which may originate from individual banks, individual sovereigns or from downward pressure on asset prices. 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 not transmitted further onto other agents. The modelling approach inspired by Nier, et al. (2007) and Chan-Lau (2010), was first introduced in our previous research in Klinger (2011) and Klinger & Teply (2013). In this thesis, we elaborate on the model construction[3] and add new features such as funding liquidity shocks or inclusion of sovereigns in the financial system.

4.1 Creating the Network

The infrastructure of the model is formed by a network of banks and sovereigns. First, the model creates an interbank network, which is a graph defined by two parameters set exogenously at the beginning of each simulation and describing the random graph of banks. These are the following:

1. Node count N^b, determining the number of agents in the interbank network,
2. Probability p_{ij}, with which there exists an oriented edge from bank i to bank j, i.e. the probability that bank i is exposed to bank j by holding a claim against it. We assume this parameter fixed among all edges between all nodes $i, j \in (1, \dots, N^b)$ and denote it as p^b. As the exposures are not netted, two links in opposite directions may exist between each pair of banks.

[3] Please note that some parts of the basic model infrastructure definition may overlap with (Klinger, 2011).

The interbank network is created in two steps. First, there are N^b banks added to the system, and second, for each oriented pair of banks, an edge is created with probability p^b.

Second, we add the sovereign agents and link them with their domestic banks by exposures held by each bank to its home sovereign. We abstract from other types of connections such as exposures of states-to-banks, states-to-states or banks-to-foreign-sovereigns as they would clutter the model with parameters we do not wish to focus on. For introduction of sovereigns, the system takes one more exogenous parameter, initial node count $N^{s,INIT}$, determining the number of sovereigns. For each bank $i \in (1, \dots, N^b)$, one sovereign $k \in (1, \dots, N^{s,INIT})$ is sampled randomly and an oriented edge is created between these two. The bank-sovereign edges represent claims of banks on the domestic sovereign, i.e. the exposure that bank i holds to sovereign k. At the end of the edge initialization, the sovereigns having no links with any of the banks are removed from the system and the number of sovereigns left is denoted as N^s.

4.2 Initializing the Balance Sheets

Table 1: Balance sheet variables of a modelled bank

a_i...TOTAL ASSETS	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...net worth (capital buffer)

Source: Author

Next, the model builds balance sheets of individual banks for the given network realization. First, we calculate the aggregate variables of the system. The total value of all assets 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 such as households, foreign sovereigns and non-financial institutions or derivatives.

The banks' balance sheets are then populated according to the following algorithm:

1. The sum of external assets in the system $\boldsymbol{E}$, sum of sovereign debt towards all banks $\boldsymbol{S}$ and the share of interbank assets in total assets θ are given exogenously. The total value of all assets in the system $\boldsymbol{A}$ is determined by these as follows:
$$A = \frac{E+S}{(1-\theta)}.$$
2. The sum of interbank assets is calculated from the total assets and the share of interbank assets in total assets:
$$I = \theta A.$$
3. In line with Nier, et al. (2007), for Monte Carlo simulation purposes, the interbank exposures are assumed homogenous.[4] Denoting the sum of all interbank edges in the system as $\boldsymbol{Z^b}$, the value of each individual edge is thus calculated as:
$$w_{ij}^{b} = w^{b} = \frac{I}{Z^{b}}.$$
4. The value of each sovereign's debt is given as $\frac{S}{N^s}$. for Monte Carlo simulations, it is assumed homogenous across sovereigns.[4] Denoting the sum of outgoing edges from banks to $\boldsymbol{k}$-th sovereign as z_k^{IN}, the value of each individual edge is thus calculated as:
$$w_k^s = \frac{S}{N^s z_k^{IN}}.$$

When the aggregate variables are determined, the model initializes the balance sheets of individual banks:

5. The value of interbank assets (q_i) and liabilities (b_i) of each bank are determined by the interbank edge weight and number of edges in the system as:
$$q_i = w^b\ z_i^{IN},$$
$$b_i = w^b\ z_i^{OUT},$$

[4] In the empirical part they are calibrated according to the real-world data

where z_i^{IN} is the number of i-th bank's incoming edges and z_i^{OUT} is the number of its outgoing edges.[5]

6. The value of sovereign debt held on each bank's balance sheet (s_i) is equal to the value of domestic government held by the bank.

$$s_i = w_k^s,$$

7. External assets' value of each bank is determined by a two-step algorithm described in Nier, et al. (2007):

   a. First, the difference between the internal liabilities and internal assets is balanced by a certain amount of external assets $\tilde{e}_i$:

   $$\tilde{e}_i = \begin{cases} b_i - q_i & \text{if} \quad b_i - q_i > 0 \\ 0 & \text{if} \quad b_i - q_i \leq 0 \end{cases}$$

   b. The rest of the total sum of external assets is distributed uniformly among all banks so that the following holds for each bank's external assets value:

   $$e_i = \tilde{e}_i + \left[\frac{E - \sum_{i=1}^{N^b} \tilde{e}_i}{N^b} \right].$$

8. Each bank's capital buffer (c_i) is determined as a share of its total assets (a_i) according to the capital ratio γ_i. In line with Nier, et al. (2007) or Chan-Lau (2010), for the Monte Carlo simulation purposes, the capital ratios are assumed the same across all banks and are denoted as γ:

$$c_i = \gamma a_i.$$

9. The value of each bank's external liabilities (d_i) is calculated so that the balance sheet identity holds:

$$d_i = a_i - c_i - b_i.$$

When the balance sheets are populated, the system is initialized. The final setting of banks' balance sheets is depicted in Table 1.

[5] On the aggregate level, it holds that $\sum_{i=1}^{N^b} z_i^{IN} = \sum_{i=1}^{N^b} z_i^{OUT} = Z^b$.

4.3 Introducing Negative Shocks

When the network is prepared, the system stays inactive until we impose an adverse shock event, initiating the first simulation lap. There are several types of such events:

- A share of external assets is deducted from a random bank's balance sheet. We call this a *"local shock"*.
- The external assets price drops. In this case, a certain percentage loss on these assets is applied to balance sheets of all banks. We call this a *"global shock"*.
- A sovereign defaults on a portion of its debt. In this case, the shock is transmitted to all banks that hold exposure towards this sovereign, i.e. the banks "domestic" to the defaulting state. We call this a *"sovereign shock"*.

Similarly, at the beginning of each next lap, each bank may receive a total asset-side shock of $\Delta = \delta + PriceShock + GovtShock$, whose individual components are described in detail on the following pages.

4.4 Shock Reaction and Contagion

If the banks affected by the primary shock do not possess 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 writes 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 a shock of size $\Delta_{i,t}= l_{i,t} - a_{i,t}$, 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 $c_{i,t} > \Delta_{i,t}$, 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 $c_{i,t} < \Delta_{i,t}$, the residual shock overflows to the interbank liabilities b_i, in which case its value up to the value of the interbank liabilities is uniformly divided into losses of all creditor banks. Formally, in case of m creditor banks, in the next round each creditor bank j receives from bank i a shock of

$$\delta_{ij,t+1} = min\left(\frac{\Delta_{i,t} - c_{i,t}}{m_{i,t}}, \frac{b_{i,t}}{m_{i,t}}\right). \tag{1}$$

As the propagating 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 $b_{i,t} > \Delta_{i,t} - c_{i,t}$, the shock is absorbed completely by the bank's capital and interbank liabilities.

   ii. If $b_{i,t} < \Delta_{i,t} - c_{i,t,}$, the shock overflows to external liabilities, meaning that the residual loss is covered by the depositors.

4.5 Liquidity Risk Modelling

Generally, there are two types of liquidity issues that can affect a stressed financial system: market illiquidity and funding illiquidity (Gersl & Komarkova, 2009). The former, described firstly by Kyle (1985), represents a situation when transactions in which the assets are sold have a negative impact on the asset prices.[6] The latter refers to inability to meet obligations when they are due. In the recent financial crisis, we witnessed both: a sudden gap in short-term bank financing caused funding illiquidity on the liability side and the subsequent fire-selling of assets as the only means for cash replenishment resulted in further rapid decline in asset prices. Therefore, both these types are accounted for in the model.

4.5.1 Market Liquidity

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

[6] 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. One example of such market liquidity index is the one used in Teply, et al. (2012).

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

$$P(\boldsymbol{x})_t = \exp\left(-\frac{\alpha}{E}\sum_{i=1}^{N^b} x_{i,t}\right), \tag{2}$$

where $x_{i,t}$ is the total value of assets (external and interbank) sold by the i-th bank in the system in the current lap, α represents the market's illiquidity (i.e. the speed at which the asset price declines) and $P(x)_t$ is the new discounted price of external assets calculated in each lap.[7] The additional loss caused by the asset sales are then added to the initial shock on i-th bank in the current lap and transmitted accordingly. Furthermore, assuming marking to market accounting procedure, 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 to a price shock of $PriceShock_{i,t+1} = e_{i,t}(P(\boldsymbol{x})_{t-1} - P(\boldsymbol{x})_t)$ to all banks.

4.5.2 Funding Liquidity

As the failing bank liquidates all of its assets, it may withdraw a certain portion of its claims on other banks classified as short-term credit. As a result, the debtors of the failing bank may receive a funding liquidity shock which decreases their liabilities and may require them to sell a portion of their assets to balance out the gap in funding (Chan-Lau, 2010).

If i-th bank defaults, the portion λ of interbank liabilities $b_{ji} = q_{ij}$ of its debtor j gets erased from the debtor j's total liabilities such that

$$l_{j,t} = l_{j,t-1} - \lambda b_{ji,t}.$$

Subsequently, the j-th bank is forced to fire-sale external assets in the value of the funding shock. This amount of external assets is added to the total amount offered by the banks in the current lap and the j-th bank receives for them $\lambda P(\boldsymbol{x})_t b_{ji,t}$. The value of the loss $(1 - P(\boldsymbol{x})_t)\lambda b_{ji,t}$ is added to the j-th bank's credit shock δ.

[7] Upon the system's initialization, the price is set to $P(\boldsymbol{x})_0 = 1$.

4.6 Sovereign Assistance

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

a. *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 $x_{i,t}$ assets as described in the basic model definition, but only $(1-k^{AR})x_{i,t}$ is sold on the market since $k^{AR}x_{i,t}$ is bought-out by the bank's domestic government. Assuming $1-k^{AR}$ fixed across all banks and all sovereigns, the Equation 2 is replaced by:

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

The amount of $deficit^{AR} = k^{AR}x_{i,t}$ is then added to the external debt of the i-th banks' domestic sovereign as the domestic government needs to find external financing for this rescue measure.

b. *State guarantees execution* (SG) – the sovereigns may reimburse the creditors of their domestic banks to a certain degree to lower the negative shocks. In case this measure is executed, the Equation 1 is replaced as each creditor j of bank i receives a credit shock of:

$$\delta_{j,t+1} = (1-k^{SG})min\left(\frac{\Delta_{i,t}-c_{i,t}}{m_{i,t}}, \frac{b_{i,t}}{m_{i,t}}\right).$$

The amount of $deficit^{SG} = \min\left(\frac{\Delta_{i,t}-c_{i,t}}{m_{i,t}}, \frac{b_{i,t}}{m_{i,t}}\right)k^{SG}$ is then added to the external debt of the i-th banks' domestic sovereign as the domestic government needs to find external financing for this rescue measure.

c. *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 i receives a shock of $\Delta_{i,t}$, the sovereign covers $k^{BR}\Delta_{i,t}$, adding this value to the bank's external assets. Again, the amount of $deficit^{BR} = k^{BR}\Delta_{i,t}$ is then added to the external debt of the i-th banks' domestic sovereign as the domestic government needs to find external financing for this rescue measure.

d. *Funding liquidity provision* (FLP) – the sovereigns may provide funding liquidity to balance out the funding shocks received by their domestic banks. In this case, the sovereign provides funding of $k^{FLP}\lambda b_{ji,t}$ to its domestic bank j in case of a shock coming from a failing bank i. As with all the previous measures, the sovereign needs to finance such measure by raising additional debt of $deficit^{FLP} = k^{FLP}\lambda b_{ji,t}$.

4.7 Sovereign Distress

According to Caruana (2012) and other studies mentioned in the second chapter, possible credit risk of sovereigns may feed back into the banking system, mainly via direct holdings of government debt by the financial sector. Moreover, Arslanalp & Tsuda (2012) confirms that domestic banks hold a significant portion of sovereign debt and Pisani-Ferry (2012) or Merler & Pisani-Ferry (2012) based on the 2010 and 2011 European Banking Association (EBA) stress test data[8] point out that the bank holdings of sovereign debt show substantial "home bias". In the 2010 EBA Stress test sample, the average home bias in the banks' holdings of government bonds was near 60% and was the strongest in case of banks of the most distressed sovereigns of PIIGS countries. Hence, holdings of the home sovereign debt are perhaps the most important part of the negative feedback loop and as they fit well into the network modelling framework, we include them in the model.

First, 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. As mentioned previously, 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 and is given as

$$deficit_{k,t} = deficit_{k,t}^{AR} + deficit_{k,t}^{SG} + deficit_{k,t}^{BR} + deficit_{k,t}^{FLP}.$$

Second, 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

[8] These stress tests resulted in several EBA recommendations for bank recapitalization. The results of the implementation of the latest project, the EBA Capital Exercise may be found in EBA (2012).

CDS spreads.[9] 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) and (Pokorna & Teply, 2011). 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):

$$p_{k,t}^{default} = \zeta\left(1 - \frac{1}{\left(1 + \frac{CDS_{k,t}}{1 - RR}\right)^{\tau}}\right), \tag{3}$$

where $p_{k,t}^{default}$ is the probability that a given sovereign defaults in one year, $\boldsymbol{CDS_{k,t}}$ is the annual CDS spread expressed as a decimal (e.g. if the spread is 500 basis points, $\boldsymbol{CDS_{k,t}}$ is equal to 0.05), $\boldsymbol{RR}$ is the recovery rate and t is the number of years for the cumulative default probability calculation (in our case, $\tau = 1$). Moreover, as we fully agree with the criticism of using CDS implied probability of default pointing out that the additional premiums such as the market price of risk or liquidity premium included in the spread may result in biased estimations (e.g. (Amato, 2005) or (Remolona, et al., 2007)), we parameterize this relationship by a factor $\zeta \in (0,1)$ to account for the overestimation of the default probabilities.

Third, 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:

$$CDS_{k,t+1} = CDS_{k,t} + \beta \frac{deficit_{k,t}}{GDP_k}. \tag{4}$$

[9] This approach corresponds to Brigo & Mercurio (2006, p. 701), who state that "*CDS's are now actively traded and have become a sort of basic product of the single-name credit derivatives area, … As a consequence, the need is no longer to have a model to be used to value CDS's, but rather to consider a model that can be calibrated to CDS's.*"

Putting the previous three points together, at the end of each lap the model collects the total amount of each sovereign's deficit and feeds it into Equation 4 which is then itself plugged into Equation 3. The resulting probability of default of a sovereign k in lap $t+1$ is then

$$p_{k,t+1}^{default} = \zeta \left(1 - \frac{1}{\left(1 + \frac{CDS_{k,t} + \frac{c_1 \left(deficit_{k,t}^{AR} + deficit_{k,t}^{SG} + deficit_{k,t}^{BR} + deficit_{k,t}^{FLP} \right)}{GDP_k}}{1 - RR} \right)} \right).$$

At the beginning of each simulation lap, a sovereign k may default with probability $p_{k,t}^{default}$. In that case, each creditor bank incurs a loss of $GovtShock = s_i(1 - RR)$ and revalues the sovereign debt on its balance sheet accordingly.

5 Monte Carlo Simulations

This chapter presents the results of the Monte Carlo simulations performed with our model. First, we describe the simulation process and how the model is controlled. Second, we analyse the model's behaviour under various settings of the network structure and global parameters. Third, we introduce sovereign assistance to the banks and examine efficiency of the individual support measures given that the states have unlimited access to funds. Fourth, we describe the system behaviour when a sovereign defaults and show what parameters have the greatest effect on systemic stability in this case. Finally, putting it all together with the risk transfer mechanism from the banks to sovereigns and a feedback loop back to the banking system, we provide a comprehensive model allowing us to test the individual support measures under various circumstances.

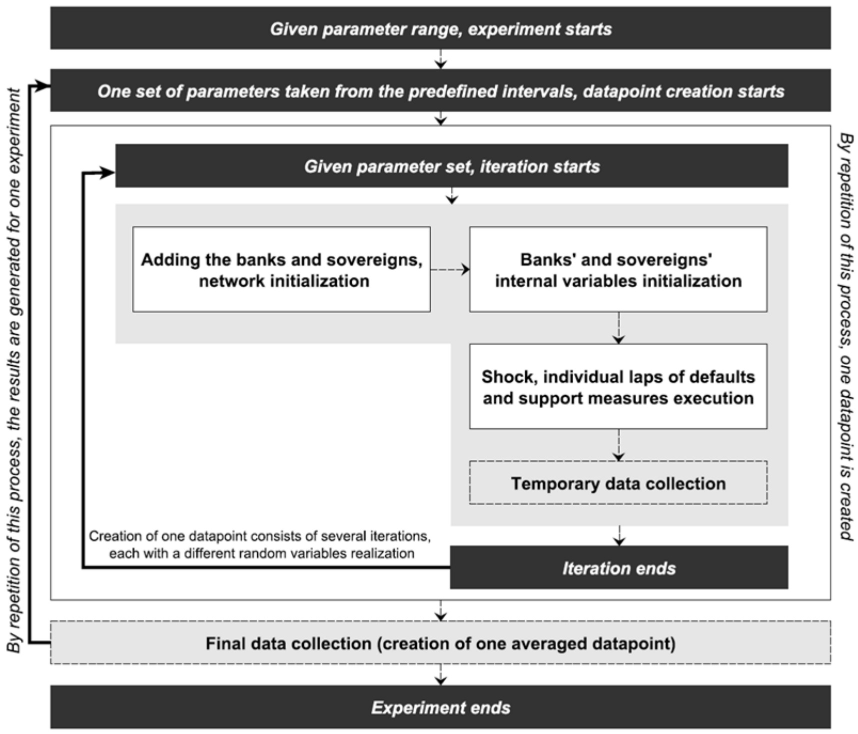
5.1 Model Control[10]

The Monte Carlo simulations are based on comparative statics experiments where the simulations are performed under varying combinations of input parameters. In each experiment, the model is run under a set of different parameter settings where some of the parameters are fixed and some vary as they are fed to the model in a form of a loop on a certain predefined interval. To obtain the results for each parameter combination, we run the model in several repetitions, each with a different realization of its random variables, and we average the resulting observed variable into a single data point. This approach is in line with Nier, et al. (2007). However, since our model runs fast enough to achieve the results of much higher iteration count in reasonable time, we run each parameter setting 500 or even 1000 times instead of the original 100 iterations. This allows us to present readable charts without further smoothing and ensures higher robustness of our results Klinger & Teply (2013). Because the simulations are not based on real-world data but rather describe the general system behaviour, we are more interested in the observable patterns than in

[10] The model was implemented in Java using NetBeans 7.3. Because of the simulations' high computational intensity, some of the computations were run on the cloud computing platform Amazon EC2. Illustration of our application's GUI and the model output is provided in the Appendix in Figure 42 and Figure 43. Demonstration of the source code or the modelling process may be performed upon request.

particular numerical results. Hence, we visualize the simulation outcomes by surface or heat map plots, which allow us to observe the effects of two varying parameters at once. Still, due to the limited scope of this thesis, many relationships and parameter dependencies remain without description. Some were researched in more detail in Klinger (2011) and Klinger & Teply (2013) and some are left for future research.

Figure 8: Scheme of the modelling process



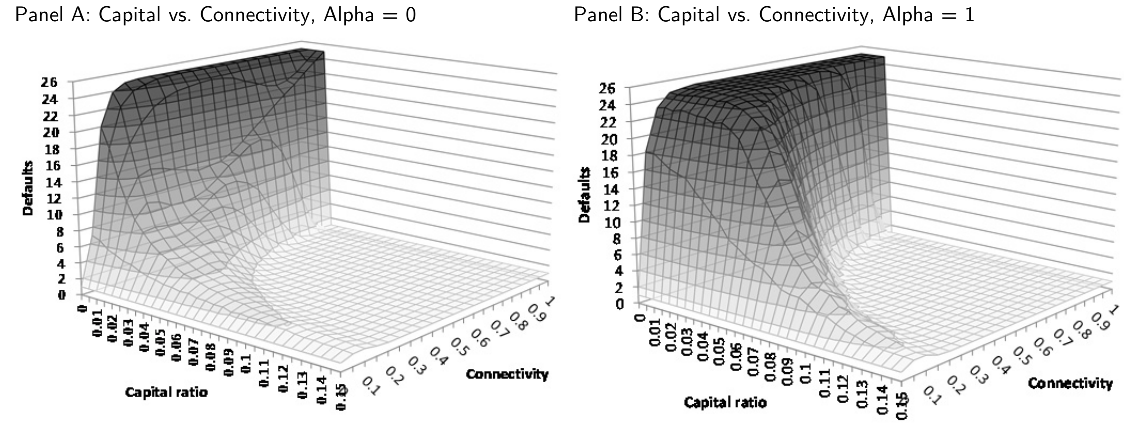
Source: Author

5.2 Basic Behaviour

First, we show how the model behaves under various settings of the three key parameters: capital ratio (γ), connection probability (p^b), and market illiquidity (α). Similarly to Nier, et al. (2007) and Gai & Kapadia (2010), the initial shock is imposed on a random bank and it amounts to the full value of its external assets. As this model is a modification of the model in Klinger & Teply (2013) and Klinger (2011), the behaviour in the basic infrastructure parameters is very similar.

Figure 9 depicts how the system behaves when we impose a local shock, i.e. erase all external assets of a random bank. In Figure 9A, we see non-linearity in both capital ratio and connectivity. The capital ratio is the main parameter determining the stability of a financial system. When it is lower than 2%, the system is so fragile that all the banks connected to the initially defaulting bank (directly or indirectly through other banks) default as well. As higher levels of connectivity mean more banks connected to the initially defaulting bank, with low capital ratios it holds that the more connected the system, the more defaults occur. With higher capital ratios, connectivity is becoming an important parameter for systemic safety as it distributes the given amount of interbank assets into more exposures. Looking at the individual connectivity values, we see that the higher the connectivity, the less capital is needed to prevent a significant systemic failure. On the other hand, the failure is more sudden when it happens below a certain capital ratio.

Figure 9: Basic behaviour under a local shock



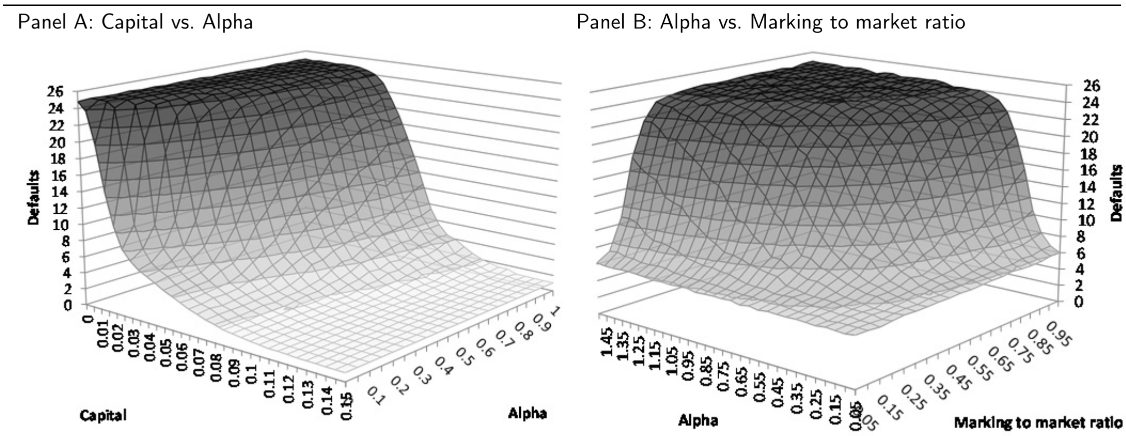
Source: Author

Figure 9B presents the simulations with the market liquidity channel switched on. The parameter set is the same except for market illiquidity ratio α and marking to market ratio μ, which are now both equal to one.[11] Already in our previous research, we found that when market liquidity distress is included in the model, the number of defaults is never lower than when it is not. Instead, the m-shaped dependency on connectivity for mid-capital situations is replaced by an area of total collapse of the system. Moreover, the systemic fragility becomes more pronounced under high-capital, low-connectivity parameter settings where the probability of default increases severalfold (Klinger & Teply, 2013).

[11]Market illiquidity ratio of $\alpha = 1$ means that 10% of external assets sold by the defaulting banks impose a 10% price shock at the external assets on the balance sheets of other banks. Marking to market ratio of $\mu = 1$ means that the price change is completely reflected in all banks' balance sheets.

Looking at both Figure 9A and Figure 9B, we see that the basic pattern is similar irrespective of the value of α. In both cases, there are "safe zones" with sufficient capital level and reasonably high connectivity, where the creditors of initially defaulting bank withstand the received shock. These areas present a desirable parameter settings for the real-world banking system and both these parameters are subject to banking regulation: minimum capital ratios are set by the Basel regulations and the control for connectivity is performed by large exposure limits, ensuring that interbank assets are diversified to reduce the credit concentration risk (Klinger & Teply, 2013).

Figure 10: Market liquidity effects in case of a local shock



Source: Author

The importance of market liquidity effects is clear from Figure 10A. At zero alpha, the resulting shape of the chart is identical to the slice of Figure 9A at connectivity equal to 0.2. With increasing illiquidity of the system, more banks fail and when alpha reaches the level of 1, the resulting slice is identical to Figure 9B at connectivity equal to 0.2. Also, Figure 10A demonstrates that the less capital, the more pronounced is the effect of system illiquidity. Conversely, the higher the alpha level, the more capital is needed for the system to stay in the "safe zone" and the shorter interval of capital ratios it takes for the system to fail.

Market liquidity effects are also closely tied to the issue of revaluation of assets according to the fair value accounting and our model can contribute to the discussion about the relationship between marking to market and financial crises. Generally, there are two options for asset valuation. First, the assets may be valued at amortized cost in which case the users of the financial reports do not have the full up-to-date picture about the assets' true value. On the other hand, such way of reporting ensures certain stability of the system as short-term price changes do not affect the companies' balance sheets. The second way of valuation prices assets according to their fair value, which is the price that the markets would pay for their immediate sale. In other words, these are marked to market and the unrealized gains or losses directly impact the shareholders' equity. This way of valuation provides the users with financial reports more up-to-date information, but also causes that a company's performance may be affected by random short-term price fluctuations or a price decrease resulting from market illiquidity. Because of this property, fair value accounting has been blamed for contributing significantly to the situation of the recent financial turmoil, for example according to Wallison (2009, p. 8), *"...if we retain fair value accounting in its current form after the current crisis is behind us, we will always be living on the edge of another financial abyss"*.[12]

Returning to the simulation results analysis, Figure 10B depicts the impact of marking the asset values to market prices in liquidity distress.[13] Clearly, this parameter has a very similar negative effect on the systemic stability as has the market illiquidity. We see that the more the assets are marked to market, the greater and the more sudden is the effect of market illiquidity and conversely, the less liquid the market, the more serious is the effect of fair value accounting. If not stated otherwise, we set this parameter equal to one to see clearly the impact of market liquidity effects. However, modelling these effects provides an important insight on the fair value accounting and enables us to better see the effects of funding liquidity shocks, which is the next issue for our observation.

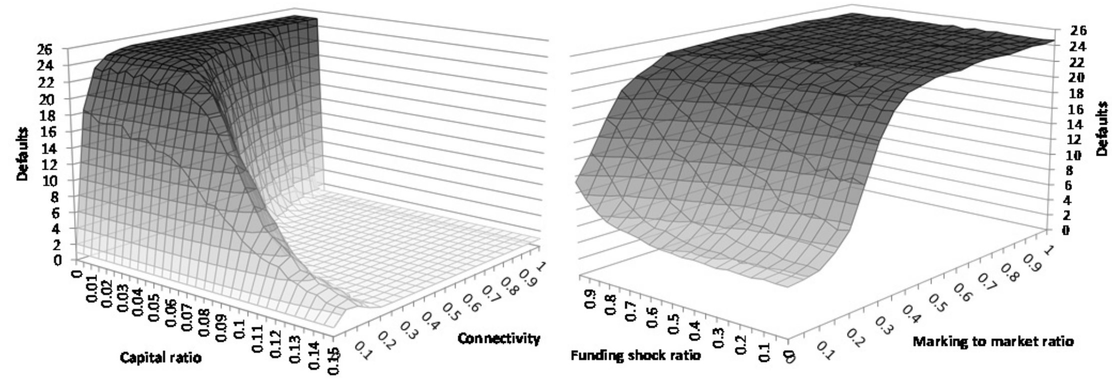
Figure 11 shows simulation results related to funding liquidity effects, which are modelled by a funding shock received by the debtors of a creditor bank which finds itself in significant distress. In this situation, the debtor bank is forced to fire-sale some of its assets to close the gap between assets and liabilities. Hence, modelling these effects makes sense only when there are additional losses to the debtor bank caused by the fire sales, or in other words when $\alpha \neq 0$. Consistent with our previous simulations, Figure 11 presents the results for $\alpha = 1$. Figure 11A depicts the systemic stability given various settings of capital ratio and connectivity and it is very similar to Figure 7B, where the funding liquidity effects are switched off. Comparing these two plots, it might seem that except for a very slight increase in defaults on connectivity levels about 0.1 and the capital ratio in the interval of [7%, 11%], the

[12] However, there are also reports that say otherwise such as Laux & Leuz (2010) or Shaffer (2010).
[13] The Marking to market ratio may be interpreted as the portion of the external assets which are affected by the new distressed asset price.

funding liquidity effects are not an important factor for systemic stability. However, it is necessary to note that these results are generated with the marking to market ratio set to one. When we look at Figure 11B, showing the funding liquidity effects with respect to various marking to market ratio levels, we see that when the external assets are fully marked to market, market liquidity effects are so pronounced that the system is in total collapse and funding liquidity effects do not play a significant role. However, for marking to market ratio lower than 0.5, funding liquidity shocks introduce significantly more risk into the system.

Figure 11: Funding liquidity effects in case of a local shock

Panel A: Capital vs. Connectivity, FS = 1, Alpha = 1 | Panel B: Funding shock vs. Marking to market ratio

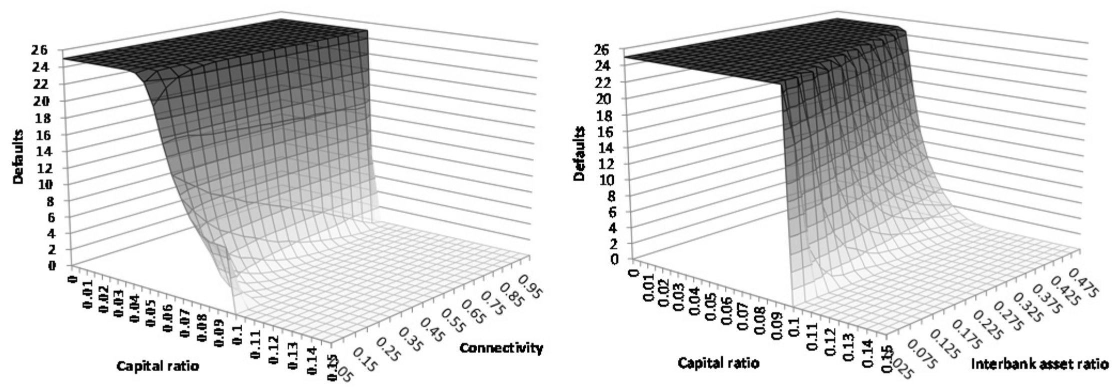


Source: Author

Next, we will examine the system behaviour under different types of bank shocks. Figure 12A depicts how the system behaves when instead of hitting one bank severely, we impose a global shock of 0.1 (i.e. all banks are shocked by write-downs of 10% of assets). These simulations represent situations when a global asset drops in price and is properly marked to market by all banks. Panel A depicts how the systemic stability depends on various settings of capital ratio and connectivity. We see that for low capital ratios, the initial shock to each bank is larger than its capital buffer and hence all banks default. For capital ratios around 5%, increasing connectivity has a slightly negative effect as the defaulting banks cause collapse of their first-line creditors, who have been severely weakened by the global shock but still maintain operation. On the other hand, for capital ratios in the interval from 7% to 10%, increasing connectivity eases the crisis severity as the secondary shocks from the initially failing banks are more distributed in the system and do not cause so many subsequent defaults.

Figure 12: Basic behaviour under a global shock of 0.1

Panel A: Capital vs. Connectivity, Alpha = 0 | Panel B: Capital vs. Interbank asset ratio, Alpha = 0



Source: Author

Still, we see that with decreasing capital ratios, it takes a very small interval for the system to go from safety to total collapse. This is caused mostly by the character of the model, where the heterogeneity among the individual banks is ensured only by the random creation of the interbank network. As we see in Figure 12B, increasing interbank asset ratio increases the heterogeneity in the system and hence smoothes the transition to a system-wide breakdown. This is the main reason why in contrast to Nier, et al. (2007), in this study we usually use the value of 0.4 instead of 0.2 for the interbank asset ratio parameter (θ).[14]

Figure 13 demonstrates some further possibilities our model gives us in terms of the initial shock setting. Figure 13A depicts the situation where the bank failure results from an aggregate shock with particularly adverse consequences. Along with Gai & Kapadia (2010), this is modelled by erosion of external assets of all the banks combined with a major loss of one particular institution. In reality, this kind of situation may be interpreted as a default of one bank combined with asset price depression resulting from low confidence in the market. With zero connectivity, there is a sudden systemic breakdown at the capital level of 10% as there the global shock causes all the banks to default. On an interval of low connectivity where the connection probability is between zero and 0.3, there are serious effects even on much higher capital levels as the one bank that received the major hit propagates the shock further into the system and the first, second and sometimes even the third line creditors subsequently default. On the other hand, with higher connectivity levels

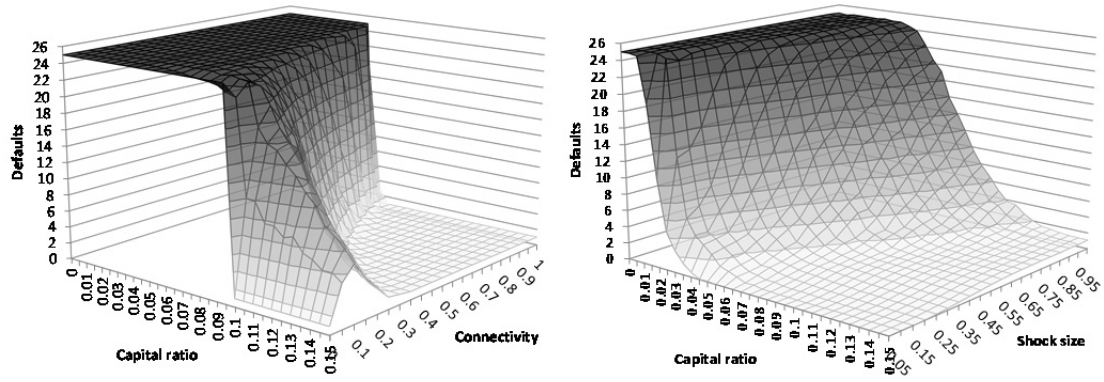
[14] When studying the real-world data, the interbank asset ratio may be lower – e.g. in our dataset which we will introduce in the next chapter, the ratio is even below 10%. However, it always depends on how many and which subjects are considered as members of the network.

and enough capital, the system is again in the "safe zone". Moreover, with connectivity higher than 0.6, even less capital than 10% is needed to prevent the systemic breakdown as the initial shocks are better absorbed by the system. Note that the area of the total systemic collapse in low-capital, high-connectivity situations is somewhat similar to the one in Figure 9B. This is because given proper marking to market, the market liquidity channel that is causing the systemic collapse in Figure 9B is conceptually similar to the "global" part of the shock that is causing it in Figure 13A. Finally, Figure 13B shows how the severity of a local shock affects the system. Similarly to lower capital levels, higher shock values also result in more systemic risk, which is in line with our expectations.

Figure 13: Further modifications of the initial shock

Panel A: Capital vs. Connectivity, Alpha = 1, Local shock = 1, Global shock = 0.1

Panel B: Capital vs. Local shock size, Alpha = 0, Local shock = variable, Global shock = 0



Source: Author

5.3 Sovereign Assistance

This section studies the positive impact of state support on systemic stability as well as the cost of the support measures. Note that the feedback loops are not introduced yet and although it shows the costs of support measures, the following analysis does not include the propagation of sovereign weakness back into the banking system. As we already mentioned, the model accounts for four types of state support: bailouts and recapitalization, execution of state guarantees, asset relief and funding liquidity provision.

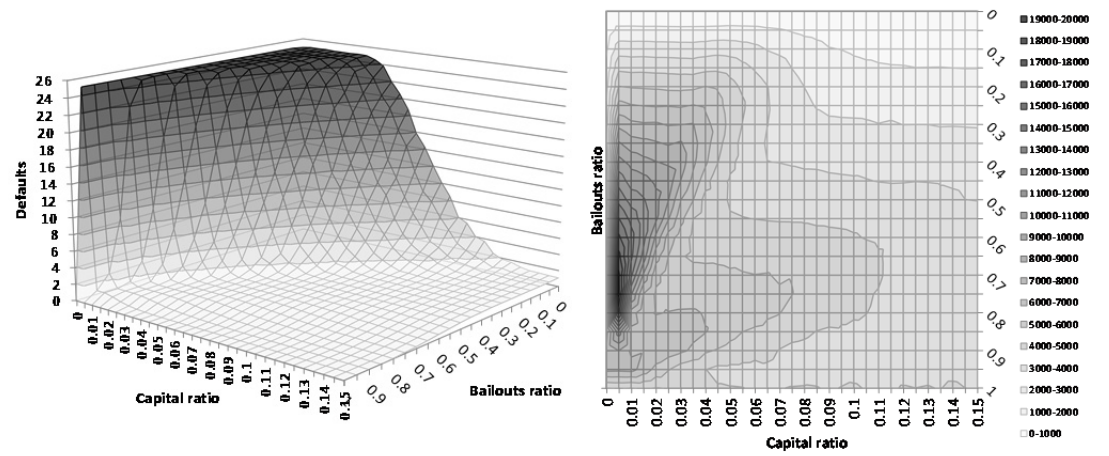
5.3.1 Bailouts and Recapitalization

The first support measure we will examine are bailouts to institutions who are receiving negative shocks. As mentioned in Section 4.6 this support is provided in a manner that the domestic sovereign pays for some fraction of the losses before the receiving institution writes down its capital. This is conceptually the same as providing additional capital to the receiving institution. Figure 14A demonstrates the relatively high efficiency of this measure which manages to prevent the systemic breakdown. With low bank capital ratio levels, there is always a relatively short interval of the amount of state support on which the support measure becomes effective and it holds that the lower the capital ratio, the shorter this interval.

Figure 14: Bailouts and recapitalization effects

Panel A: Total defaults - Capital vs. Bailouts ratio

Panel B: Total cost - Capital vs. Bailouts ratio



Source: Author

Figure 14B shows the "costs" of the bailouts represented by the total extra deficit resulting from the measure. We see that at low capital levels, the relationship between the deficit and the intensity of the bailout measure is positive and linear up to a certain bailout ratio behind which it becomes negative, falling back to relatively low levels. At a given capital level, the highest bailout costs arise at the level of bailout intensity which is high enough to represent a significant cost to the domestic sovereign but still too low to prevent the shocks from spilling over the banks' capital barriers onto the next line of creditors. Moreover, in this situation the failing bank liquidates its assets, further worsening the situation through the market liquidity channel. Behind such level of bailout intensity, the number of defaults suddenly drops as the bailout measure becomes effective. This argumentation is further illustrated in Figure 44 in the Appendix, depicting the number of simulation laps (i.e. lines of creditors receiving the shock) it takes for the system to stabilize, and in the cost-benefit analysis provided in Figure 18 further in this chapter.

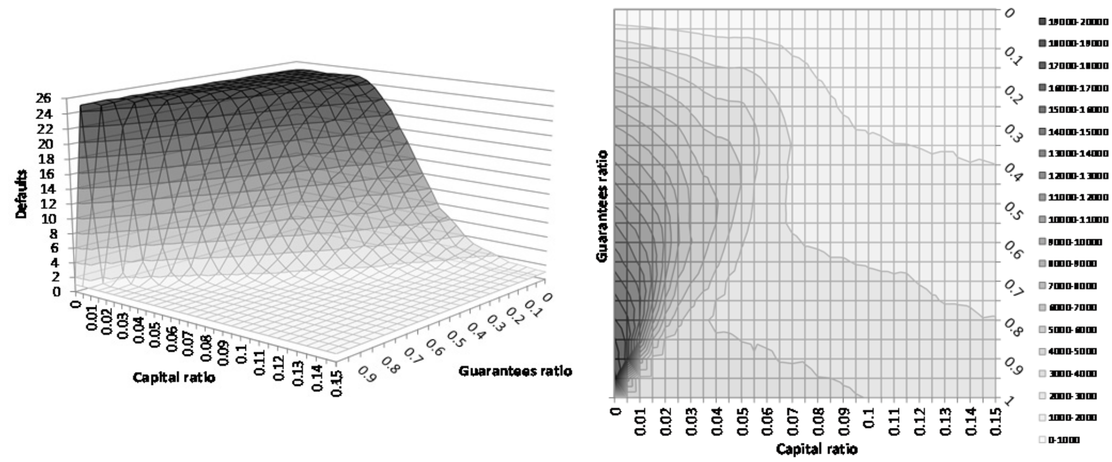
5.3.2 State Guarantees

Instead of providing funds outright to the failing banks to prevent their bankruptcy, the domestic states may control the institutions' default process. This way, even though the receiving bank finally goes bankrupt, the shock it imposes on the rest of the financial system will be mitigated. Similarly, guarantees issued by the domestic sovereign for the receiving bank's debt may be executed. These situations lead to a support measure which is modelled as easing the shock which the receiving institution propagates on its first line of creditors. As mentioned in Section 4.6, in this case, the domestic sovereign pays for some fraction of the interbank liabilities of the receiving institution after it writes down its capital. Figure 15A shows that the effect of this measure is similar to the case of outright bailouts. However, looking at Figure 15B, we see that the costs of this measure are differently laid out in the capital-support space. At low capital ratios and high guarantees intensity, the cost peak is almost at the maximum possible level of support, which is caused by the fact that under this setting the failure of the initial shock receiver is inevitable whatever the guarantee ratio. Moreover, the peak costs reach higher maximum level than in the case of outright bailouts. However, in mid-capital, high-support situations, the guarantees may reach slightly better cost efficiency as will be further documented in Figure 18.

Figure 15: State guarantees effects

Panel A: Total defaults - Capital vs. Guarantees ratio

Panel B: Total cost - Capital vs. Guarantees ratio

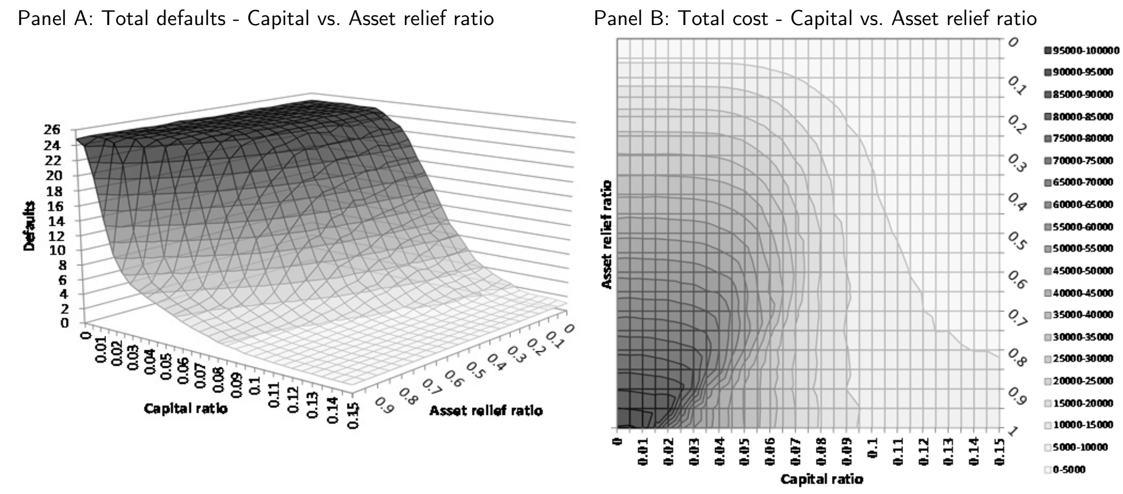


Source: Author

5.3.3 Asset Relief

In contrast to bailouts and state guarantees, asset relief represents a different concept in the model. It is linked to the liquidity channels (both market and funding) as it eases the drops in asset prices by ensuring that the banks are able to sell the assets without significant fire-sale losses. Figure 16A depicts that at low levels of support intensity (asset relief ratio), the asset relief is almost ineffective as it does not suffice to prevent the banks' balance sheet erosion caused by the fire sales. On asset relief ratio levels from 0.5 onwards, we see the support measure gaining its effectiveness, managing to ease the extent of the systemic crises on capital levels of 5% to 10% and effectively preventing the total breakdown at lower capital levels of 2% to 5%.

Figure 16: Asset relief effects

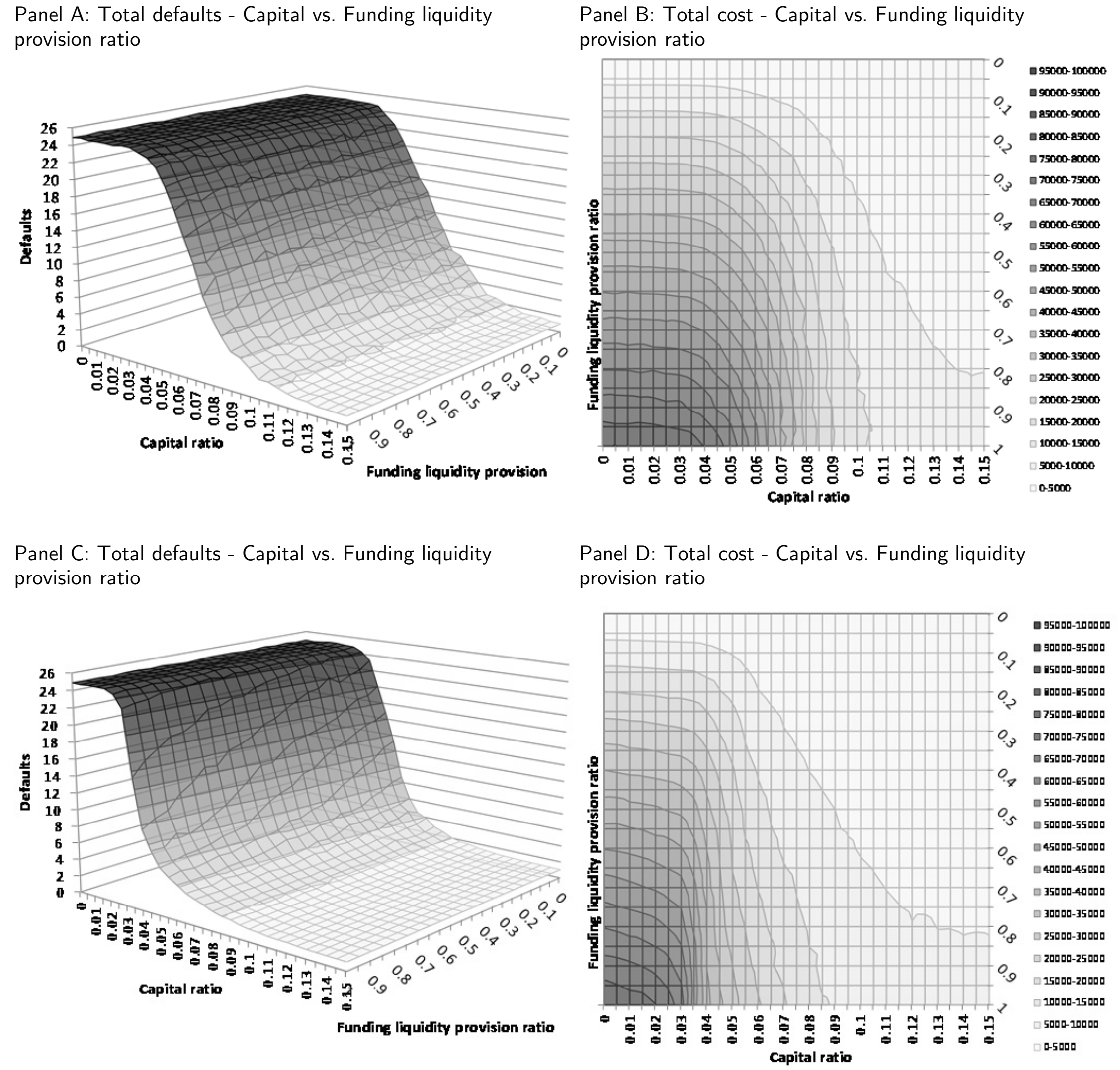


Source: Author

However, Figure 16B shows that this stability improvement comes at significant cost. Note that the scale of the plot is five times higher than in case of Figure 14B or Figure 15B. It is necessary to mention that in contrast to the previously-mentioned two support measures which lead to outright losses of the sovereign's capital, in case of asset relief the domestic sovereign will gain assets of non-zero value out of the transaction. However, given the market situation and the aim not to depress the asset prices by fire-selling the assets back into the market, in short term, asset relief weakens the domestic sovereign significantly more than bailouts or guarantee execution as the sovereign needs to fund this action by government deficits. As to the shape of the cost function in the capital-support space, we see a similar pattern to Figure 15B but the peak cost is much wider, reaching capital ratio levels of 2% at full asset relief intensity. This is caused by the fact that this support measure tackles much more global problem as the individual sovereigns need to buy out all the assets of the failing banks.

5.3.4 Funding Liquidity Provision

Figure 17: Funding liquidity provision effects



Source: Author

The last type of sovereign assistance to the banking system modelled in our simulations is provision of funding liquidity to the institutions which received funding shocks. As previously mentioned in Section 4.6, this situation happens when a creditor of the receiving bank defaults and hence the receiving bank suffers a sudden cut in funding resulting from the need to repay the short-term revolving credit to the bank in liquidation.

Figure 17A demonstrates that under the current parameter setting, the funding liquidity provision measure does not have any significant effect on the systemic stability.[15] As described in comments to Figure 11, this is caused by the market liquidity channel overwhelming the funding liquidity: even when the funding liquidity is supplied, the market liquidity effects stemming from the failing banks liquidating their asset positions cause systemic collapse. On the other hand, despite the inefficiency of this measure, its costs are significant and at their peak, they reach values over four times higher than in the case of bailouts and deposit guarantees. The reason for high costs despite low efficiency is that in these parameter settings, although there are many funding shocks, the funding liquidity channel is not the main issue determining the systemic resilience.

For the funding liquidity shock to be a significant cause of the systemic instability, the market liquidity channel has to be switched off while the system illiquidity remains serious. In the model, this situation is attained by decreasing the marking to market ratio as depicted in Figure 17C and Figure 17D, where this parameter was set to 0.2 instead of the base value of 1. These figures show that on a certain level of capital ratios (roughly 2% to 6%) the funding liquidity provision measure has a significant positive effect on systemic stability.

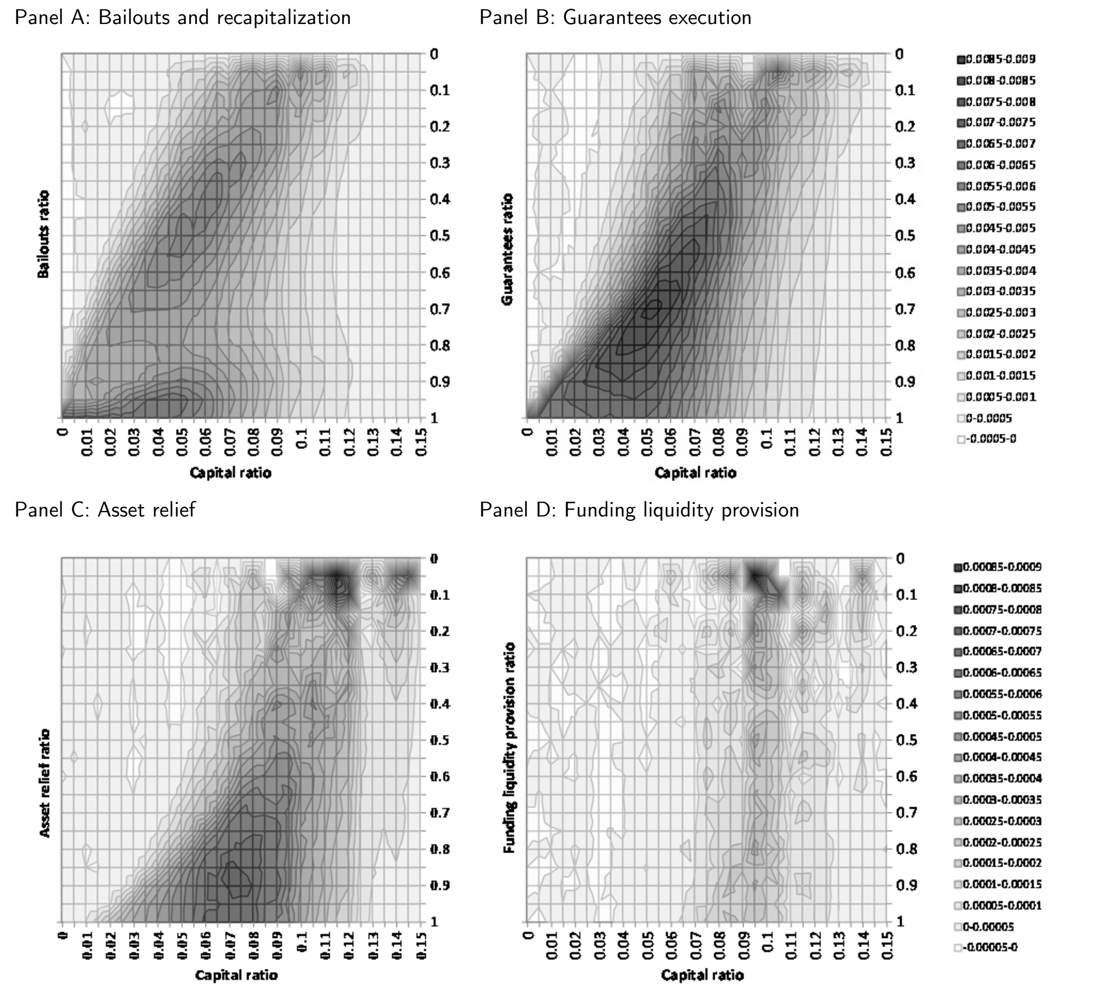
5.3.5 Cost Efficiency of the Support Measures

Finally, the individual support measures may be compared in terms of cost-benefit efficiency, as shown in Figure 18. To obtain the values of cost efficiency for each support intensity value (horizontal axis), we first calculated how many less banks fail compared to the situation of no state support. This measure, representing the benefit of the individual measures, is then divided by the extra deficit associated with its execution. As a result, the individual panels of Figure 18 depict how many banks are saved by one currency unit of state support. The first finding of this analysis is that direct support such as bailouts and guarantees proves much more efficient than measures which aim only on the resulting liquidity issues. Due to such disproportion in effectiveness, in Figure 18A and Figure 18B, the support efficiency is plotted on ten times higher scale than in case of Figure 18C and Figure 18D. Second, on both

[15] The funding liquidity provision measure also brings arbitrage opportunities. One example may be the ECB‘s Longer-term refinancing operation (LTRO), a measure providing cheap liquidity for the banks which they subsequently use as a financing for increasing their profitability through purchasing securities bearing higher yields such as short-term government bonds. For example, Victor Massiah, the CEO of Unione di Banche Italiane stated that “*Given the current costs of funding, it’s more profitable for Italian banks to do arbitrage using ECB facilities.*” (Benedetti-Valentini, 2013)

Figure 18A and Figure 18B, we see a diagonal pattern where the state support is most efficient. These areas correspond to the intervals between safety and total collapse seen on Figure 14A and Figure 15A. Also, the diagonal pattern for bailouts is located more at the left side than the one for state guarantees since bailouts mitigate the shocks right at their origin while guarantees only tackle their further propagation. Hence, the bailout measure is effective even at lower capital ratio values (or lower support intensity values). Third, at the peak, guarantees may be more cost-efficient than outright bailouts. On the other hand, it is necessary to note that in case of bailouts, the domestic sovereign saves its home institution whereas by guarantees, it eases shocks the home bank sends to other banks, possibly in other states. Therefore, if the model accounted for the effects associated with the real economy performance, bailouts may prove to be a more efficient measure.

Figure 18: Cost-benefit analysis of state support measures



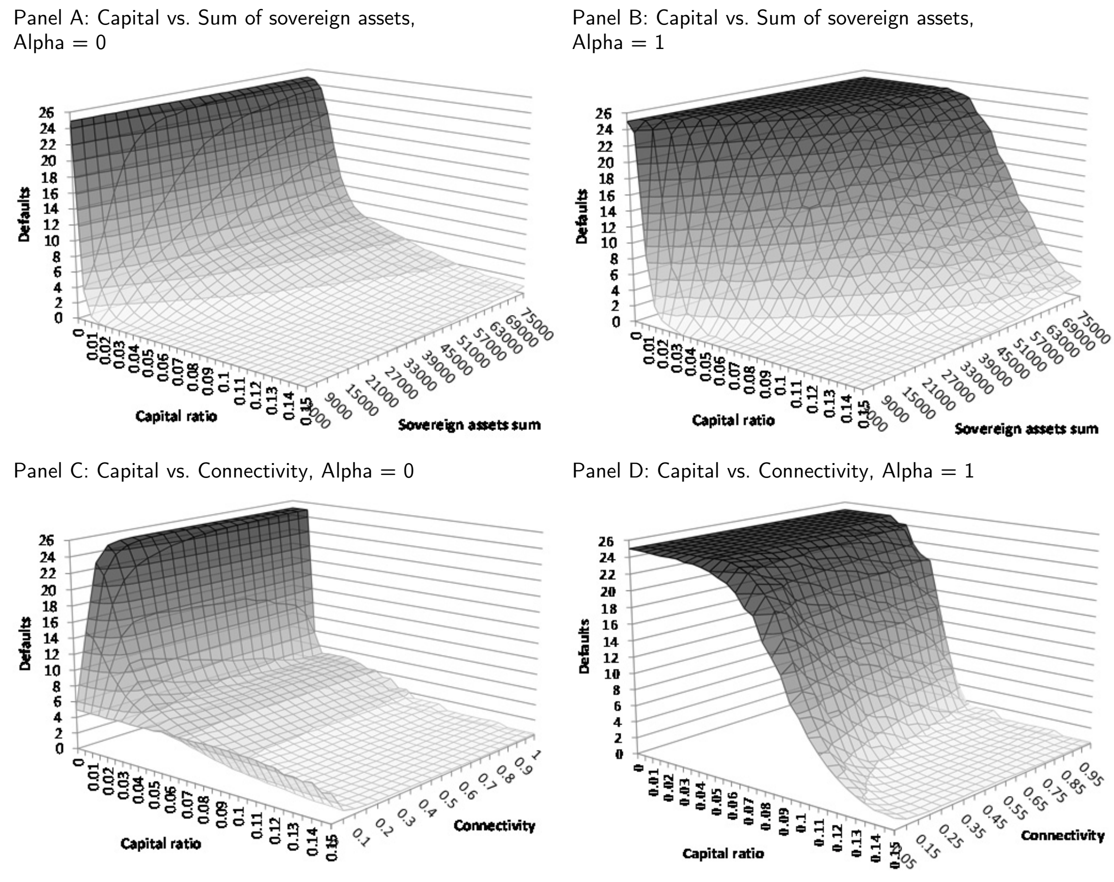
Source: Author

Note: The scale of the response variable in panels A and B is ten times larger than in C and D.

Further, Figure 18C shows that although the efficiency in case of asset relief is ten times lower, the pattern is similar, only with the area of higher efficiency shifted further to the right. Again, this is caused by the asset relief being even less direct support measure in relation to the initial shock than state guarantees. Finally, it is clear from Figure 18D that given this parameter setting, funding liquidity provision is not an effective support for systemic stability.

5.4 Sovereign Defaults

Figure 19: Basic behaviour under a sovereign shock of 0.4



Source: Author

To be able to introduce the feedback loops, we must first describe how the system behaves in case of a sovereign default. This section provides results of simulations where the initial shock to the banks originates from the sovereign they are exposed to. Figure 19 demonstrates that clearly the sovereign shock impact on the systemic stability depends on how the financial sector is exposed to the sovereigns. On both

Figure 19A and Figure 19B we see that at low capital ratios, even if the exposures against sovereigns are small, they may have a devastating effect on the state of the financial system. Moreover, with the liquidity channel switched on, the negative effect of a domestic state's default is much more pronounced as we can see in Figure 19B.

Panels C and D of Figure 19 depict the systemic stability in relation to capital and connectivity. Figure 19C shows the situation when the market remains liquid and one random sovereign fails. We see that the results in low-capital settings are similar to Figure 9A, but from capital ratios of 4% onwards, the systemic stability depends more on connectivity than in case of a single bank's default. In contrast, Figure 19C resembles rather the results of a global shock depicted in Figure 12A and the system's connectivity is a key determinant of resilience. These findings are in accordance with our anticipation since the sovereign shock hitting the domestic banks is conceptually somewhere between the local shock which hits only one bank, and the global shock which hits all banks in the system. Moreover, with increasing illiquidity, the shock becomes more global since it is affecting more banks' balance sheets through marking to market.

5.5 Feedback Loops

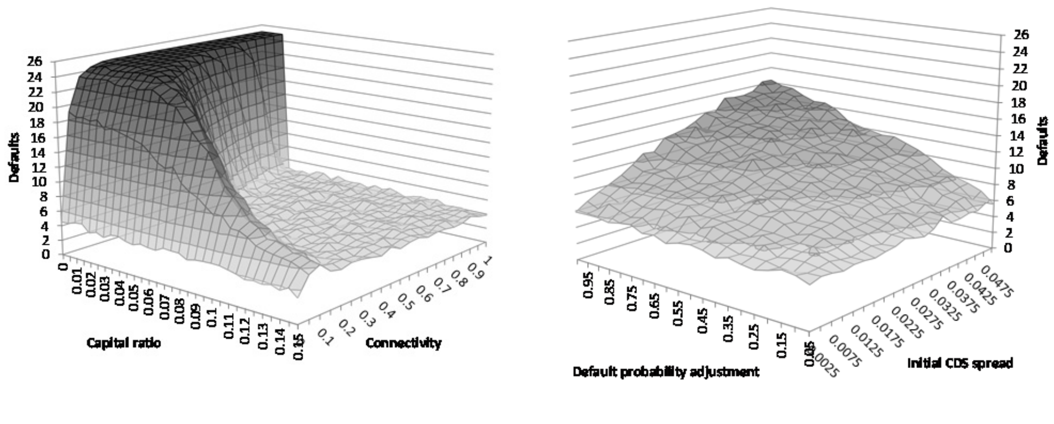
Finally, putting together the results of banking crises, state support and the effects of state defaults, we close the feedback loop by implementing a mechanism connecting the state support and state defaults. First, according to Equation 3 from the model definition in Section 4.6, a sovereign may default with probability implied from its CDS spread. The impact of CDS-implied defaults of sovereigns is visible in Figure 20A, which is similar to Figure 9A but shifted upwards as the sovereign risk adds to the total systemic instability. As we mentioned in the model definition, the CDS spreads contain not only the premium for credit risk of the insured bonds but also additional premiums such as the market price of risk or liquidity premium. Hence, we adjust the CDS-implied probability by a parameter $\zeta \in (0,1)$, which is in our simulations set to 0.5. Although the decision on its value is rather arbitrary, we see in Figure 20B that the results' dependence on this parameter is linear with moderate slope and so the choice of its value does not degrade the robustness of the model.

Finally, to implement the relationship between state support and sovereign risk, according to Equation 4, in each simulation lap the CDS is updated based on the volume of support the sovereign provided to domestic banks. In the rest of this section, we study the effects of bailouts, guarantees and asset relief. As in the modelled situation the funding liquidity measure did not prove to be effective, we omit it from this analysis.

Figure 20: Adding the implied default probabilities

Panel A: Capital vs. Connectivity

Panel B: Implied default probability adjustment vs. Initial CDS spread



Source: Author

5.5.1 Bailouts and Recapitalization

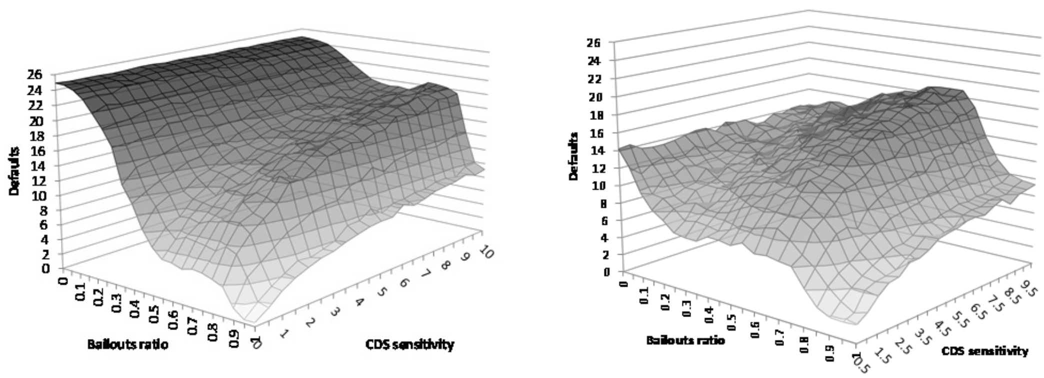
Figure 21 shows the behaviour of the system when the crisis is tackled by outright bailouts of the troubled banks. Figure 21A depicts a collapsing system at capital ratio of 4%. Here we see that at low CDS sensitivity to deficits resulting from the support measures (parameter β), bailouts are truly effective for crisis mitigation. Especially in the first half of the bailout intensity interval, state action manages to decrease the number of defaulted banks significantly. However, with increasing CDS sensitivity, the measure becomes less and less effective. Also, at higher CDS intensity levels, an interesting pattern appears where higher bailout intensity does not necessarily mean less total defaults. This is because at bailout intensity of 0.8, state action weakens the sovereigns more than it supports the banks. On even higher bailout intensities, however, the measure becomes effective again as it almost completely blocks the systemic crisis, restraining it to only zero to ten failed banks, depending on the CDS sensitivity.

Figure 21B depicts the situation at higher capital ratio of 8%. We see that still, state support may slightly ease the situation at very low CDS sensitivity levels. However, when the market perceives additional deficits as more risky and hence the CDS sensitivity is high, state support weakens the sovereigns significantly and is potentially harmful to the system. However, it holds again that with full bailout intensity, the bailout measure is effective for crisis mitigation. For more information on the dependence of this measure's effectiveness, refer to the appendix to Figure 45A and Figure 45B.

Figure 21: Bailouts and recapitalization with feedback loops

Panel A: Bailouts ratio vs. CDS sensitivity, Capital ratio = 0.4

Panel B: Bailouts ratio vs. CDS sensitivity, Capital ratio = 0.8



Source: Author

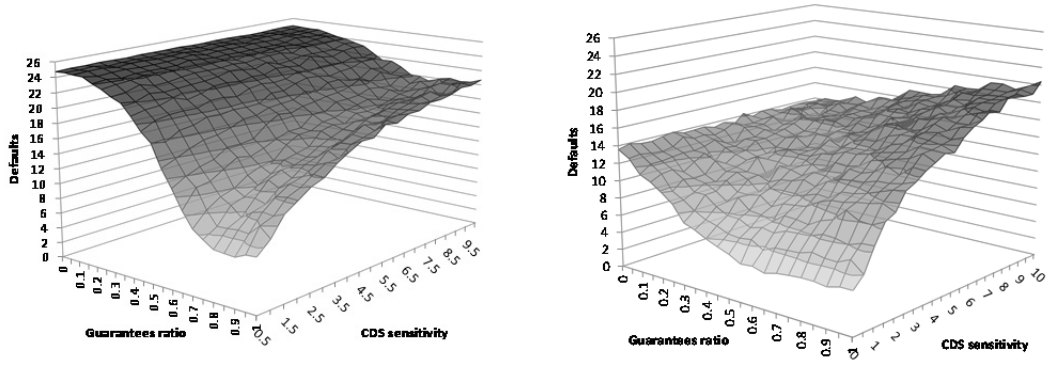
5.5.2 Guarantees Execution

Figure 22 demonstrates that the effect of state guarantees execution is somewhat similar to the effect of bailouts. Again, Figure 22A presents the system with capital ratio level at 4% while in Figure 22B, this parameter is set to 8%. We see that at lower capital settings, with low CDS sensitivity the guarantees execution may effectively mitigate a systemic breakdown and again, the higher the CDS, the weaker the effect. Comparing this support measure with the previous one, there are two main differences: First, the guarantees are a little less effective at low CDS sensitivity as the slope in case of guarantees is less steep than in case of bailouts. Second, at full support intensity, execution of guarantees does not manage to cut the number of failed banks as bailouts do. This is caused by the fact that while by bailing a bank out, we tackle the shock upon receiving, and hence we may prevent even the initial shock receiver from defaulting and liquidating its assets, further deteriorating the balance sheets of other banks through marking to market and the market liquidity channel. In contrast, state guarantees only solve the problem of further shock propagation.

Figure 22: Guarantees execution with feedback loops

Panel A: Guarantees ratio vs. CDS sensitivity, Capital ratio = 0.04

Panel B: Guarantees ratio vs. CDS sensitivity, Capital ratio = 0.08



Source: Author

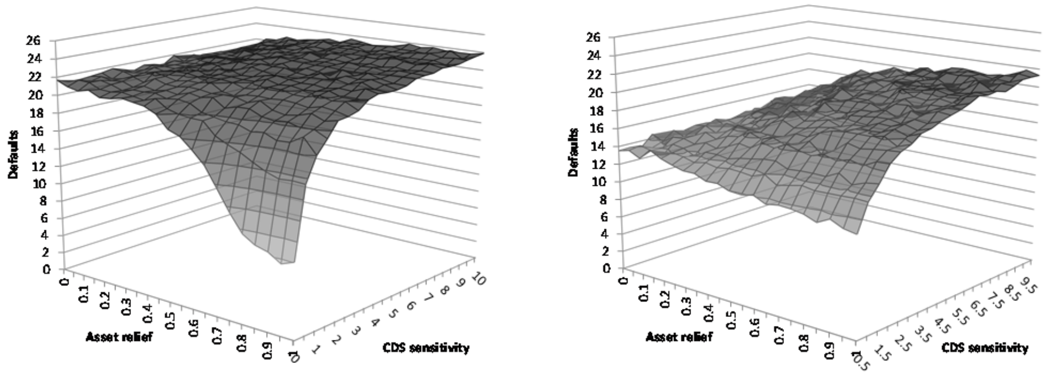
Similarly, we may observe the model behaviour at capital ratio level of 8%. Here, we clearly see how state assistance turns from beneficial at low CDS sensitivity levels through neutral to downright harmful.

5.5.3 Asset Relief

Figure 23: Asset relief with feedback loops

Panel A: Asset relief ratio vs. CDS sensitivity, Capital ratio = 0.06

Panel B: Asset relief ratio vs. CDS sensitivity, Capital ratio = 0.08



Source: Author

The last type of sovereign assistance we will observe is asset relief. At the capital level of 4% which we considered for studying the previous two support measures, asset relief proves to have virtually no positive effect and the whole system collapses.

Hence, Figure 23A shows the results at capital ratio level of 6%. There we see that at low CDS sensitivity, asset relief has a significant positive effect while at high CD sensitivities, the support measure can again be rather harmful. These effects are even more pronounced in case of capital ratio level of 8%. Here the system is not yet in total collapse and asset relief may only worsen the situation.

5.6 Results Summary

In line with other studies such as Nier, et al. (2007) or Gai & Kapadia (2010), our system proves to be "robust-yet-fragile", meaning that even though the probability of a systemic crisis may be low, when it occurs, it leads to systemic collapse. We showed that given the basic parameter set, banks capitalization is the main determinant of systemic stability, and together with the system's connectivity, it determines whether a crisis occurs or not. The extent of the crisis is shown to be affected by the market illiquidity of the system, while the funding illiquidity worsens the situation only given lower marking to market ratios when the funding liquidity channel is not overwhelmed by the market liquidity channel. Also, we demonstrated that in case of a global shock, systemic stability is more or less binary: either the system is stable or it finds itself in an area of a total collapse. This holds especially in cases when the portion of interbank assets is low. Table 2 presents the most significant parameters of the model we studied in the basic analysis and their impact on systemic stability.

Table 2: Impact of selected parameters

Parameter	**Impact**	**Description**
Capital ratio	+++++	▪ Determines the size of the banks' capital buffers ▪ Capital buffer size decides whether a bank withstands a credit or market liquidity shock or whether it fails
Connectivity	+++	▪ Determines the density of the banks' exposures ▪ More connected systems absorb smaller shocks more easily but are prone to larger extent of a crisis in case of a large shock
Alpha	+++	▪ Lowers the price for which assets can be sold ▪ Large amounts of assets sold together with large levels of alpha result in asset price collapse and impose losses
Marking to market ratio	+++	▪ Determines how the changes in asset prices are reflected in the banks' balance sheets ▪ Full marking to market together with large alpha levels may result in total systemic break-down caused by external assets prices collapse
Funding shock ratio	+	▪ Determines the size of a funding gap a debtor bank incurs when a creditor bank defaults ▪ Proved significant only given low marking to market ratios and is not a key determinant of systemic stability

Source: Author
Note: The number of plus signs "+" represents the degree of positive impact on the financial system stability

In case of negative shocks, the banks may be supported by state aid measures such as bailouts, guarantees, asset relief or provision of funding liquidity which on one hand may weaken the sovereigns but one the other hand may contribute significantly to systemic stability. In the simulation setting, bailouts and guarantees proved to be the best measures in terms of effectiveness as well as cost efficiency. Asset relief was also effective but due to its large costs did not measure up to the former two. Finally, funding liquidity provision had very little effect on systemic stability but is rather expensive for the sovereigns. Table 3 provides the summary of the individual support measures.

Even though some are effective in the short run, in longer run the support measures weaken the sovereigns through extra deficits and increase the probability of a sovereign default. Failing sovereigns then return the shock to the banking system through negative feedback loops. Generally, for systems in total collapse, state aid may significantly ease the extent of the crisis despite sovereigns being weakened by the support. However, especially in situations when only some part of the system is destabilized and when the sovereigns' default probabilities are very sensitive to extra deficits, the result of state support may be actually worse than in case of no state intervention.

Table 3: Impact of individual support measures

Measure	Effectiveness	Cost-efficiency	Description
Bailouts and recapitalization	+++++	+++++	Captures shocks before they hit the receiving bank
Guarantees execution	++++	++++	Captures shocks the receiving bank propagates onto its creditors
Asset relief	+++	+	Eases the asset price decline by absorbing a portion of external assets that would be otherwise fire-sold on the market
Funding liquidity provision	+	0	Captures funding shocks by providing liquid assets to the banks whose creditor defaults and who would not be able to renew their credit lines

Source: Author
Note: The number of plus signs "+" represents the degree of positive effect. Zero "0" represents mixed or neutral effect.

6 Empirical Analysis

In the following chapter, we will 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 and the 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.

6.1 Data Definition

To calibrate the model to the real-world figures, we collected balance sheet data and other data from several sources. Table 4 shows the main items which we describe further in greater detail.

Table 4: Banking system balance sheet with data sources

TOTAL ASSETS (EBA Database, Central banks)	
Domestic 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

6.1.1 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 (BCBS, 2013). 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.[16]

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). For example, UniCredit SPA headquartered in Italy, which is the global ultimate owner of all banks in the UniCredit group, will report to Banca d'Italia (Italian national bank and member of the Eurosystem) all exposures of its own and of its branches and subsidiaries against banks that are not members of the UniCredit group. The exposure of UniCredit Bank AG (German subsidiary) against Erste Group Bank AG headquartered in Austria, which is not a member of the UniCredit group, is accounted for in the statistics. On the other side, an exposure of UniCredit Bank AG (German subsidiary) against UniCredit Bank Czech Republic AS is netted out as well as the exposure of UniCredit SPA against UniCredit Romania SA. This way, any exposure external to the group is assumed to be an exposure of UniCredit SPA and adds to its total risk position. In contrast, the locational data provides information on gross positions of banks in selected major banking centres against banks located in other countries on residence or nationality principle and even though it is better for international banking activity monitoring, it does not capture the total risk positions so well.

On the other hand, we realize several shortcomings of our approach. First, using the consolidated statistics further underestimates the real risk positions and complexities of the global financial system and thus increases the inaccuracy caused by using aggregate data. Second, in many instances, the domestic supervisors of the host countries require that the foreign subsidiaries are ring-fenced so that the parent bank does not have full access to its subsidiary's resources (Chan-Lau, 2010). This is prevented by both controls on dividends that must not jeopardize a subsidiary's

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

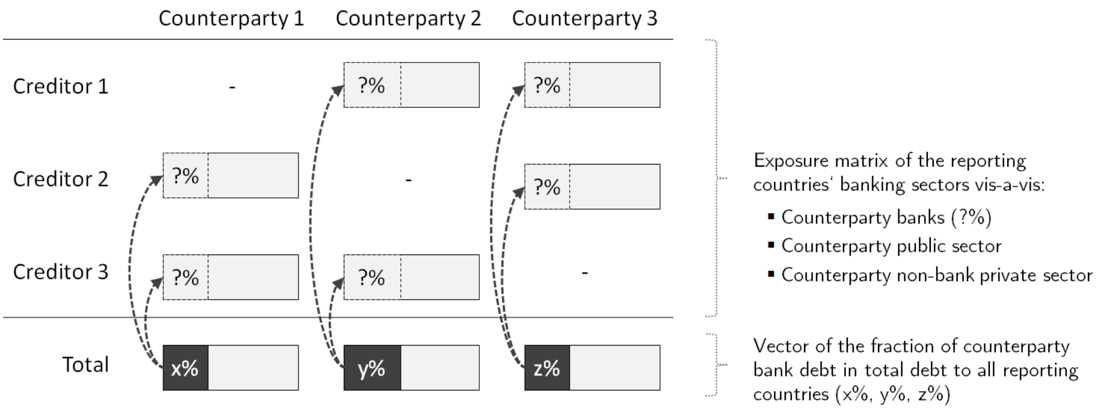
stability and liquidity and on credit exposures where supervisory limits apply for intra-group transactions (Cerutti, et al., 2010). Still, implementing the locational data would cause greater inconsistencies, as accounting for the intra-group flows would lead us to a false conclusion that exposures between two countries where large subsidiaries belonging to the same group pose more significant risk than the external exposures. The use of the consolidated data is consistent with Chan-Lau (2010).

The consolidated claims of the reporting countries are collected in several categories: (i) cross border claims, (ii) local claims of foreign affiliates in foreign currency, and (iii) local claims of foreign affiliates in local currency. While categories (i) and (ii) together are called International claims in the BIS terminology, categories (i), (ii) and (iii) together are called foreign claims. As all the mentioned categories are relevant for capturing the risk exposures of individual banking sectors, the latter group is employed in the analysis.

The consolidated statistics of foreign claims are then further divided into data on immediate borrower basis vs. ultimate borrower basis. While the former one considers the counterparty as the one where the original risk lies, the latter recognizes the one who is ultimately liable for the funds borrowed. For example, if a German bank lends to a French one and secures the transaction by CDS or a guarantee issued by an Austrian bank, the immediate borrower statistics would record the German banking system as the creditor and the French one as the counterparty. In contrast, the Ultimate borrower basis statistics would record the Austrian banking system as the counterparty since that is where the risk of the transaction was transferred. For this reason, using the Ultimate borrower statistics may be superior for modelling situations where the risk materializes by a counterparty default. However, the exposure data is not available on a bank-to-bank basis as the aggregate exposures of the reporting countries include also bank-to-public-sector and bank-to-non-bank-private-sector claims. Hence, trying to infer the risk transfer exposures and trying to implement them in the analysis would add another layer of approximation and along with Chan-Lau (2010), we consider it inappropriate and use the Immediate borrower basis data.

Nevertheless, as it is not possible to obtain directly the pure bank-to-bank exposures between the individual countries' banking sectors, 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. Figure 24 visualizes this calculation.

Figure 24: Estimation of the bank-to-bank exposures



Source: Author

When the network is created, it can be plotted as in Figure 25.[17] 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 funds (i.e. the creditor, the bearer of the risk). For example, there is a strong exposure of Switzerland against the United States and it is coloured blue according to the colour of Switzerland. On the other hand, Panel B provides the situation from the counterparty viewpoint and hence the exposures of all parties to the United Kingdom are coloured in green, as well as the UK itself. 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

[17] As the model will be calibrated for 2011, Figure 25 shows the interbank network as of Q4 2011. Nevertheless, historical network visualizations as well as the most up-to-date one for Q3 2012 are presented in the Appendix.

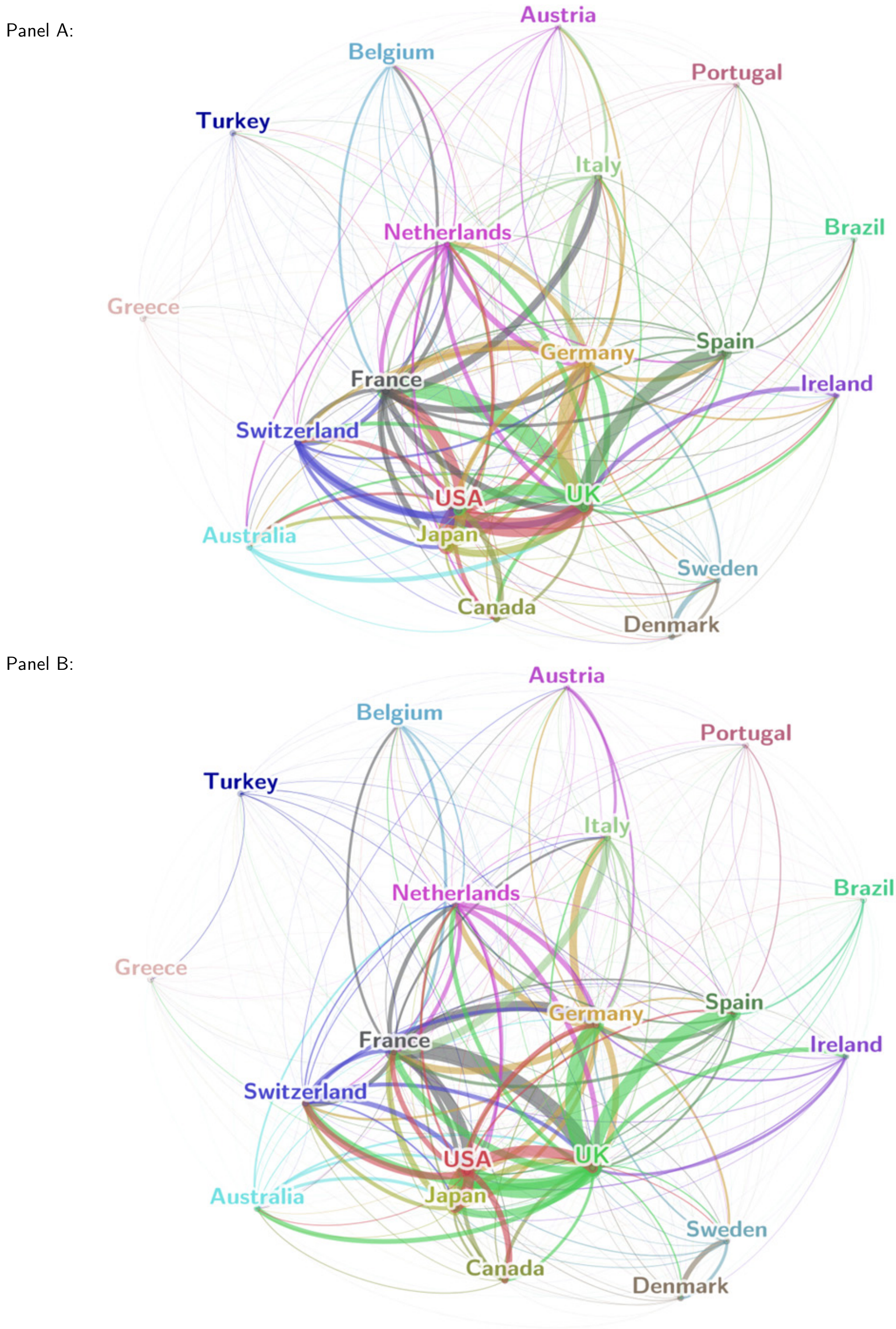
the visualization algorithm[18] takes into account the relationships in the network and places the nodes accordingly, we can see patterns that are in line with our anticipation based on the individual countries' location or cultural relationships. Note for example the pairs of countries being placed 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.

Figure 26 depicts the same data aggregated for each country's banking system. The bars in positive values represent the aggregated value of its exposures against other countries in the interbank network, the bars in negative values represent the aggregated value of claims the other network members hold against it. The black dots stand for net positions of the given countries. We see that the most negative banking positions are held by the United Kingdom, France and Canada. These positions have to be offset by claims external to the network, such as loans to private sector or purchases of derivatives and other securities. The most positive positions are then held by the United States, Germany and, perhaps surprisingly, Spain. Again, these positions are offset externally by taking deposits or selling securities. However, most of the countries' banking systems have their positions relatively balanced, even in case of Japan, which is involved quite heavily in the interbank network.

The interbank debt structure hints that in case of the UK's default, the system would be hit most severely, whereas the United States is likely to get the largest shock given a default of other countries. However, these are shocks in absolute value and do not imply any information about vulnerability of the individual countries. To be able to model the systemic risk on the interbank network, we need to introduce other variables.

[18] 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, interested reader may find more information on graph clustering and layouting in Noack (2007).

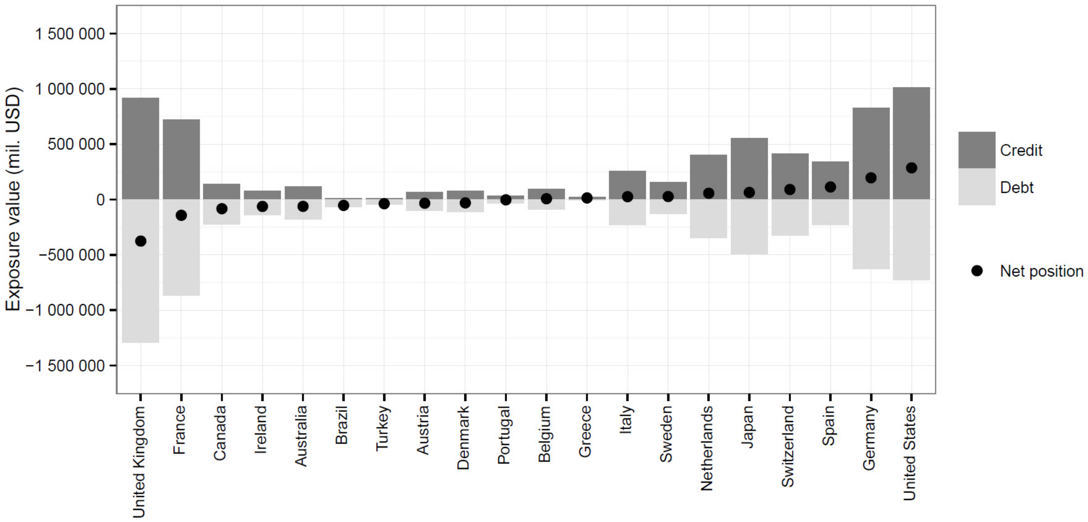
Figure 25: Interbank network of the selected countries as of Q4 2011



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)

Figure 26: Positions of selected banking systems as of Q4 2011



Source: Author based on data from BIS International Financial Statistics

It is also 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 26 does not provide the entirely complete picture of the global banking system, and in our model, bank financing of this type is captured in the rest of the bank's balance sheet, in particular in the external assets. However, we will see that the large disproportion between the relatively small interbank assets and the rest of the total assets value captured in external assets is one of the main shortcomings of interbank network models such as Chan-Lau (2010).

6.1.2 Total Assets

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.[19] To keep our dataset

[19] 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.

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 data is summarized in Table 5 along with visualizations of their time-development and cross-sectional context. There, we can see a clear rise of the asset volumes consistent with the initial risk build-up as mentioned in Section 2.1.1, where the first phase of the crisis was described. Also, the data show the effect of the crisis on the total amount of banking assets, mainly in the financial centres such as Switzerland, the United Kingdom and the United States where the deleveraging is most visible. Looking at the 2011 figures and comparing them across the individual banking sectors, the countries with the largest banking sectors are France, Germany, the United Kingdom and the United States. On the other hand, Greece and Turkey have the smallest banking sectors, which are each more than twenty times smaller than the one of the United States.

Table 5: Total assets of individual banking systems in USD billion

	2005-2011	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	2011
Australia		1 097	1 404	1 957	1 890	2 387	2 801	2 954	
Austria		849	1 040	1 301	1 474	1 483	1 312	1 303	
Belgium		1 248	1 484	1 914	1 774	1 667	1 521	1 546	
Brazil		738	973	1 428	1 257	1 876	2 308	2 485	
Canada		1 764	2 051	2 622	2 608	2 739	3 082	3 586	
Denmark		880	1 081	1 428	1 516	1 591	1 515	1 477	
France		6 457	8 147	10 467	10 718	11 026	10 492	10 825	
Germany		8 094	9 444	11 161	10 971	10 708	11 128	10 828	
Greece		338	424	576	646	709	690	615	
Ireland		1 363	1 920	2 445	2 407	2 353	2 046	1 693	
Italy		3 067	3 789	5 009	5 135	5 395	5 078	5 244	
Japan		7 480	7 494	7 686	8 133	8 003	8 148	8 511	
Netherlands		2 003	2 433	3 187	3 102	3 192	3 028	3 133	
Portugal		426	525	647	670	749	749	740	
Spain		2 605	3 335	4 418	4 739	4 963	4 651	4 700	
Sweden		778	1 032	1 257	1 261	1 348	1 431	1 471	
Switzerland		2 170	2 624	3 072	2 873	2 596	2 908	3 002	
Turkey		284	346	484	460	537	657	643	
United Kingdom		9 976	12 911	14 656	12 131	12 901	12 295	12 524	
United States		10 879	11 862	13 034	13 841	13 087	13 319	13 892	

Source: Author according to the Banking Sector Statistics Database from the European Banking Federation and according to individual central banks.

6.1.3 Equity

As seen in the Monte Carlo simulations section, 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. BankScope offers several types of capital ratios used for regulatory purposes and should provide good information on the banks' capitalization, e.g. Tier 1 or Total regulatory capital. However, these series are very incomplete and sometimes reaching values that seem unreliable and too high compared to the interbank network data. Hence, we adopted a more conservative approach and chose common equity (common shares plus retained earnings) to total assets as the proxy for banks' capitalization. This variable is easily available for all banks in the database and ultimately, our approach is consistent with the latest opinion of the Bank for International Settlements that: *"It is critical that banks' risk exposures are backed by a high quality capital base. The crisis demonstrated that credit losses and writedowns come out of retained earnings, which is part of banks' tangible common equity base"* (BCBS, 2010, p. 2).

Table 6: Equity to asset ratios of individual banking systems

	2005-2011	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	2011
Australia		5.49%	5.34%	5.85%	5.79%	6.21%	6.27%	5.40%	
Austria		5.21%	6.20%	6.44%	5.64%	6.38%	7.05%	6.73%	
Belgium		3.85%	4.12%	4.56%	3.04%	4.10%	4.40%	3.97%	
Brazil		9.01%	9.41%	9.44%	7.73%	7.79%	7.81%	7.83%	
Canada		8.04%	9.96%	9.71%	10.60%	13.00%	15.02%	14.79%	
Denmark		4.27%	4.49%	4.22%	3.85%	4.09%	4.22%	4.34%	
France		4.02%	4.14%	3.83%	3.16%	4.01%	4.19%	4.05%	
Germany		3.87%	3.93%	4.03%	3.48%	3.66%	4.09%	4.92%	
Greece		5.98%	6.86%	8.25%	6.34%	7.49%	6.83%	0.18%	
Ireland		2.95%	3.19%	3.41%	2.28%	2.14%	1.46%	5.36%	
Italy		7.63%	7.80%	7.87%	7.34%	8.15%	8.17%	7.16%	
Japan		3.25%	4.29%	4.72%	4.08%	3.04%	4.18%	4.51%	
Netherlands		3.56%	3.55%	3.55%	2.77%	4.00%	4.12%	4.14%	
Portugal		4.72%	5.46%	4.95%	4.73%	5.50%	5.10%	4.71%	
Spain		5.75%	5.98%	6.15%	5.56%	6.23%	6.33%	6.31%	
Sweden		4.17%	4.33%	4.27%	3.91%	4.46%	4.54%	4.23%	
Switzerland		3.65%	4.05%	4.01%	3.48%	4.55%	4.65%	4.49%	
Turkey		12.65%	11.72%	12.62%	10.92%	12.17%	12.57%	11.28%	
United Kingdom		4.06%	4.04%	3.88%	2.64%	4.29%	4.68%	4.75%	
United States		7.92%	7.95%	7.52%	6.80%	8.55%	8.60%	8.99%	

Source: Author's calculations according to the BankScope database

Table 6 presents the obtained figures, which were calculated as weighted averages of equity-to-assets ratios where the weights are the individual banks' total assets in the given year.[20] The most-capitalized banking sector is the one of Canada, which corresponds to the fact that no Canadian bank needed recapitalization during the recent crisis (Ratnovski & Huang, 2009). On the other hand, the least capitalized is

[20] For the analysis, we considered the banks with the following specialisations: commercial banks, savings banks, cooperative banks, real estate & mortgage banks, bank holdings & holding companies

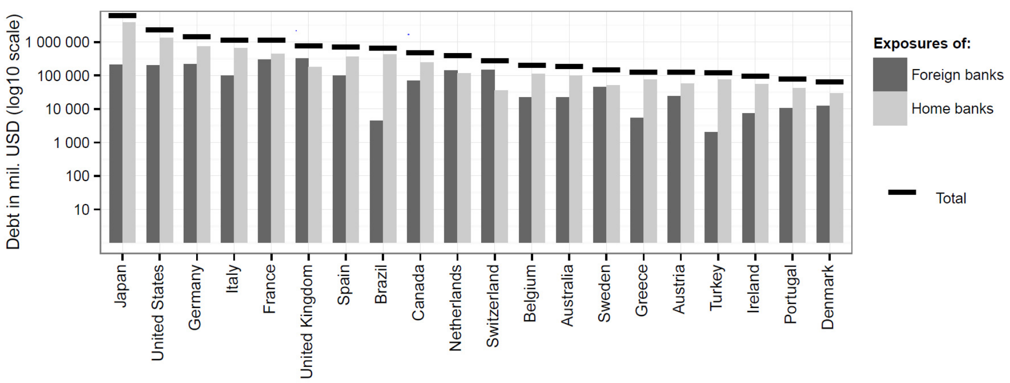
the Greek banking sector which was severely hit in 2011. On a related note, Ireland is at its historical minimum under 1.5% in 2010. Finally, looking at the figures from the time perspective, we see a clear drop in most capital ratios in 2008 with fast recovery in most countries' banking systems as the banks were extensively recapitalized.

6.1.4 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.[21] 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 27: Selected banking systems' exposures to sovereign debt as of Q4 2011

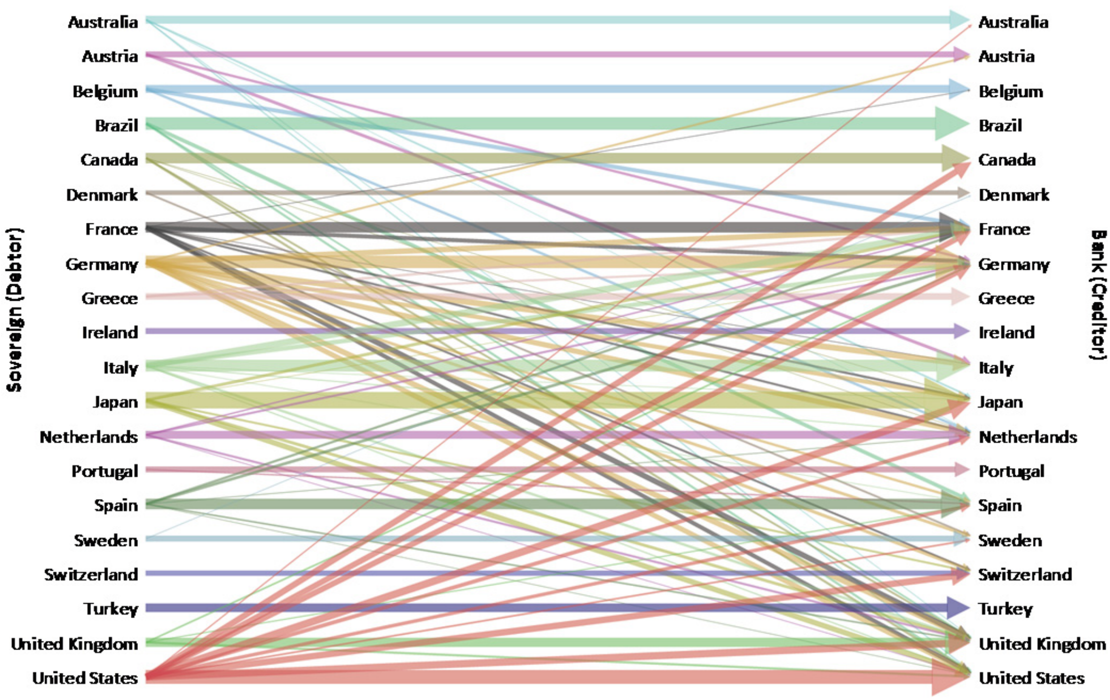


Source: Author's calculations based on data from Arslanalp & Tsuda (2012), IMF International Financial Statistics and BIS International Financial Statistics

[21] The calculation may be visualized by Figure 24, only the question marks (*?%*) would now represent the value of the banks' exposures to counterparty public sectors instead of counterparty banking sectors.

Figure 27 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. With debt to banks amounting to over $4 trillion, Japan is the most indebted sovereign in our sample and also reports the strongest home bias as the overwhelming majority of Japan's large public sector debt to banks is held by the domestic institutions.[22]

Figure 28: Detailed banking systems' exposures to sovereign debt as of Q4 2011



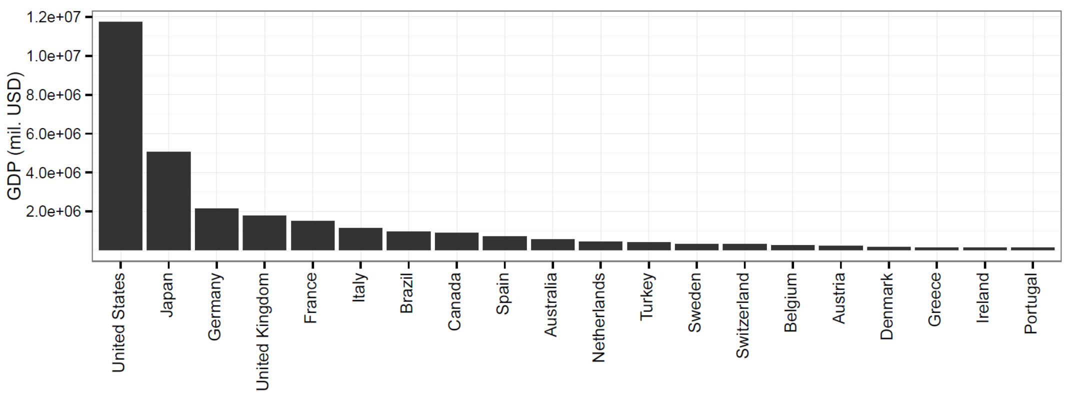
Source: Author's calculations based on data from Arslanalp & Tsuda (2012), IMF International Financial Statistics and BIS International Financial Statistics
Note: The edges are coloured by the creditor node (e.g. exposure of US sovereign against the Canadian banking system is coloured in red). The edges' 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.

[22] According to (IMF, 2013b), Czech Republic is second after Japan in bank holdings of sovereign debt. These amount to over 17% of total banking assets.

For better insight into the interlinkages between banks and sovereigns, one has to study also the detailed exposures, including the international ones. Figure 28 presents these data as a plot of the bipartite network of sovereigns and banking systems in our sample. Similar to Figure 25, the edges represent the sovereign debt towards the individual banking system. Here we see again the home bias phenomenon as the largest links are always to the domestic banking system and also for the individual countries, interesting patterns emerge. Again, the debt to foreign banks is determined largely by geographical or cultural proximity of the individual countries. Notice for example that the largest foreign borrowing of Austria is from German and Italian banking systems, Belgium is connected mostly to France and the Netherlands, Denmark is connected to Sweden and vice versa. As to the cultural proximity, Brazil borrows mostly from Spanish banks and Australia from the UK banking system (and from Japan, which is again close geographically). Also Canada is linked to the United Kingdom and the United States. Finally, there are several “international borrowers”, such as the United States, Germany, France and to some extent also Japan.

6.1.5 GDP and CDS Spreads

Figure 29: GDP of the selected countries in constant 2000 US dollar



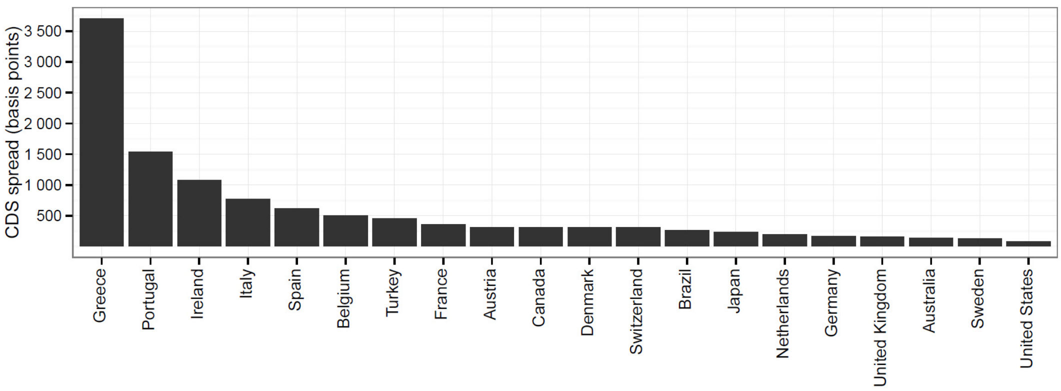
Source: Author according to the World Bank database

Besides balance sheet data for the individual countries’ banking systems, the model requires two more datasets for 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). From the available series, the one in constant US dollars of the year 2000 was selected in order to prevent exchange rate fluctuations and inflation to bias the data in case of using the model on a time series. Figure 29 captures the absolute value of GDP of the analysed countries in 2011and shows large disparities among the economies. The sample mean value of this indicator is \$1.45

trillion, approximately the product of France. The US output is far the largest with the value exceeding $11.7 trillion. On the other side of the scale, Portuguese GDP accounts for only 1/100 of the US one and is the lowest from the sample. Also, Portugal experienced the second largest proportional drop compared to the previous year. As expected, the leading position in this matter belongs to Greece whose annual growth rate stood at -7.1%. The fastest growing country was Brazil which was expected due to its status of emerging economy. However, Sweden and Germany also experienced a healthy annual growth rate exceeding 3%.

Data on 5-year credit default swap spreads were obtained from the Bloomberg database. Figure 30 captures the average value of CDS spreads for selected countries in 2011. The median value reaches 307 basis points which is approximately the CDS spread of Austria. Apparently, the PIIGS countries are markedly more prone to default as their CDS spreads significantly exceed the common levels, in case of Greece, the value is 11 times higher than the median, in case of Portugal, approximately five times higher. According to the market perception, the United States are the least likely to experience a default.

Figure 30: CDS Spreads of the selected countries

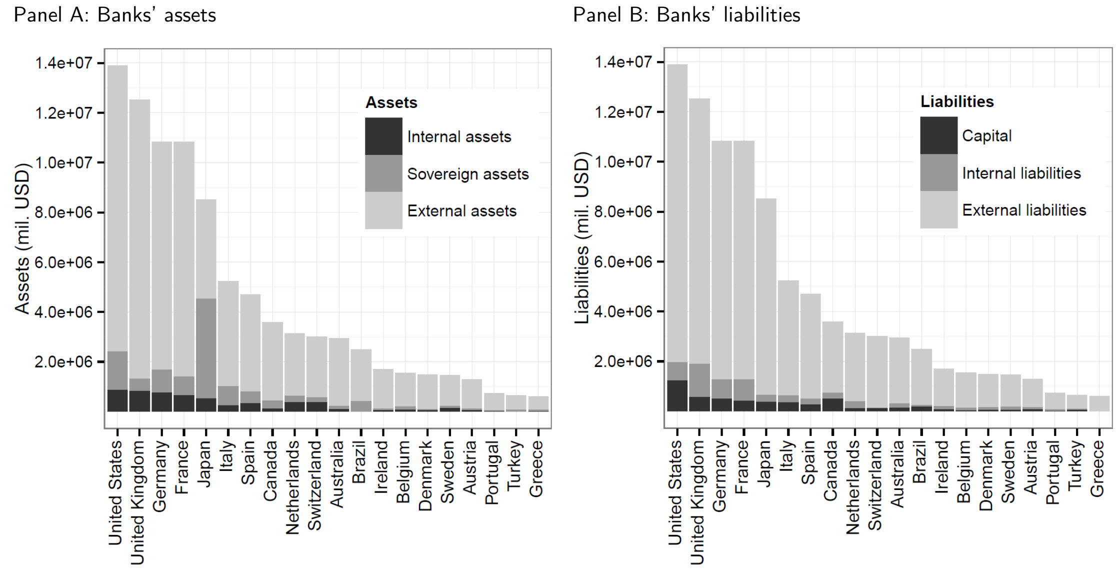


Source: Author according to Bloomberg

6.2 Model Calibration

Put all together, the collected data provide a complex picture of the modelled global banking system according to Table 4. 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. While the calibrated model will be tested for 4Q 2011 data, we plan to provide time series of the model's estimation in the future research.

Figure 31: Balance sheets of the calibrated model as of Q4 2011



Source: Author's calculations

Figure 31 provides the final overview of the calibrated balance sheets which are loaded into the model.[23] As we can see on Figure 31A, 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 31B, 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

[23] In case of the empirical analysis, instead of generating the system according to a number of parameters, the model constructs it according to the real-world data. The datasets are loaded into the application in form of four xml files: 1) interbank network definition, 2) sovereign-bank network definition, 3) bank balance sheet data, and 4) sovereign data.

demands further data collection which would enable us to break the external assets into more detail. More information on this issue will be provided in the next chapter on further research opportunities.

As opposed to Chan-Lau (2010), we incorporate the full size of the banking system and incorporate 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).

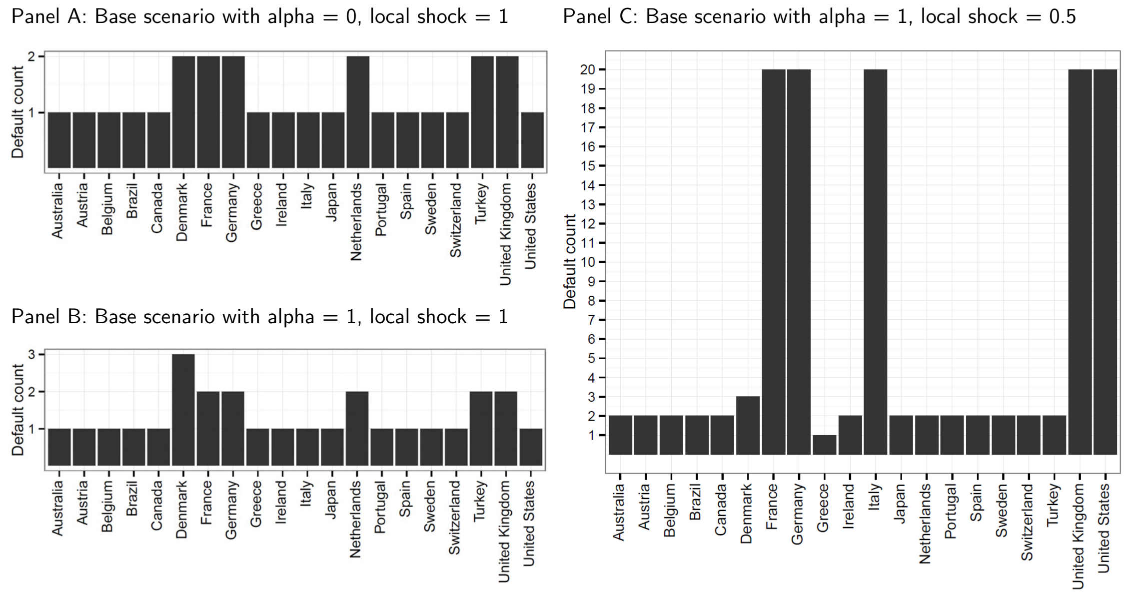
6.3 Results

In this section, we present the simulation results of the calibrated model. We will observe the systemic importance of the individual banking subsystems or sovereigns as the initial shock propagators and we will study how and at what cost state support may ease a systemic crisis. Finally, we implement the feedback loops as in the previous chapter.

6.3.1 Basic Shocks

First, we show how the model behaves under various settings of the key parameters and given various initial shock propagators. Similarly as in Chapter 5 on Monte Carlo simulations, we begin by imposing basic shocks to the individual banking subsystems. When we hit each of them one by one by erasing all their external assets and leave the liquidity channel switched off, the system seems to be relatively stable as depicted in Figure 32A. Almost in all cases the only bank which defaults is the originally shocked bank, only in case of France, Germany, the Netherlands, Turkey and the United Kingdom, the shock transmitted on Greece induces its default. Moreover, in case we impose the original shock on Denmark, the shock imposed on Sweden is larger than its capital buffer and hence it defaults as well. The first outcome is given by significantly low capitalization of Greece, making it very vulnerable to default, and the second outcome is given by a strong link between Denmark and Sweden, which we described already in Section 6.1.1 on the description of the interbank network. As mentioned in Section 6.2 on model calibration, the relative stability of the system is given by relatively small share of the interbank assets on the total assets in the system. As the capital ratios are calculated from total assets, most of the shocks that are purely of the direct credit contagion type are not large enough to break through the capital barriers. The system does not break down even when the liquidity channel is switched on by setting the value of Alpha to one as then the only difference is that in case of initially shocking Denmark, two banking subsystems now fail: those of Sweden and Greece. Figure 32B depicts this scenario.

Figure 32: Model results under various scenarios



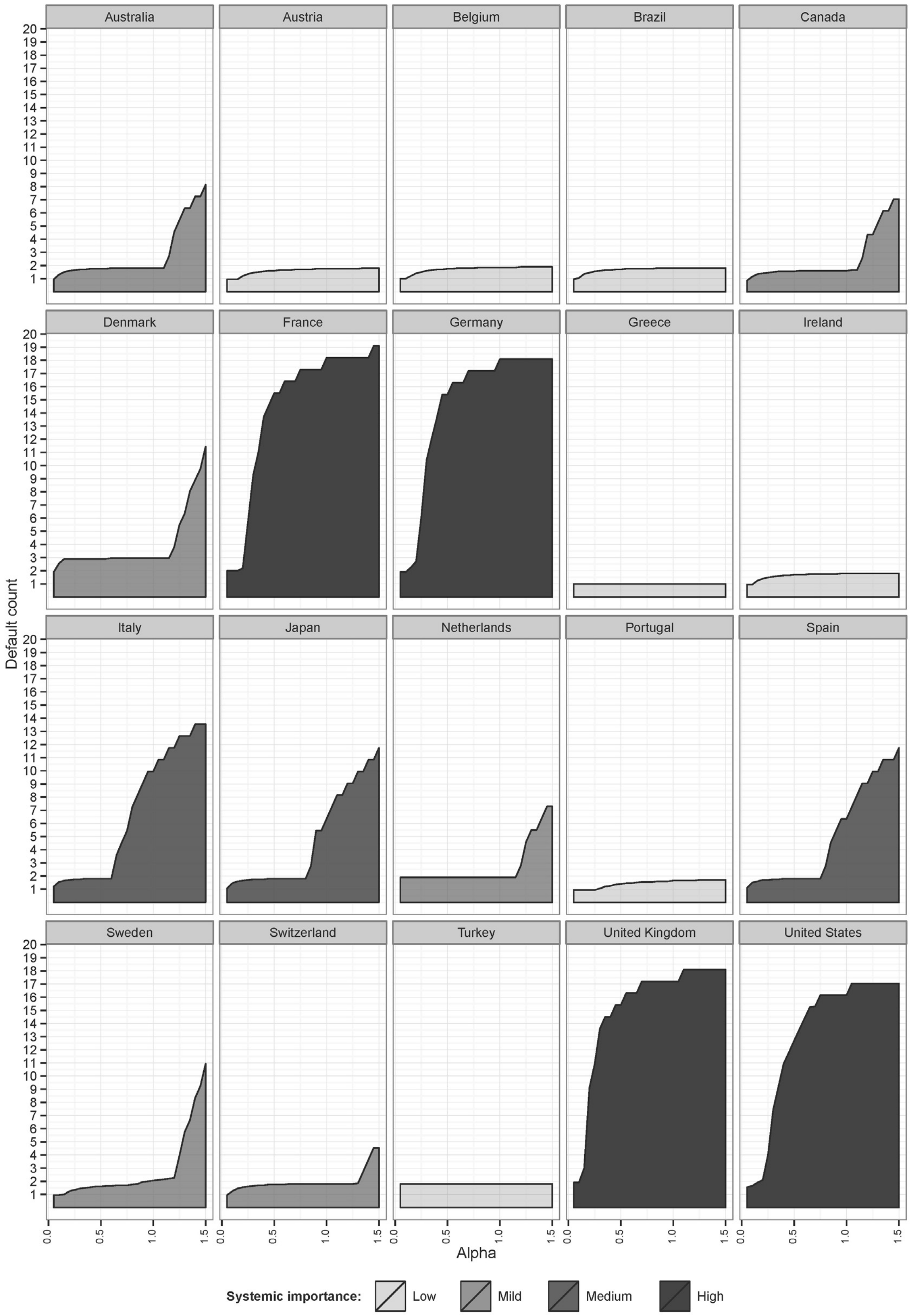
Source: Author's calculations

However, the situation changes when the system is shocked by a local shock equal to 0.5, which means that only half of the external assets of the initial shock receiver is erased. In this case, demonstrated in Figure 32C, there is much more assets to sell during the shock receiver liquidation, which in case of a non-zero alpha puts a significant pressure on the external asset prices. As a result, Greece fails in all cases and moreover, when the initially shocked banking subsystems are France, Germany, Italy, the United Kingdom or the United States, the global system reaches a state of a total collapse. We saw in the Section 6.1.2 on total assets, that these countries' banks have one of the largest asset volumes. Interestingly, despite having a large asset volume, Japanese banks do not induce a total systemic break-down as they hold less external assets on their balance sheets and instead, they are exposed against the home sovereign.

The pattern seen in Figure 32C is similar when we run the simulations with 20 different values of local shock $[0.05, 0.1, 0.15, \ldots\ 0.095, 1]$ average them into datapoints and plot them against various levels of alpha. Usually, under each parameter setting, initially hitting one country's banking sector results either in defaults of a few other banking sectors, or a total systemic collapse. Again, this is given by the fact that in our model the liquidity effects are the most important channel of contagion and the banks hold a large portion of external assets. To get a comprehensive map of systemic risk, we need to look at several various local shocks and alpha values. Figure 33 provides such map for each initial propagator by aggregating data for various local shocks and averaging them to obtain relatively continuous plots of systemic risk's dependence on the system illiquidity (represented by the parameter alpha). As expected and in line with the Monte Carlo simulations, after breaking a certain threshold, lower liquidity usually leads to more defaults. However, in our analysis, there are certain initially shocked banking systems for which the threshold is not reached on the assumed interval of alpha and hence we categorize them as of low systemic importance. We see that even for high levels of alpha for Austria, Belgium, Brazil, Ireland, Portugal and Turkey, the number of defaults in the system is limited to two, which usually means the originator banking system plus Greece. Moreover, as Greek banking sector is not systemically important, the only banks that default in case the shock begins in this country are the Greek ones.

On the other hand, mostly large banking sectors such as Australia, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, the United Kingdom or the United States proved to be systemically important and especially France, Germany, the United Kingdom and the United States are clearly too big to fail even at relatively conservative levels of alpha. The banking sector with the soonest outbreak of systemic crisis under increasing alpha is the United Kingdom and interestingly, at high alpha levels French banks prove the highest systemic importance. As to the lower-tier systemic banking sectors, Italian, Japanese and Spanish banks are still relatively important with crisis outbreaks starting at alpha levels lower than one and with crisis extent reaching over the half of the whole system at the maximum alpha level. Finally, Australia, Canada, Denmark, the Netherlands, Sweden and Switzerland are of mild systemic importance.

Figure 33: Banking subsystems' average systemic importance

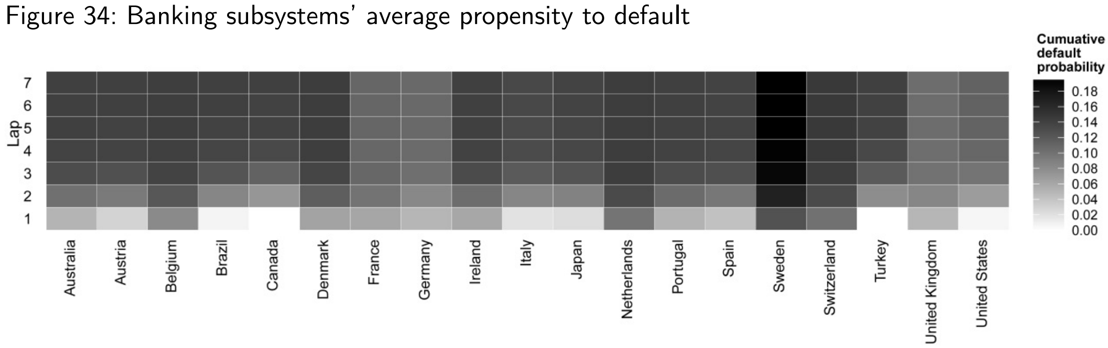


Source: Author's calculations

A different view at the same issue is provided in Figure 34 where we observe systemic weakness of individual banking systems instead of systemic importance. The data for this analysis was obtained from averaging simulations across 20 different values of local shock $[0.05, 0.1, 0.15, \ldots\ 0.095, 1]$, across 20 different levels of alpha from the same interval and across all the 20 initial propagator banking systems. The plot depicts the cumulative probability of default of each country's banks in the first to the seventh lap of the simulation. As we mentioned earlier, if our model reaches a state of a systemic collapse, in the last simulation lap usually all banks ultimately default. However, if the system experienced an earlier recovery, we see that the banking systems of some countries are not very likely to default. For example, Canada and Turkey have a zero probability of default in the first lap of shock propagation because of their good capitalization while Sweden seems to be rather vulnerable, mostly to its relatively low capitalization and large exposure to Denmark as described earlier in this chapter. Greek banks had to be omitted from the visualization because with cumulative probabilities only slightly below 80% right from the first lap of propagation, they were deforming the scale of the plot.

Finally, combining the observations from Figure 33 and Figure 34, we may even say which countries a potential regulation or aid policy should mostly focus on. For example, not only would the French banks have the most impact on the system in case of their default, but in contrast to other banking systems (and mainly the United States), they are more likely to default early in case of a crisis.

Figure 34: Banking subsystems' average propensity to default



Source: Author's calculations
Note: Greek banks were omitted because their cumulative default probabilities only slightly below 80% right from the first lap of propagation were deforming the scale of the plot.

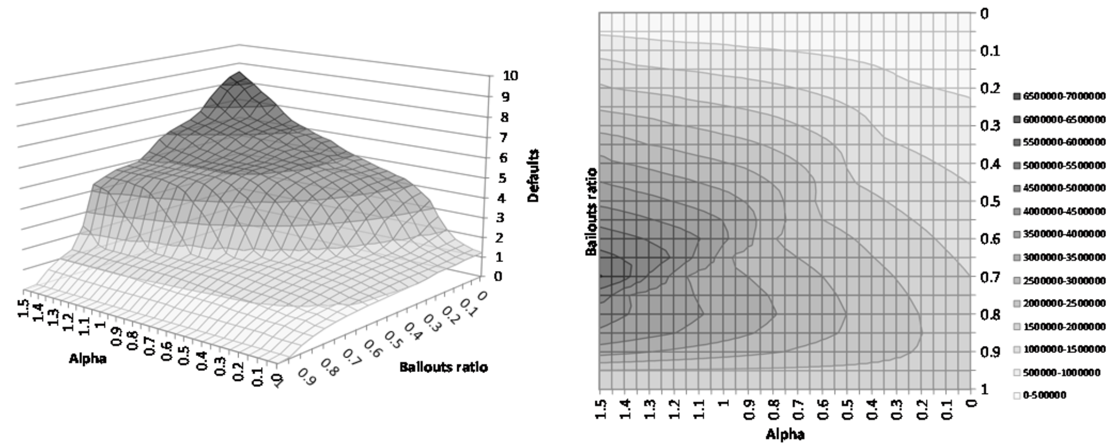
6.3.2 Sovereign Assistance

In this section, we will explore the effects of sovereign assistance on the calibrated global banking system. As in Chapter 5 on Monte Carlo simulations, we will describe the impact and costs of the three support measures: Bailouts and recapitalization, guarantees execution and asset relief. In line with the Monte Carlo simulations, when testing the fourth measure (funding liquidity provision) on the calibrated data, although it had some very small positive effect, it proved almost insignificant to systemic stability and hence we leave it out from our analysis.

Figure 35: Bailouts and recapitalization effects

Panel A: Total defaults - Alpha vs. Bailouts ratio

Panel B: Total cost – Alpha vs. Bailouts ratio



Source: Author

Again, first we look at bailouts as the most direct support measure. Figure 35A depicts the number of bankrupt banking subsystems given various levels of alpha[24] and various support intensities. The positive effects of this measure are clearly visible and with maximum bailout support, no bank defaults as the shock is mitigated 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 35B demonstrates that at very low levels of alpha, the costs increase almost linearly with the support intensity. However, similarly as we saw in the Monte Carlo simulations, 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

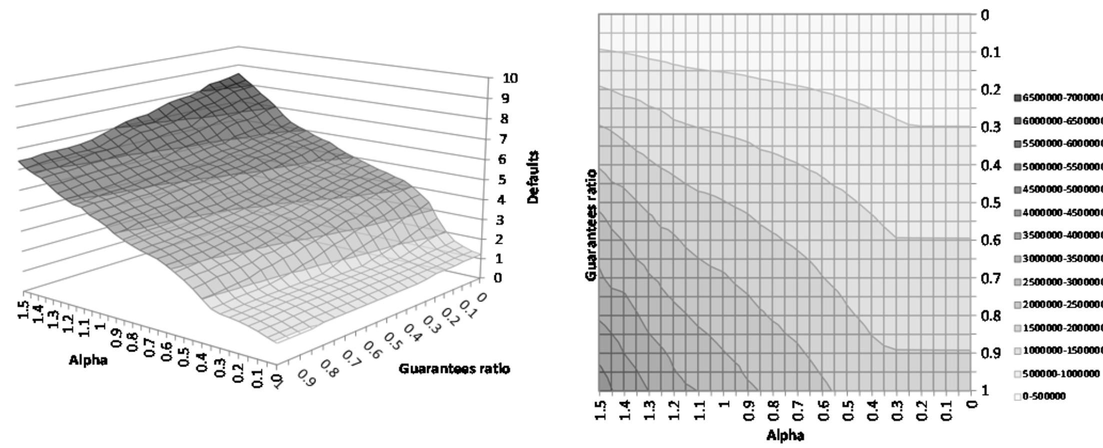
[24] As the banking network is now based on real data and thus the connectivity parameter no longer exists, and also because now we are more interested by liquidity effects, the second parameter we observe in the figures is the system's illiquidity.

effectively blocking the contagion through market liquidity channel and corresponds to the sharp drop of defaults in Figure 35A.

Figure 36: Guarantees execution effects

Panel A: Total defaults - Alpha vs. Bailouts ratio

Panel B: Total cost - Alpha vs. Bailouts ratio



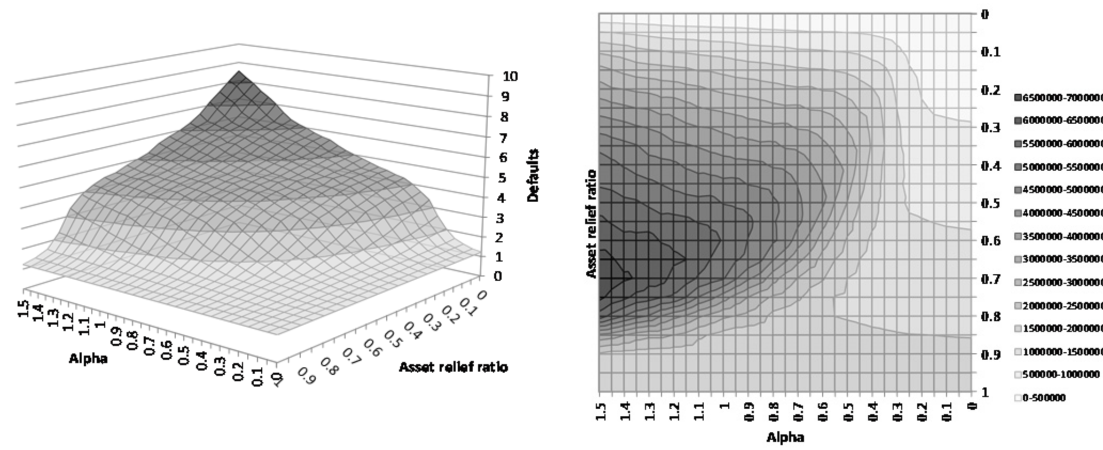
Source: Author

Second, we observe the effects of sovereign guarantees and their execution. Figure 36A demonstrates that this support measure mitigates the crisis only mildly and especially at high levels of alpha it is much less efficient than bailouts. This is given by the fact that the shock is captured by the guarantees only after it already negatively affects the asset prices through the liquidity channel. As to the deficits needed to finance this kind of support, Figure 36B demonstrates that they are slightly lower than in the case of outright bailouts and they rise monotonously with the support intensity at all levels of alpha.

Figure 37: Asset relief effects

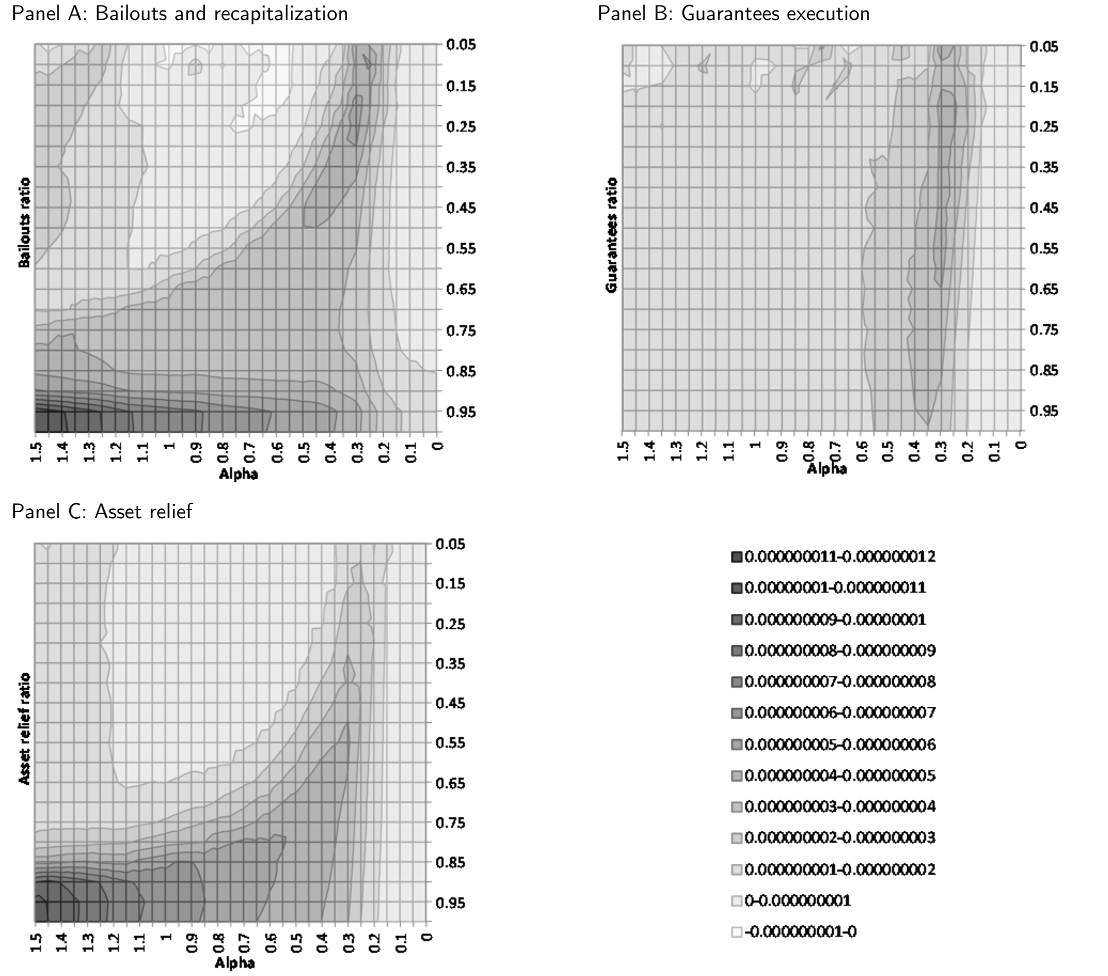
Panel A: Total defaults - Alpha vs. Bailouts ratio

Panel B: Total cost - Alpha vs. Bailouts ratio



Source: Author

Figure 38: Cost-benefit analysis of state support measures on the calibrated model



Source: Author

Thirdly, looking at the effects of asset relief programmes as depicted in Figure 37A, 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 $(1 - \alpha)$. Also, in contrast to outright bailouts which may be targeted at 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 37B shows that at the peak they are slightly 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 much more efficient for the calibrated model than for the simulations is that in case of the simulations, interbank assets formed a larger portion of total assets of the system and hence the liquidity effects were not as strong as in the calibrated case.

Finally, as in the fifth chapter, we briefly mention the cost efficiency of the individual measures. In line with the previous analyses, Figure 38 depicts that while guarantees are relatively very inefficient, both bailouts and asset purchases are a relevant tool for crisis mitigation. As mentioned, this is caused by the liquidity channel, which is not addressed by the guarantees measure. Regarding the distinction between bailouts and asset relief, bailouts are more efficient in lower alpha, lower support intensity setting where they address the pure credit links among individual banking subsectors (that is why even guarantees are more efficient in this area). Moreover, at the peak alpha and peak support intensity, bailouts are also slightly more efficient than asset relief.

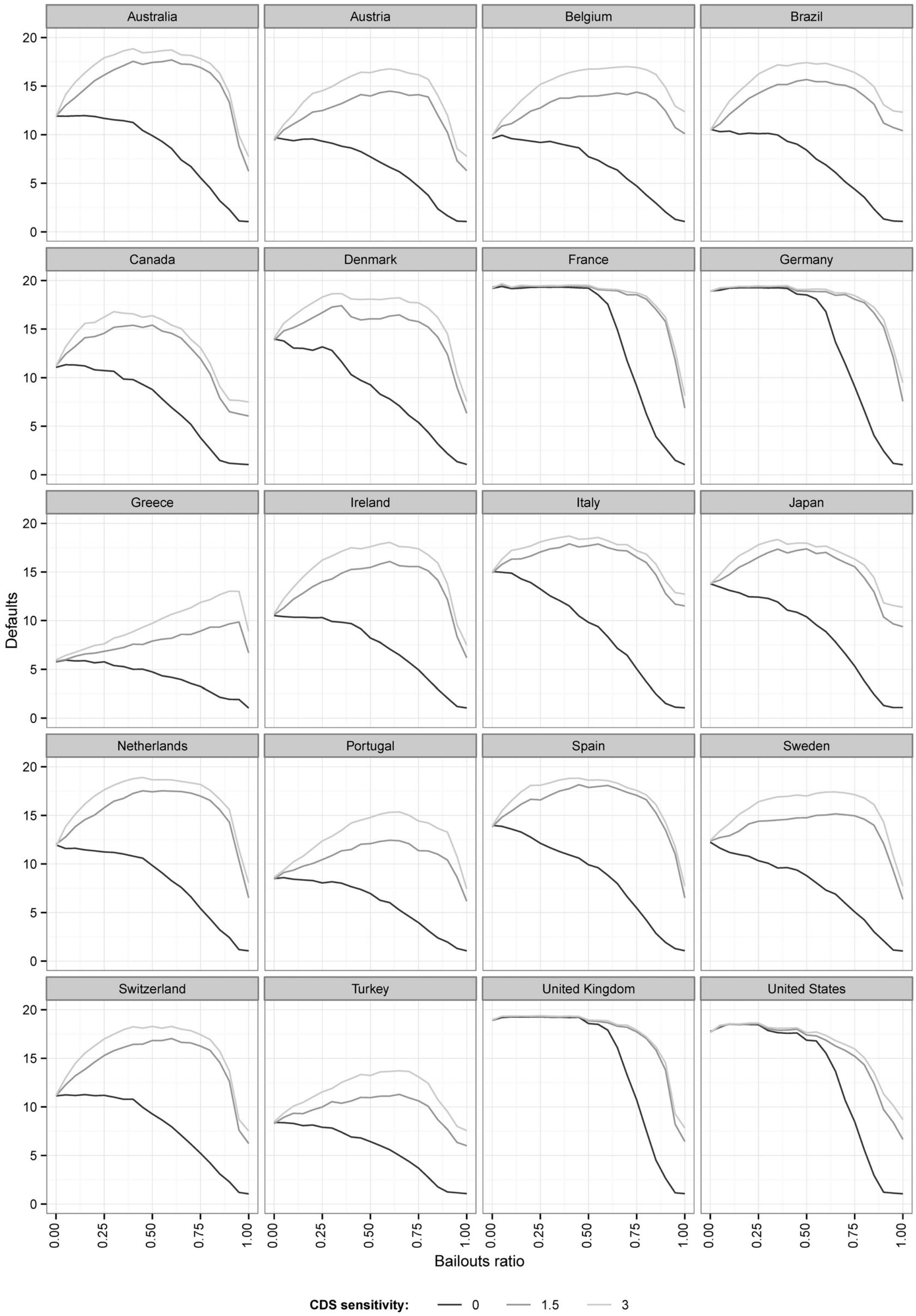
6.3.3 Feedback Loops

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 on the following pages depict the number of failed banking systems in dependence on state aid intensity and accounting for different levels of CDS sensitivity.

First, Figure 39 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,[25] 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 banks is a decreasing function of the support intensity.

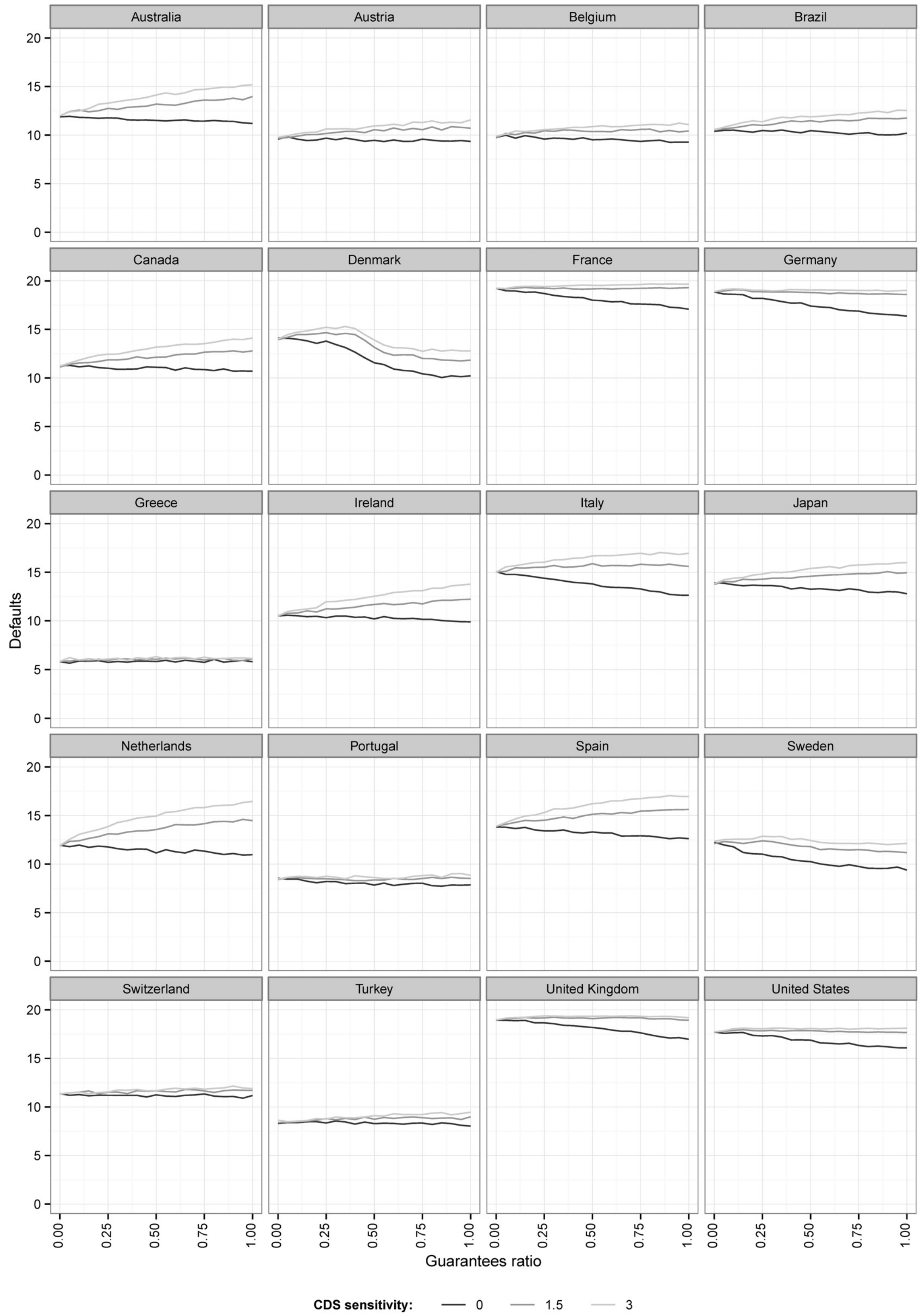
[25] Our choice of CDS sensitivity values of 1.5 and 3 in the figures is in line with econometric studies such as Sand (2012) or Cottarelli & Jaramillo (2012).

Figure 39: Bailouts and recapitalization with feedback loops on the calibrated model



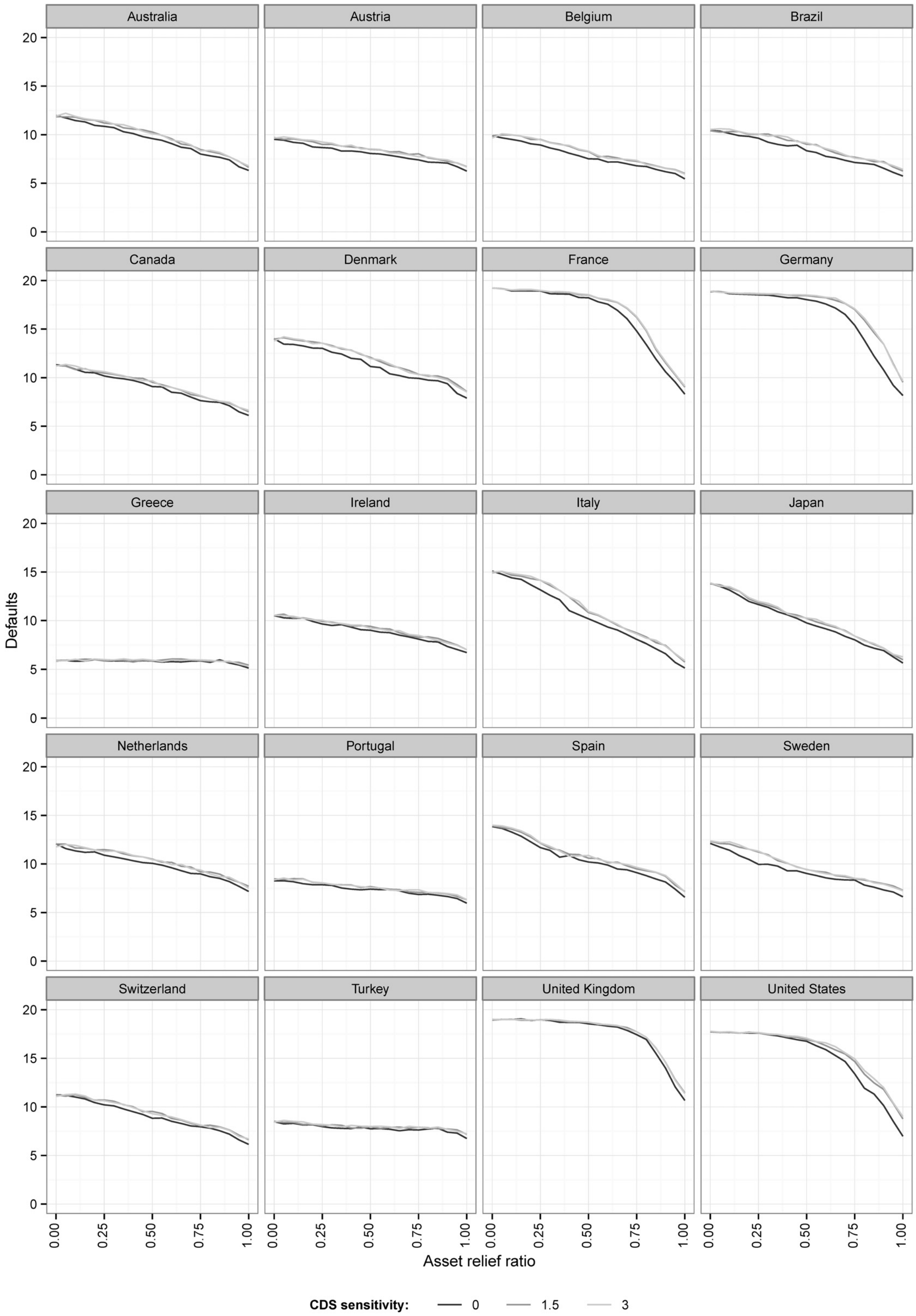
Source: Author

Figure 40: Guarantees execution with feedback loops on the calibrated model



Source: Author

Figure 41: Asset relief with feedback loops on the calibrated model



Source: Author

For large banking systems (France, Germany, the United States and the United Kingdom, having high systemic importance in Figure 33), the effects come only at relatively high support intensity as the systemic break-down is prevented only at bailouts ratio exceeding 50%. Moreover, for these countries' banks, 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. This fact corresponds with Figure 21A where we showed that for low-capitalized systems the state support almost always has a positive effect on an otherwise collapsing system and we saw in Figure 33 that hitting initially these four countries results in the worst crises. Moving to other banking systems, 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.

Second, Figure 40 depicts the effects of guarantees execution. It confirms our previous finding that in the current setting where the liquidity channel is the main determinant of systemic stability, this measure does not have as large positive effect as the previous one. While for zero CDS sensitivity level, it supports the system in case of several initial propagators such as Denmark, France, Germany, Italy, Sweden, the United Kingdom or the United States, for non-zero CDS sensitivities the effect is usually either neutral or negative. The reason why the guarantees are not a good support measure under this calibration setting is that they come into effect only after the shock hits the receiver banking system. Hence, even though the credit shocks from this banking system onto the others are mitigated, this measure does not prevent the liquidation of the receiver banks triggering a systemic collapse through the liquidity channel. The only exception is when we initially hit Danish banks. As we saw in Figure 32 in case of Denmark, the pure credit contagion channel is more pronounced and thus in Figure 40 we see that it is the initial propagator where for non-zero CDS sensitivities the effect of guarantees execution on the global banking system is significantly positive.

Third, Figure 41 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.

6.3.4 Results Summary

For the empirical analysis we calibrated our model to 4Q 2011 data collected from several sources. We found that majority of the total assets in the system are constituted by external assets, which hints that our results are different from those of Chan-Lau (2010) who considers solely the interbank network documented by the BIS data, forming only 8% of the global banking system.

When the liquidity channel is switched off, the system is relatively stable and not vulnerable to systemic crises. The only banking systems which may fail due to contagion effects are Greece, which defaults when France, Germany, the Netherlands, Turkey or the United Kingdom are initially shocked and Sweden, which fails when Denmark is hit at the beginning of the simulations. When the liquidity channel is switched on, the situation is the same except for the situation when Danish banks are initially hit, which results in default of both banking systems of Sweden and Greece. When the initial shock is smaller and thus the failing banks have more assets to liquidate, the liquidity contagion channel is activated in full force, triggering systemic crisis in case of default of French, German, Italian, UK or US banks. Finally, when considering an average across various values of local shock, we may categorize the countries according to their systemic importance as shown in Table 7.

Table 7: Systemic importance and weakness of individual banking systems

Country	Systemic importance:	Imminent systemic weakness[26]
Australia	*Mild* ● ●	*Medium* ● ● ●
Austria	*Low* ●	*Mild* ● ●
Belgium	*Low* ●	*High* ● ● ● ●
Brazil	*Low* ●	*Low* ●
Canada	*Mild* ● ●	*Low* ●
Denmark	*Mild* ● ●	*High* ● ● ● ●
France	*High* ● ● ● ●	*Medium* ● ● ●
Germany	*High* ● ● ● ●	*Medium* ● ● ●
Greece	*Low* ●	*High* ● ● ● ●
Ireland	*Low* ●	*Medium* ● ● ●
Italy	*Medium* ● ● ●	*Low* ●
Japan	*Medium* ● ● ●	*Mild* ● ●
Netherlands	*Mild* ● ●	*High* ● ● ● ●
Portugal	*Low* ●	*Medium* ● ● ●
Spain	*Medium* ● ● ●	*Mild* ● ●
Sweden	*Mild* ● ●	*High* ● ● ● ●
Switzerland	*Mild* ● ●	*High* ● ● ● ●
Turkey	*Low* ●	*Low* ●
United Kingdom	*High* ● ● ● ●	*Mild* ● ●
United States	*High* ● ● ● ●	*Low* ●

Source: Author
Note: The dot sign "●" represents the degree of systemic importance or systemic weakness

Considering the cost and effect of the individual support measures on the calibrated system, we found that in line with the simulations, the most efficient measure is bailouts and recapitalization. However, as due to the asset structure the liquidity channel is the most important one and the BIS data provide insight only into aggregated interbank exposures, asset relief is the second-most efficient measure. Also, guarantees execution has only slight positive effect on the systemic stability and in line with the Monte Carlo simulations, the effects of funding liquidity provision proved insignificant.

Finally, implementing the feedback loops we found that a 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

[26] Imminent systemic weakness represents the relative probability that the given banking system defaults in the first contagion lap according to Figure 34.

worsen the situation. Table 8 provides the complete overview of the feedback loops analysis.

Table 8: 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 ▪ At higher CDS sensitivities and in the middle of the support intensity interval, the effects are: – Negative when the initially failed bank has lower systemic importance – Neutral when the initially shocked bank 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
Guarantees execution	▪ At zero CDS sensitivity, this measure has a significantly positive effect only in a small number of cases ▪ At non-zero CDS sensitivity levels, the effect of this measure is neutral or positive with the only exception of the Danish banks being the target of the initial shock
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
Funding liquidity provision	▪ No significantly positive effects found in the previous analyses

Source: Author

6.3.5 Further Research Opportunities

This section provides possible further extensions and improvements of our model or the calibration dataset. First, the scope of this thesis did not allow us to observe in detail the effects of all parameters already programmed in the model. Comprehensive study of the effects of liquidity, the number of banks and sovereigns in the system, percentages of interbank or sovereign assets, recovery rates or different levels of global and sovereign shocks will be examined in our further research. Moreover, for the Monte Carlo simulations, different network topologies may be implemented to build structures that better correspond to reality such as small-world or tiered scale free networks.

Second, for the simulations on the calibrated model, we may run the analyses on data for other time periods than the currently employed dataset of 4Q 2011. At the time of writing this thesis, the latest available BIS interbank exposure data was for

3Q 2012 but other data needed for complete calibration of the model was not yet available for 2012.

Third, we saw that the interbank and sovereign assets in the network form only a small fraction of total assets and the rest of the assets were classified as external. We believe that the BIS exposure data do not provide a full picture of the real sovereign and interbank linkages. For this reason, we will focus our next research on obtaining more complete dataset that would break a significant part of the external assets down into details and reclassify them as interbank or sovereign assets. For example, data on TARGET2 balances or derivatives exposures may be added into the model instead of treating them as external. We suppose that getting the full picture of the global banking system will be progressively easier as the trend of open data and higher transparency is finally arriving to banking and the BIS is planning to significantly improve its International Banking Statistics database (BCBS, 2012).

Fourth, another issue with the dataset is that it represents aggregated banking systems instead of individual banks. To tackle this, we plan to test our model on a sample of real-world banks for which it is possible to construct an interbank exposure network based on a probability map. This approach is in line with the recent research of the ECB (Halaj & Sorensen, 2013), who constructed such network for the banks that reported during the 2010 and 2011 EBA stress tests.

Finally, because of the agent-based modelling approach, we may extend our model with other features such as endogenous network creation or other types of financial market agents such as large multinational institutions, pension funds, insurance companies[27] 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.

[27] Shortly, we assume a stronger interconnectedness between banks and insurers in the EU as a result of Basel III and Solvency II requirements. We predict that in the years to come, the situation of many EU banks will deteriorate because of their weak balance sheets and the expected problems in the Eurozone. Consequently, “healthy” EU insurers might be affected.

7 Conclusion

The current financial crisis pointed out the importance of the link between the financial and the sovereign sector. The first phase is characteristic with risk build-up connected to banking deregulation after the collapse of the Bretton Woods system when the banks started racing for leverage. In the second phase, after the unsustainability of this setting surfaced and the crisis broke out, the sovereigns started playing an active role through several types of measures for financial system support, such as bailouts and recapitalization, state guarantees, asset relief or provision of funding liquidity. In the third phase, however, it became obvious that the risks did not disappear but instead, they were transferred to the sovereigns. As a result, sovereign bond yields and CDS spreads rose and the access to new funding became increasingly more expensive. As the sovereigns found themselves in crisis with their balance sheets deteriorating, the risk returned back into the financial system through feedback loop channels, such as the banks holding a large portion of sovereign debt.

To be able to better understand the effects and implications of these interlinkages, in this thesis we built an agent-based network model of an artificial financial system, which is suitable for stress testing of banks, determining the ideal parameters of banking regulation and perhaps most importantly for testing the effects of the four individual types of state support in the short as well as in the longer run. Subsequently, we performed two analyses on this model: in the first one, we tested the individual parameters in Monte Carlo simulations, and in the second one, we calibrated the model to the real-word data collected from various sources.

The first analysis supports all our three hypotheses. In the short term or when the feedback loop is not yet active, all the support measures improve the systemic stability. When the feedback loops are implemented, the effects of state support depend on several parameters: there are settings in which it significantly mitigates the systemic crisis and settings in which it contribute to the systemic collapse. Finally, there are differences among the measure types. While bailouts and recapitalization are the most efficient, the results of liquidity measures are significantly worse.

The second analysis performed on the calibrated model pointed 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. Running the simulations, we saw that given our calibration dataset, the market liquidity is the most important contagion channel and we were able to classify banking systems according to their systemic importance and weakness. Testing the support measures, we again found out 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.

Finally, it is important to stress out the flexibility and extensibility of our modelling approach, which may lead to many more conclusions. For example, in the future we may calibrate it to the increasingly available and more complete real world data or extend it with features of financial systems that will be subject to most current discussions.

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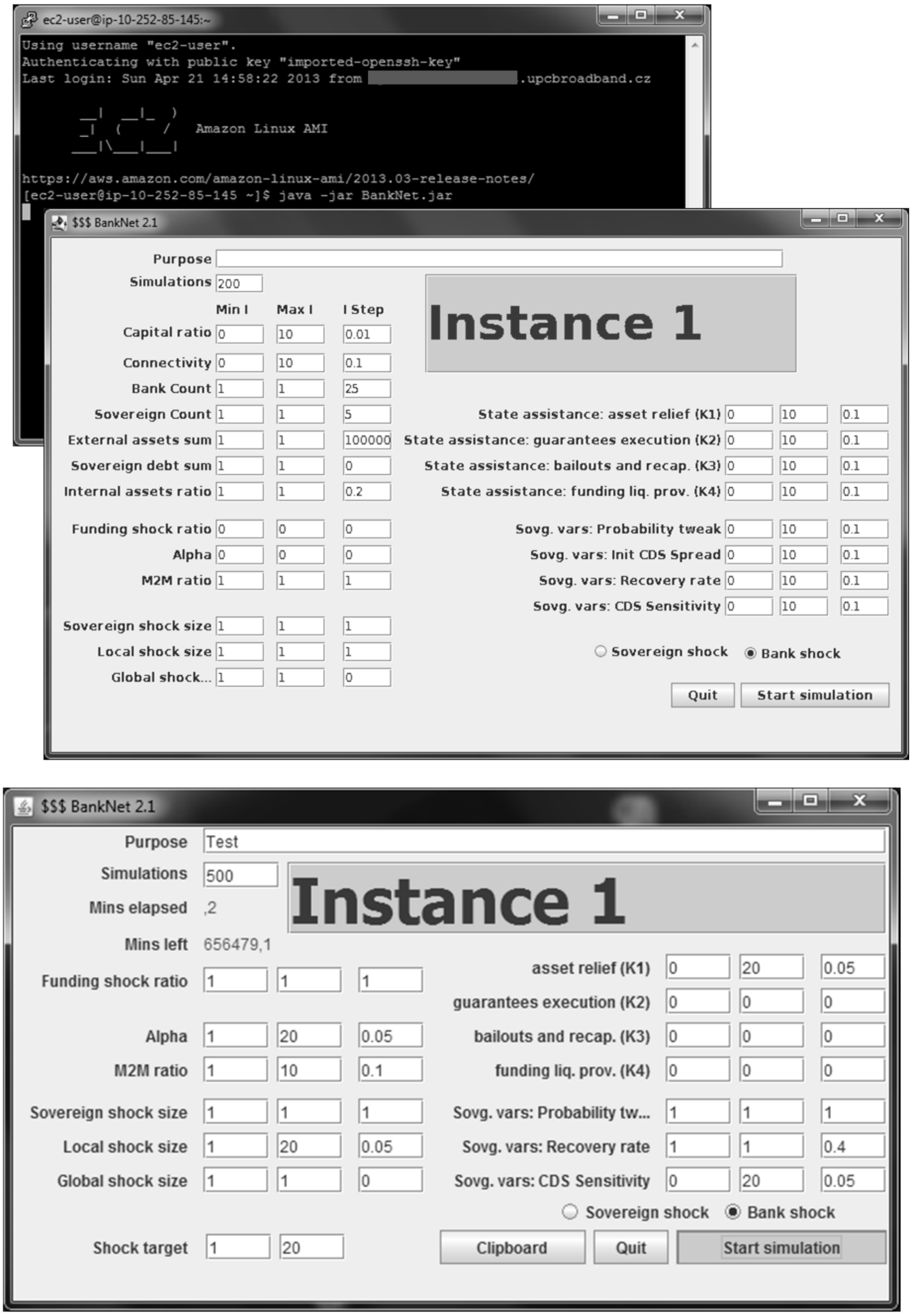
Appendix

Figure 42: Illustration of the application's GUI



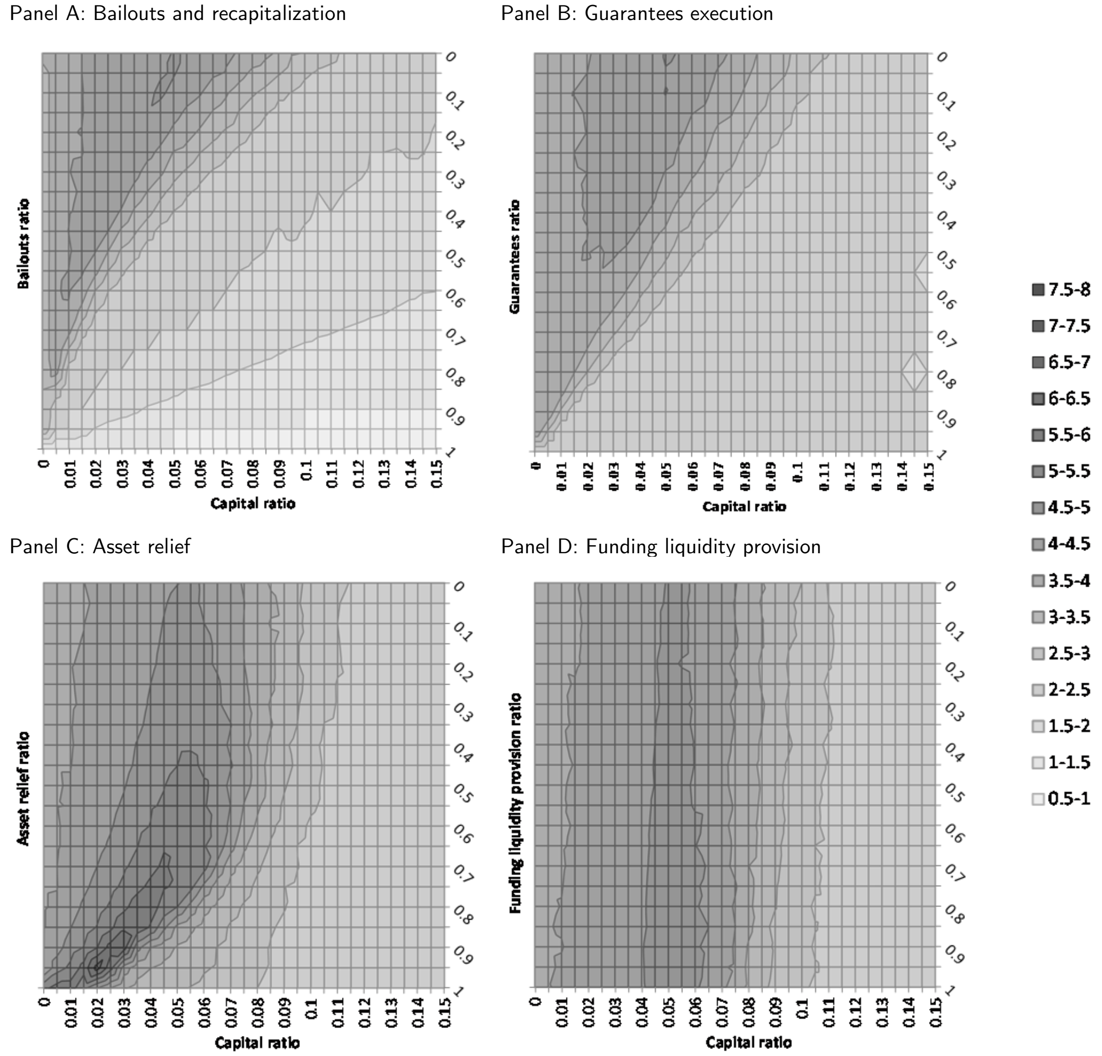
Source: Author

Figure 43: Illustration of the application's output file

```
$$$ BankNet v2.1

##############################################################################
###   PURPOSE:  Testing sovereign defaults
##############################################################################
###   **START** time and date:   04-20__04,20,18    ##########################
##############################################################################

##############################################################################
###   *** PARAMETERS ***   ###################################################
###   -----------------------------------------------------------------------
###    ;node_count: ;;;1;1;25;;fixed 25
###    ;connectivity: ;;;0;10;0.1;;VARIABLE
###    ;sovereign_count: ;;;1;1;5;;fixed 5
###    ;external_assets_sum: ;;;1;1;100000;;fixed 100000
###    ;sovereign_debt_sum: ;;;0;10;10000;;VARIABLE
###    ;internal_assets_ratio: ;;;1;1;0.4;;fixed 0.4
###    ;init_capital_ratio: ;;;0;15;0.1;;VARIABLE
###    ;alpha: ;;;0;15;0.1;;VARIABLE
###    ;funding_shock_ratio: ;;;0;1;1;;VARIABLE
###    ;M2M ratio: ;;;1;1;1;;fixed 1
###    ;local_shock: ;;;1;1;1;;fixed 1
###    ;global_shock: ;;;1;1;0;;fixed 0
###    ;sovereign_shock: ;;;0;10;0.1;;VARIABLE
###    ;SHOCK TYPE: ;;;;SOVEREIGN SHOCK
###    ;K1: ;;;0;0;0;;fixed 0
###    ;K2: ;;;0;0;0;;fixed 0
###    ;K3: ;;;0;0;0;;fixed 0
###    ;K4: ;;;0;0;0;;fixed 0
###    ;probability_adj: ;;;0;0;0;;fixed 0
###    ;init_CDS_spread: ;;;0;0;0;;fixed 0
###    ;recovery_rate: ;;;0;0;0;;fixed 0
###    ;CDS_sensitivity: ;;;0;0;0;;fixed 0
###   -----------------------------------------------------------------------
###    Number of simulations for each parameter set: 200
##############################################################################
Capital ratio;Internal assets ratio;Funding shock ratio;Alpha;Connectivity;M2M
ratio;Bank count;Sovereign count;External assets total;Sovereign debt total;Local
shock;Global shock;Sovereign shock;K1 AR;K2 GE;K3 BR;K4 FLP;Probability adj;CDS
Spread Init;Recovery Rate;CDS Sensitivity;defaults;d_loss;last_lap;sovg cum
deficit
0.0;0.4;0.0;0.0;0.0;1.0;25.0;5.0;100000.0;0.0;1.0;0.0;0.0;0.0;0.0;0.0;0.0;0.0;0.0;
0.0;0.0;0.0;0.0;1.0;0.0
0.0;0.4;0.0;0.0;0.0;1.0;25.0;5.0;100000.0;0.0;1.0;0.0;0.1;0.0;0.0;0.0;0.0;0.0;0.0;
0.0;0.0;0.0;0.0;1.0;0.0

1.5;0.4;1.0;1.5;1.0;1.0;25.0;5.0;100000.0;100000.0;1.0;0.0;0.9;0.0;0.0;0.0;0.0;0.0
;0.0;0.0;0.0;0.0;0.0;1.0;0.0
1.5;0.4;1.0;1.5;1.0;1.0;25.0;5.0;100000.0;100000.0;1.0;0.0;1.0;0.0;0.0;0.0;0.0;0.0
;0.0;0.0;0.0;0.0;0.0;1.0;0.0

##############################################################################
###   ends after  681472 iterations.
##############################################################################
###   ++END++ time and date:   (04-21__13,23,42)    (started 04-20__04,20,18)
##############################################################################
```

Source: Author
Note: This figure presents the format in which data is collected from the model. After stripping the file of its header and footer, the middle part is a semicolon-separated data table which may be imported to MS Excel or any statistical software. The three grey dots in the figure represent the data in the middle of the table – for large simulations, the output may be a file reaching tens or hundreds of megabytes hundreds of megabytes.

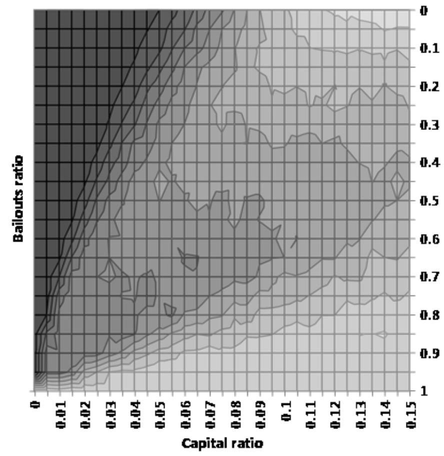
Figure 44: Number of simulation laps for individual support measures



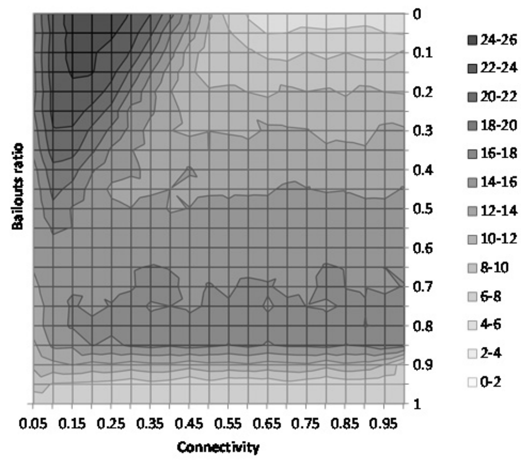
Source: Author

Figure 45: Number of simulation laps for individual support measures with feedback loops

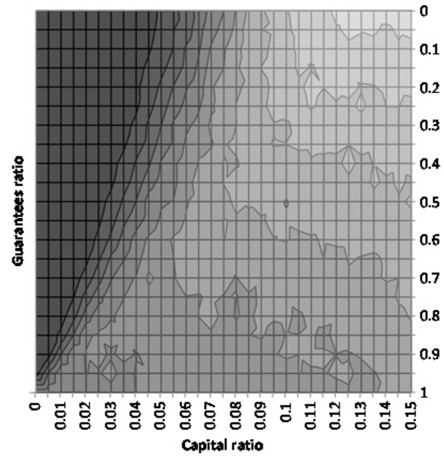
Panel A: Bailouts ratio vs. Capital ratio



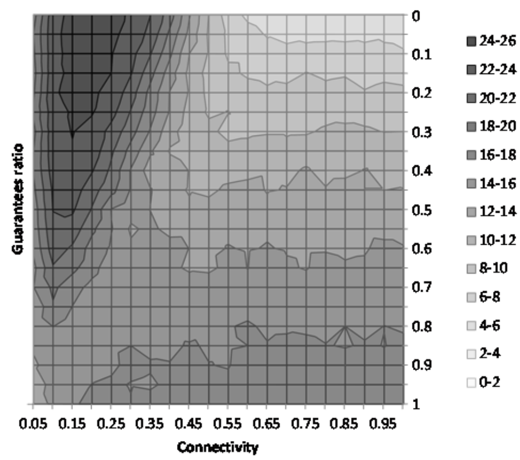
Panel B: Bailouts ratio vs. Connectivity



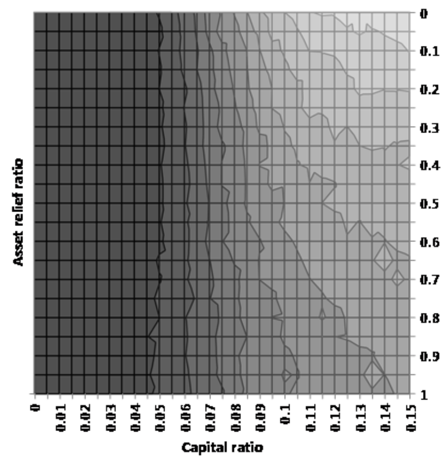
Panel A: Guarantees ratio vs. Capital ratio



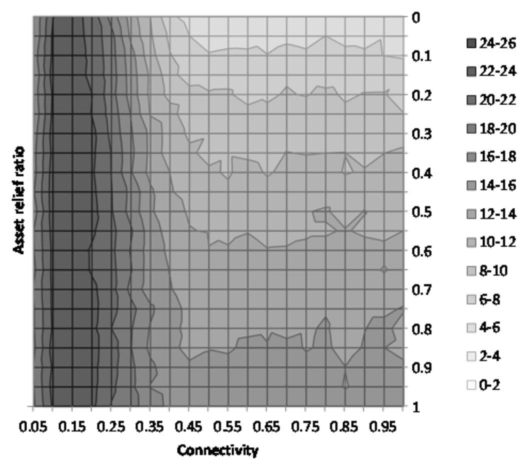
Panel B: Guarantees ratio vs. Connectivity



Panel A: Asset relief ratio vs. Capital ratio



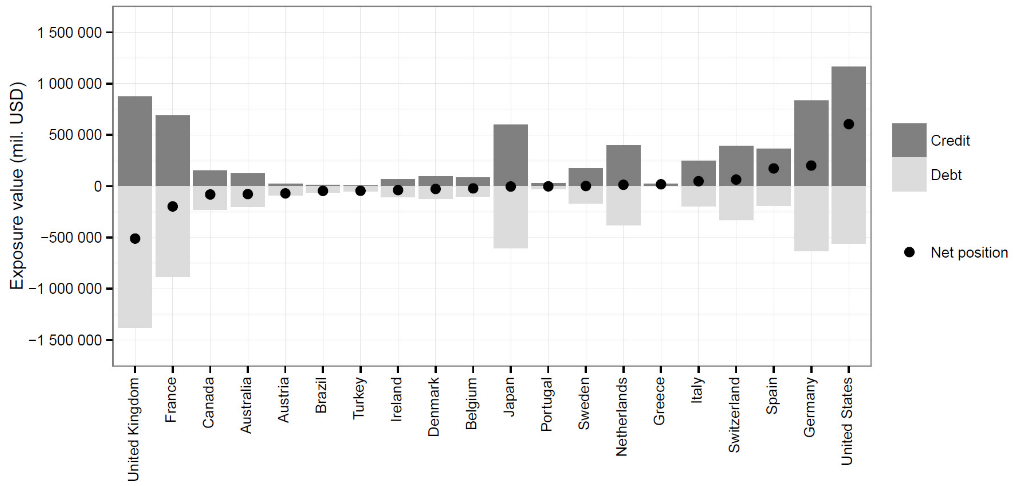
Panel B: Asset relief ratio vs. Connectivity



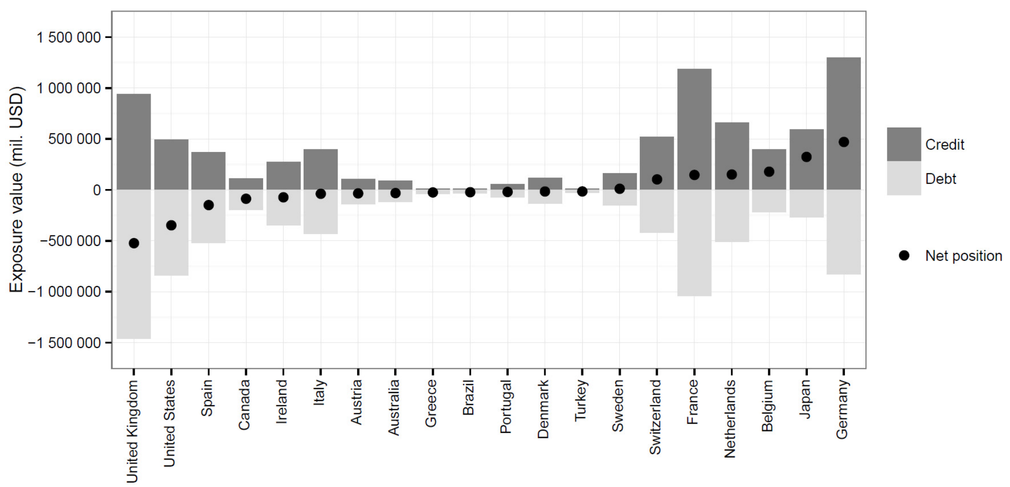
Source: Author

Figure 46: Positions of selected banking systems as of Q3 2012

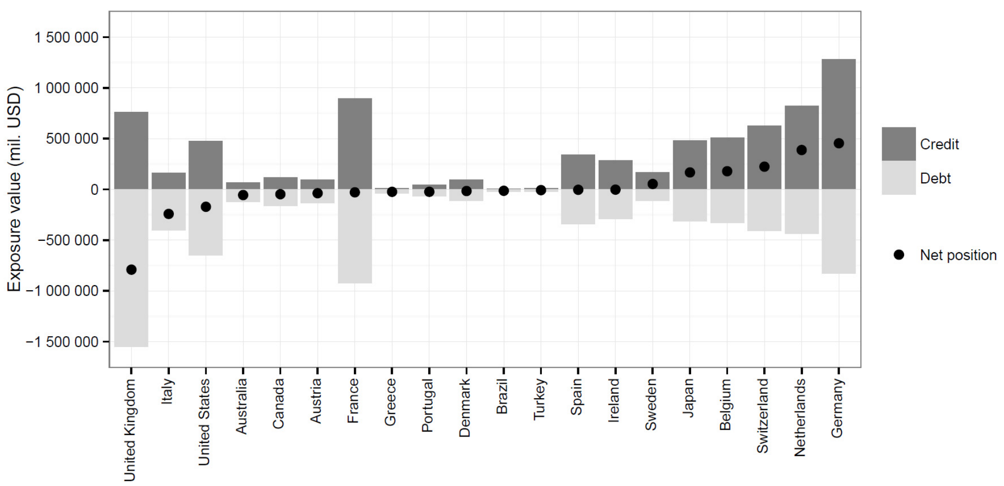
Panel A: Q3 2012



Panel A: Q4 2008

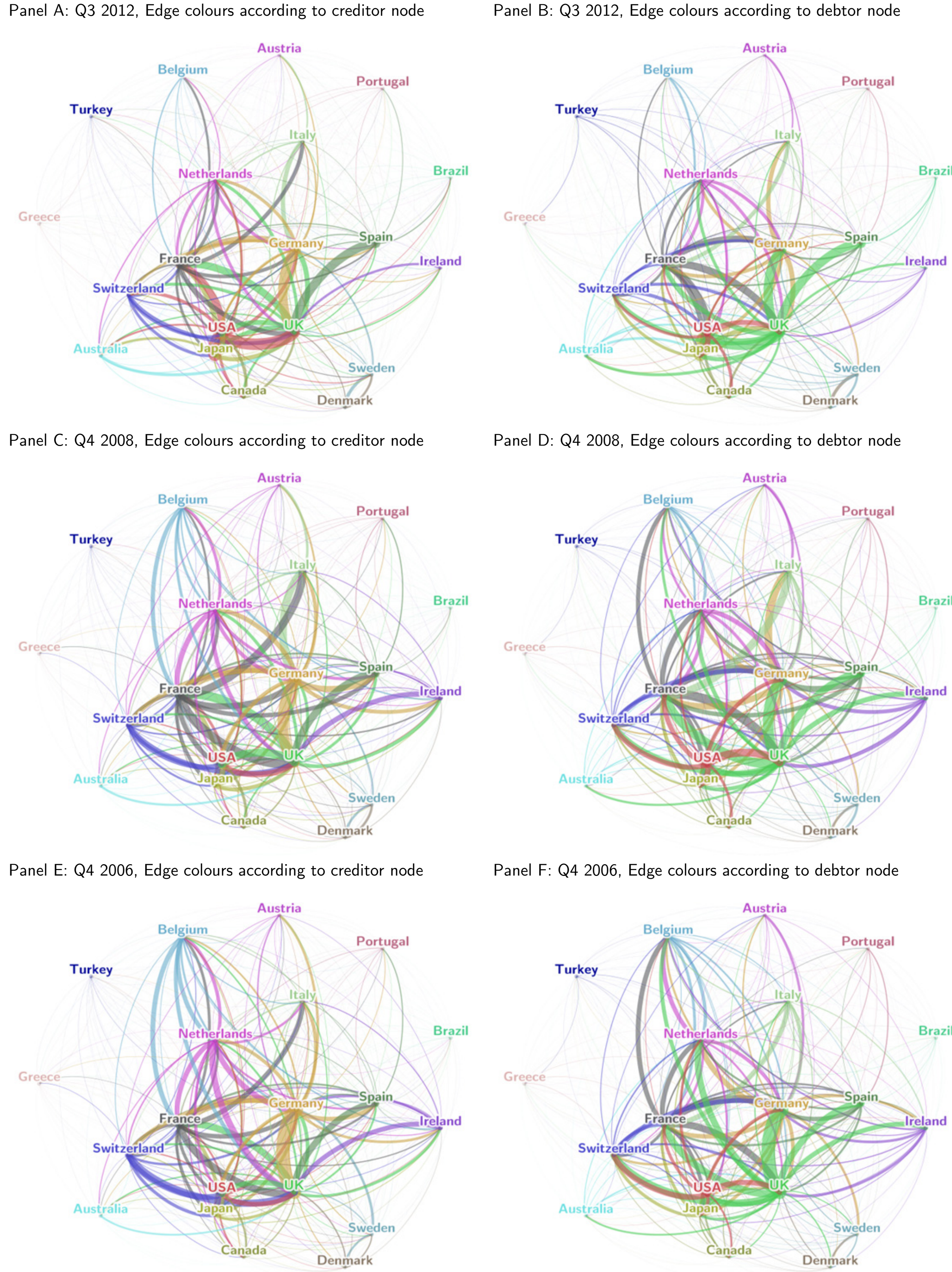


Panel A: Q4 2006



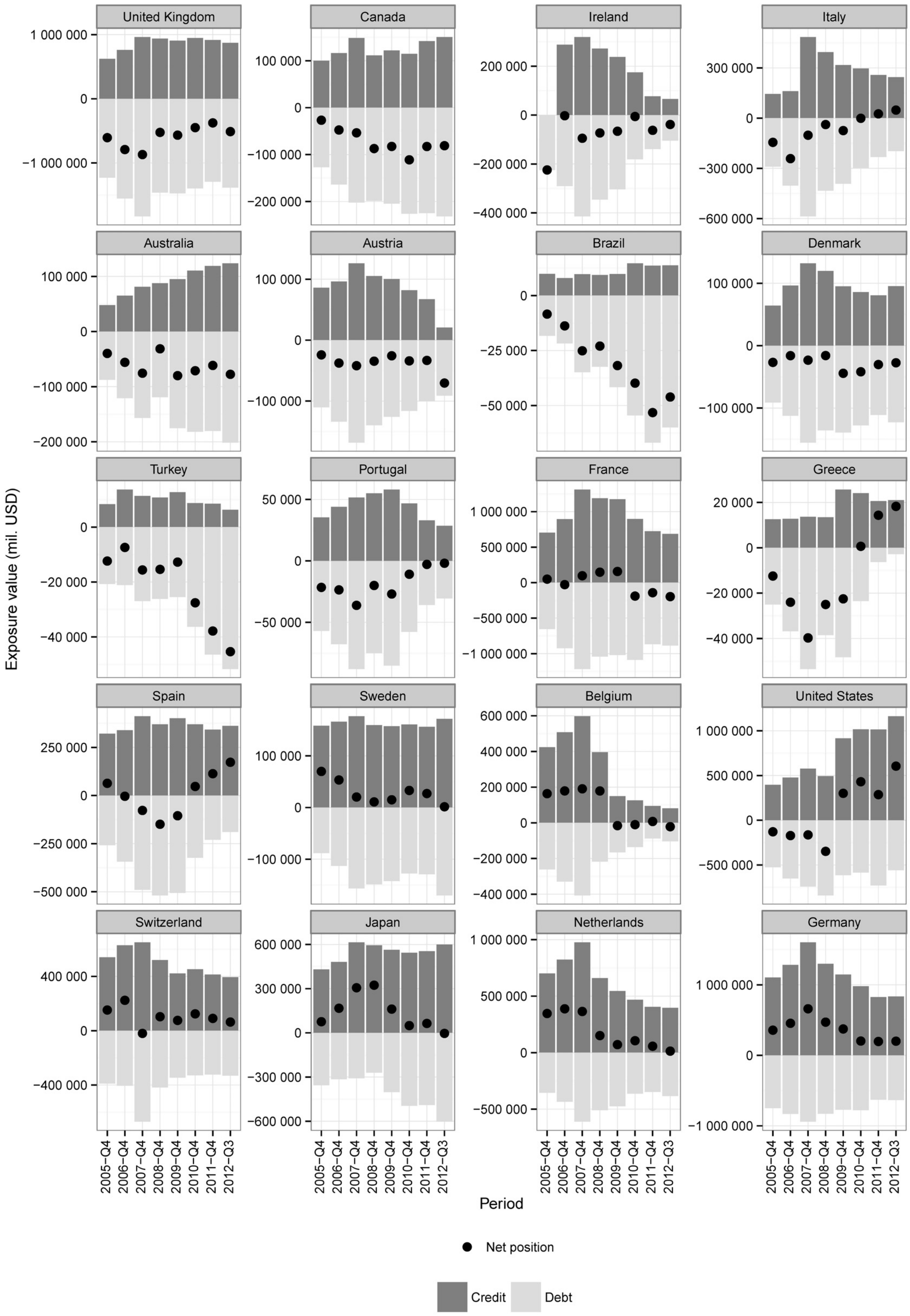
Source: Author based on data from BIS International Financial Statistics

Figure 47: Interbank lending snapshots in selected years



Source: Author based on data from BIS International Financial Statistics

Figure 48: Development of selected banking systems' positions



Source: Author