Systemic Risk in Interbank Markets

Dissertation

zur Erlangung des akademischen Grades

doctor rerum politicarum

(Dr. rer. pol.)

vorgelegt dem

Rat der Wirtschaftswissenschaftlichen Fakultät

der Friedrich-Schiller-Universität Jena

am 13.04.2011

von Dipl. Phys. Pierre Georg Georg

geboren am 08.03.1982 in Wiesbaden

3.

Gutachter

1.

2.

3.

Datum der Verteidigung:

Acknowledgements

This work would not have been possible without the enduring support of many people. First and foremost I want to thank PD Dr. Markus Pasche for his excellent supervision, motivating guidance, and continuous support over the past three years. I also wish to thank my second supervisor, Prof. Dr. Andreas Freytag for his excellent supervision and for opening doors of opportunities that would have remained closed otherwise. Furthermore, I want to thank Prof. Dr. Christoph Ohler for his dedicated sponsorship and constant encouragement.

This work would not have been possible without the generous financial support of the graduate school *"Foundations of Global Financial Markets - Stability and Change"* which is carried by the Stiftung *"Geld und Währung"* and hosted at the Friedrich-Schiller-Universität Jena. I am very greatful for this support, as it allowed me to focus on my research. I also enjoyed the hospitality of the DFG graduate school *"Economics of Innovative Change"* in an early stage of my thesis and wish to thank Prof. Dr. Uwe Cantner for his support and willingness to co-ordinate my supervision during this time. In the first year of my thesis, I was at the chair of Prof. Dr. Hans-Walter Lorenz, whom I wish to thank for giving me this opportunity.

The papers in this thesis have greatly benefitted from numerous discussions with my co-authors Jenny Poschmann, Dr. Nicola Brink, and especially Toni Ahnert. Their advise, motivation, and constructive criticism greatly improved the quality of my work.

I have enjoyed the encouraging and friendly atmosphere at our graduate school, and especially the support of Virginie Kemter and Natalia Kohtamäki with whom I had the pleasure to share an office. I am also thankful to Christian Aulepp, Matthias Bauer, Peter Burgold, Sebastian v. Engelhardt, Christian Fahrholz, Annelie Gallon, Marcus Guenther, Thomas Katzschner, Sebastian Sienknecht, Tim Thomes and all my colleagues from Halle and Leipzig.

During the time of my thesis, I have had the rare opportunity to travel the world and meet new people, many of which became friends. I want to thank Andreas Lechtenberg for supervising my internship at WGZ Bank Luxembourg. I also want to thank Dr. Pia Weiss for acting as a sponsor while I was visiting Nottingham University. I furthermore want to thank Henner Asche and Martin Beck for their supervision while I was an intern at the Department for Market Operations at Deutsche Bundesbank. I am especially greatful for the hospitality of the South African Reserve Bank and want to thank Andre Bezuidenhout, Dr. Hendrik Nel, Greg Farrell, Esti VanWykdeVries and all my friends and colleagues at the Financial Stability Department for this great time. Finally, I want to thank Prof. Dr. Viral Acharya for his willingness to act as a sponsor while I was a visiting scholar at the New York University Stern School of Business.

My work has greatly benefited from seminar discussions at Deutsche Bundesbank, University of Pretoria, South African Reserve Bank, University of Leipzig, University of Halle, University of Erfurt, ETH Zürich, New York University, the Federal Reserve Bank of Philadelphia, and the MAFIN09 conference in Reykjavik.

Above all, I want to thank my fiancée for her loving support. Thank you for all the sacrifices you made to support me over the last eight years. Thank you for pushing me when I needed to be pushed, and stopping me when I was running in the wrong direction. I could not have done it without you.

Contents

List of Figures

List of Tables

Prologue

"Fellow Icelanders,

[...]*The entire world is experiencing a major economic crisis, which can be likened in its effects on the world's banking systems, to an economic natural disaster. Large and well established banks on both sides of the Atlantic have become victims of the recession and governments in many countries are rowing for all they are worth to save whatever can be saved. In such circumstances every nation thinks, of course, first and foremost of its own interests. Even the biggest economies in the world are facing a close struggle with the effects of the crisis.*

The Icelandic banks have not escaped this banking crisis any more than other international banks and their position is now very serious. In recent years the growth and profitability of the Icelandic banks has been like something akin to a fairy tale. [...]*Over this period the Icelandic banks have grown hugely and their liabilities are now equivalent to many times Iceland's GNP. Under all normal circumstances larger banks would be more likely to survive temporary difficulties, but the disaster which is now engulfing the world is of a different nature, and the size of the banks in comparison with the Icelandic economy is today their main weakness.*

When the international economic crisis began just over a year *ago with the collapse of the real estate market in the US and chain reactions due to the so-called sub-prime loans, the position of Icelandic banks was considered to be strong, as they had not taken any significant part in such business. But the effects of this chain of events, have turned out to be more serious and wide ranging than anyone had expected.*

In recent weeks the world's financial system has been subject to devastating shocks. Some of the biggest investment banks in the world have become the victims and capital in the markets has in reality dried up. The effects have been that large international banks have stopped financing other banks and complete lack of confidence has developed in business between banks. This has caused the position of Icelandic banks to deteriorate very rapidly in the last few days.

[...]*A decision on wide-ranging rescue measures for the Icelandic banks is not only a matter of tax payers shouldering a heavier load temporarily, but concerns the position and future of the Icelandic nation as a whole.* [...]*There is a very real danger, fellow citizens, that the Icelandic economy, in the worst case, could be sucked with the banks into the whirlpool and the result could be national bankruptcy. No responsible government takes risks with the future of its people, even when the banking system itself is at stake. The Icelandic nation and its future takes precedence over all other interests.*

[...]*I said yesterday evening that it was my judgement and that of the Government that there was no reason to introduce special measures on our behalf. No responsible government introduces dramatic measures on the banking and financial system of the nation unless all other courses are closed. The position has* *today altered completely and for the worse.* [...]*We now need responsible and measured reactions.*

[...]*I would like to diffuse all doubt that deposits by Icelanders and private pensions savings in all Icelandic banks are secure and the exchequer will ensure that such deposits are reimbursed to savers in full. No one need be in any doubt on this.*

Fellow countrymen,

[...]*I am well aware that this situation is a great shock for many, which raises both fear and anxiety. In such circumstances it is extremely urgent that the authorities, companies, social organisations, parents and others who can contribute make every effort to ensure that daily life is not disrupted.*

If there was ever a time when the Icelandic nation needed to stand together and show fortitude in the face of adversity, then this is the moment. I urge you all to guard that which is most important in the life of everyone of us, protect those values which will survive the storm now beginning. I urge families to discuss together and not to allow anxiety to get the upper hand even tough the outlook is grim for many. We need to explain to our children that the world is not on the edge of a precipice and we all need to find an inner courage to look to the future.

[...]*We will have the opportunity to rebuild the financial system. We have learnt from those mistakes which were made during that period of massive growth and that experience will prove to be valuable when put to the test.* [...]*The task of the authorities over the coming days is clear: to make sure that chaos does not ensue if the Icelandic banks become to some extent non-operational.*

For this the authorities have many options and they will be used. Both in politics and elsewhere it will be important to sheathe our swords. It is very important that we display both calm and consideration during the difficult days ahead, that we do not lose courage and support each other as well as we can. Thus with Icelandic optimism, fortitude and solidarity as weapons, we will ride out the storm.

God bless Iceland."

Icelandic Prime Minister Geir Haarde in a TV speech on October 6, 2008, addressing the state of the Icelandic banks.

Chapter 1

Introduction

The goal of this dissertation is to develop a better understanding of systemic risk in interbank markets. The importance of this task has become clear during the recent financial crisis. Originating in the subprime mortgage market in the United States, and fuelled by the increasing interconnectivity of international financial institutions, the crisis quickly spread to almost all industrialized countries. At the height of the crisis, on 15 September 2008, the US investment bank Lehman Brothers filed for bankruptcy, causing an almost complete breakdown of interbank markets. These markets, however, are of uttermost importance for the liquidity provision of banks. Without functioning interbank markets, the maturity transformation of banks breaks down and the credit provision to the real economy is impaired. Even though there exist a number of interconnections amongst banks, due to their importance for financial stability, the structure and dynamics of interbank markets is the main focus of this thesis.

In order to restore the stability of the financial system, governments and central banks worldwide had to resort to unprecedented non-standard measures, many of which are still in place. In 2009, the International Monetary Fund (IMF) estimated the overall cost of the financial crisis to be US$ 11.9 trillion, including the cost of emergency measures to troubled financial institutions.[1]

[1]As quoted in *"IMF puts total cost of crisis at GBP7.1 trillion"*, The Telegraph, 8 August

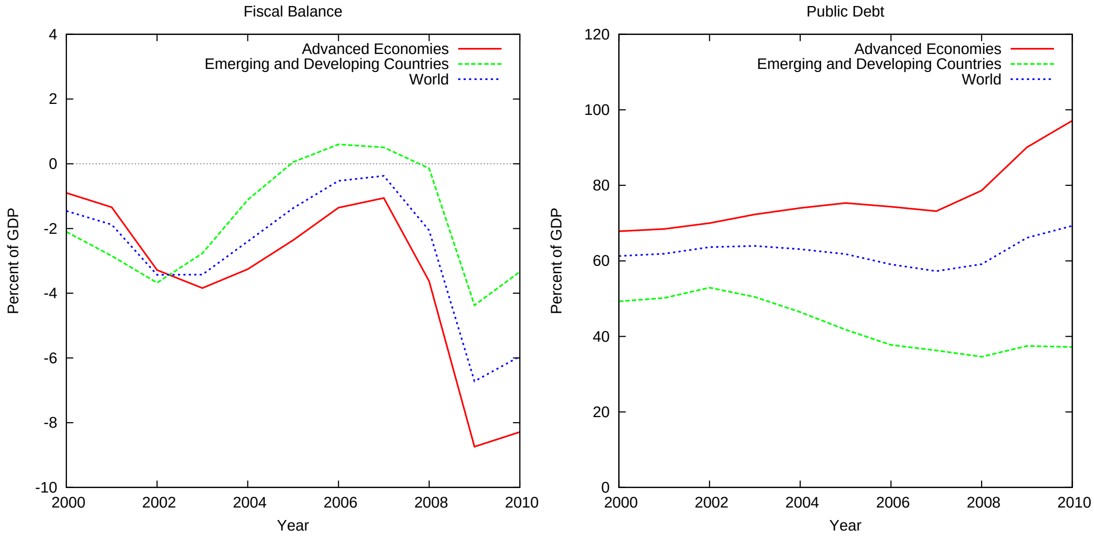

Figure 1.1: Impact of the financial crisis on fiscal balances and public debt. Source: International Monetary Fund (2010) Data and own representation.

The emergency measures that were required in many countries to stabilize the banking system had a severe impact on fiscal balances and public debt, as can be seen in Figure 1.1. In the worst period of the crisis (2007-2009), the fiscal balance in advanced economies[2] has dropped from -1.05% to -8.74% of GDP, while public debt increased from 73.2% to 90.1% of GDP. The composition of this additional debt can be seen in Figure 1.2 for the G20 countries. About 5.5% of the additional debt in advanced G20 countries stem directly from financial-sector support, and additional 2% from fiscal stimulus packages directly related to the crisis. These numbers highlight the great importance of the subject of this thesis.

The severity of the crisis was not only caused by the depth of the crisis itself, but also by the speed it unfolded. During the period of the *"great moderation"*, with low asset volatility, low inflation and small business cycle fluctuations, sys-

(**2009**).

[2] Australia, Canada, Czech Republic, Denmark, euro area, Hong Kong SAR, Israel, Japan, Korea, New Zealand, Norway, Singapore, Sweden, Switzerland, Taiwan Province of China, United Kingdom, and United States.

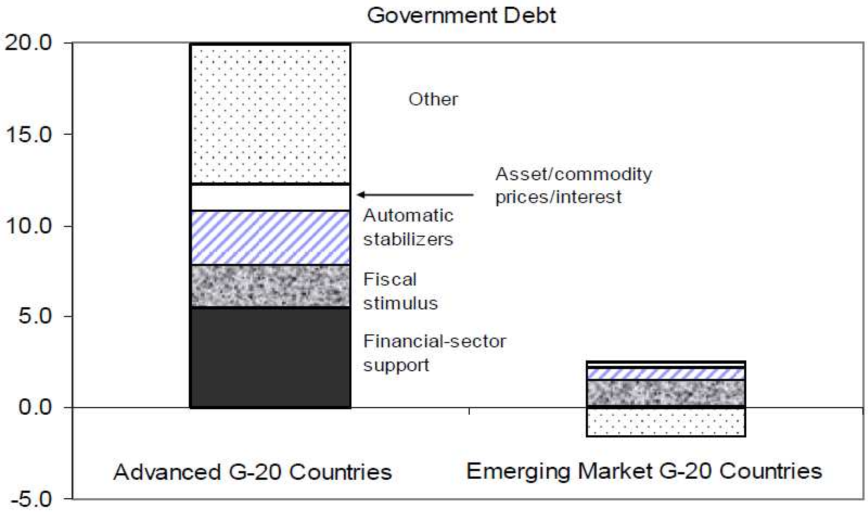

Figure 1.2: Composition of government debt as debt-to-GDP ratio for the period of 2008/2009. Source: IMF Staff Note (2009)

temic risk was building up in the form of increasing interconnectivity of financial institutions, and decreasing asset transparency. After a certain tipping point, the building systemic risk rapidly manifested and lead to the financial instability that was observed in the aftermath of 15 September 2008. This tipping point behaviour is what Haldane (2009) calls the "knife-edge", or "robust-yet-fragile" property of interbank markets and is a well known phenomenon in the analysis of complex systems.[3]

In order to understand the dynamics that is at the core of this behaviour, a number of questions have to be answered:

(Q1) What are the causes and different manifestations of systemic risk?

(Q2) How can systemic risk be measured, especially while it is building?

(Q3) How do different forms of systemic risk contribute to overall systemic risk? What is the dominant form of systemic risk?

(Q4) Are the existing reform proposals sufficient to effectively counteract sys-

[3]See also Haldane and May (2011), Battiston et al. (2009).

temic risk?

The structure of this thesis will follow along the lines of these questions. While each question is addressed in every subsequent chapter to some extent, this introduction focuses largely on question (Q1), chapter (3) focuses on question (Q2), the chapters (4) and (5) focus on question (Q3) and the concluding chapter (6) focuses to a large extend on question (Q4).

1.1 Systemic Risk

Systemic risk is a broadly defined term that has changed considerably in the course of the recent financial crisis. Until then, systemic risk was predominantly understood as the probability of contagion effects that cause cascades of defaults. The crisis, however, revealed that systemic risk might also emerge from two other sources: (i) a common shock, leading to a simultaneous default of several financial institutions at once; and (ii) informational spillovers where bad news about one bank increase the refinancing costs of all other banks.

A categorization of systemic risks is given by Bandt et al. (2009) who distinguish between a broad and a narrow sense of systemic risk. In their classification, contagion effects on interbank markets pose a systemic risk in the narrow sense, whereas systemic risk in the broad sense is characterised as a common shock to many institutions or markets. This distinction is followed by the Financial Stability Board (FSB) who defines systemic risk as *"a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy"* (see International Monetary Fund et al. (2009), as well as the background paper Financial Stability Board et al. (2009b)). The ECB suggests that systemic risk can be described as the risk of experiencing a strong systemic event that adversely affects a number of systemically important intermediaries or markets (European Central Bank (2009)). The trigger of the event could either be a shock from outside or from within the financial system. The systemic event is strong when the intermediaries concerned fail or when the markets concerned become dysfunctional. Since all these different dimensions of a systemic event interact with each other, it is clear that systemic risk is a highly complex phenomenon.

1.1.1 Contagion

Contagion occurs due to direct linkages between financial institutions. Probably the most prominent example of these linkages is contagion via interbank markets. The interbank market can be described as a financial network consisting of a set of nodes, i.e. banks or other financial institutions like hedge funds or insurance companies, and a set of edges which form the connection between these institutions. An extensive review on the literature of financial networks is given in Allen et al. (2010). The interconnection in the interbank market can lead to an enhanced liquidity allocation and increased risk sharing amongst the banks, as Allen and Gale (2000) argue. At the same time, however, increased connectivity can also amplify contagion effects.

Analyzing linkages in the form of overlapping claims, Allen and Gale (2000) find that contagion is more likely to occur if the network structure is incomplete, as in comparison with complete networks it is only able to absorb smaller idiosyncratic shocks. Gai and Kapadia (2008) support the result that higher connectivity in the financial system reduces the probability of contagion. However, they identify that the consequences in case contagion nevertheless occurs are more severe as the possibility increases that institutions might repeatedly be affected. Haldane (2009) argues that connectivity is a knife-edge property. Up to a certain point, financial networks and interbank linkages serve as a mutual insurance of the financial system and thus contribute to systemic stability. Beyond this point, the same interconnections might serve as a shock-amplifier and thus increase systemic fragility.

The stabilizing function of an interbank market might, furthermore, be affected by the structure of financial markets. Iori et al. (2006) find that contagion probability is lower in case the interacting institutions are homogeneous, i.e. they are similar their characteristics such as size or investment opportunities, as thus no institution becomes significant for either borrowing or lending. This result, however, is in contrast with Georg and Poschmann (2010) and Georg (2010), who find no significant evidence that the heterogeneity of the financial system has a negative impact on financial stability. Haldane (2009) describes the financial system in the built-up of the crisis as being characterized by complexity and homogeneity and argues why these two ingredients lead to fragility by resorting to literature on complex systems and ecology. Further structural factors are analyzed by Nier et al. (2007) who constitute that higher capitalization levels, lower interbank liabilities and a less concentrated interbank market reduce the likelihood of direct contagion in the interbank market.

Due to their high liquidity, interbank transactions are amongst the most vital connections between banks and have thus received special attention in the literature. Eisenberg and Noe (2001) develop a liabilities matrix for a general interbank system and calculate the full impact of a bank default in the system using linear algebra. A number of authors follow this work and apply it to different countries. Furfine (1999) examines the likelihood that a failure of one bank would cause the subsequent collapse of a large number of other banks in the US using the Federal Reserve's large-value transfer system Fedwire. Mistrulli (2007) uses actual interbank exposure data from the Bank of Italy Supervisory Reports database to analyze the risk of contagion in the Italian interbank market. Gabrieli (2010) analyzes the functioning of the overnight unsecured euro money market using data on unsecured Euros-denominated loans executed through the e-MID platform. Gabrieli finds that monetary policy implementation was affected by the crisis due to *"A heightened awareness of counterparty credit risk"*. Cajueiro and Tabak (2007) analyze the topology of the Brazilian interbank market by using methods from network theory. Manna and Iazzetta (2009) analyze monthly data on deposit exchanged by banks on the Italian interbank market from 1990 to 2008.

1.1.2 Common Shocks

Another source of systemic risk emerges from indirect linkages between banks in the form of common shocks. If a number of banks hold identical or similar assets, this correlation between their portfolios can give rise to a fire-sale which is typically associated with significant losses for a large number of banks. Acharya and Yorulmazer (2008) point out how banks are incentivized to increase the correlation between their investments and thus the risk of an endogenous common shock in order to prevent costs arising from potential information spillovers. The banks' returns of the last period are signals according to which risk-adverse depositors update priors about future returns. Compared with the situation in which both banks' signals are positive, depositors expect lower returns in the future if one banks signal is negative and, hence, demand higher deposit rates in order to compensate for potential failures. Accordingly, a bank with a positive signal is facing higher borrowing costs if the other bank sets a negative signal. This sets an incentive for both banks to increase the correlation between their investments to increase the probability of joint success (and joint failure).

Acharya (2009) analyzes how banks are incentivized to induce an endogenous common shock in order to avoid negative externalities arising from a bank failure. The driving factor behind this behavior is that a default imposes both positive and negative effects on the surviving competitor. Negative effects arise as not all depositors are furthermore able or willing to lend their money to a bank, so that the surviving bank faces higher refinancing costs. However, the failure also leads to a reduction of monitoring and information costs by taking over staff and technology. Depending on which effect prevails the payoffs of the surviving banks shareholders either increase or decrease in comparison to no bank failure. Accordingly, if the failure generates negative externalities banks are incentivized to increase the correlation of their portfolios ex ante and thus increase the probability of a joint failure.

Analyzing the impact of central bank activity in a network model with interbank market Georg and Poschmann (2010) highlight that common shocks constitute a larger threat on financial stability than contagion effects. Empirical studies confirm that correlation in the financial sector increased. De Nicolo and Kwast (2002) illustrate an increase in correlation between large and complex financial organizations during the 1990s, whereas Lehar (2005) finds that this development was more severe for North American than for European banks.

1.1.3 Informational Spillovers

According to Acharya and Yorulmazer (2003), as well as Nier et al. (2008), informational spillovers are another form of systemic risk that have to be taken into account. This effect is sometimes called informational contagion, but the name is misleading, since it poses a systemic risk in the broad sense of Bandt et al. (2009). The main idea of informational spillovers is that the insolvency of a bank can increase the refinancing costs of the surviving banks, since especially in times of crises financial markets exhibit a herding behaviour. Acharya and Yorulmazer (2003) develop a model of bank herding behaviour based on a banks incentives to mimize the information spillover from bad news about other banks. In their model, the returns on a banks loans consist of a systematic component (i.e. the business cycle) and an idiosyncratic component. If there are bad news about a bank, these news reveal information about an underlying common factor and thus impact on all banks. The authors show that even the possibility of information contagion can induce banks to herd with other banks. Herding behaviour in this model is a simultaneous ex-ante decision of banks to undertake correlated investments and gives thus rise to correlations amongst the banks portfolios. Bandt et al. (2009) give an overview of literature on bank herding as a source of systemic risk.

The different forms of systemic risk are not independent of each other and a bank default does not happen instantaneously. During the build-up of the default, the bank will start deleveraging and selling assets. This may cause fire-sales in certain asset classes and exacerbates the roblems of the bank. At the same time, rumors about the bank and similar banks will spread in the markets, causing market participants to tighten their liquidity provision. Since the first bank already is struggling, this tightened liquidity situation can lead to a default of this bank. This default then triggers contagion effects and possible further defaults at banks who have issued interbank loans to the first bank. As the recent financial crisis has shown, financial markets show a herding behaviour as described in Acharya and Yorulmazer (2003) and are aware of it too. In a situation of high uncertainty about the fundamental and idiosyncratic risks in the financial system, liquidity provision will dry up and market volatility will increase. While one can distinguish the various forms of systemic risk by their manifestation, it is impossible to separate them in reality. Contagion effects and common shocks will inevitably trigger informational contagion and vice versa. Therefore, informational contagion is a vivid source of systemic risk and has to be taken into account into macroprudential regulation to enhance financial stability.

1.1.4 Operationalizing Systemic Risk

In order to derive meaningful policy measures for regulating systemic risk, it is necessary for regulatory authorities to measure and operationalize systemic risks. It was recently emphasized by e.g. Borio (2010) that the distinction between the time- and cross-sectional dimensions of aggregate risk is critical. In the time-dimension leading indicators of financial distress are needed, while in the cross-sectional dimension a robust quantification of the contribution of each institution to systemic risk is necessary. There are various aproaches in the literature to achieve these goals. The European Central Bank (2010a) differentiates between four types of indicators to measure systemic risk: (i) coincident indicators of financial stability measure the current state of instability in the financial system; (ii) early-warning signal models to detect the build-up of systemic crises; (iii) macro stress-tests can assess the resilience of the financial system to aggregate macro-shocks; (iv) contagion and spillover models are used to analyze the impact of a crisis on the stability of the financial system. By using a set of such indicators, central banks and regulatory authorities try to assess the different dimensions of systemic risk. It is a precondition for a useful measurement concept of systemic risk that it takes all dimensions of systemic risks into account and will thus be a combination of at least some of the systemic risk indicators. The main problem to date is, that there does not exist a reliable indicator to measure the informational contagion of a fiancial institution's default. This leads to a significant element of uncertainty when assessing systemic risks. The time dimension of systemic risk in the sense of Borio (2010) is addressed in chapter (4), where a dynamic model of a banking system is analyzed. The Network Systemic Importance Index developed in chapter (3) captures the cross-sectional dimension of systemic risk, as it measures the systemic risk individual institutions pose to the rest of the system.

Systemic Importance of Individual Financial Institutions. A number of approaches assess the systemic importance of individual financial institutions. Their common goal is to impose additional regulatory requirements and oversight in accordance with the individual systemic importance of a financial institution. Zhou (2009) considers three different measures of systemic importance of interconnected financial institutions and correlates them with the size of the institution. The author finds that there is not always a relationship between the systemic importance of a financial institute and its size. The "too-big-to-fail" argument does not always hold true and thus alternative measures of systemic importance have to be considered. The paper follows Segoviano Basurto and Goodhart (2009) and defines a systemic importance index that resorts to multivariate Extreme Value Theory. Another approach stems from cooperative game theory. Tarashev et al. (2009) use the Shapley value to attribute each individual institution's contribution to overall systemic risk. They apply their methodology to a sample of 20 large internationally active financial institutions and derive their contribution to overall systemic risk as a function of the institution's size, probability of default and exposure to a common factor.

Adrian and Brunnermeier (2009) introduce *CoVaR* which is the Value at Risk of the financial system conditional on an individual institution being under stress. The methodology thus focuses on how much an individual institution contributes to overall systemic risk. International Monetary Fund (2009) uses CoVaR to assess systemic risk in the US banking sector using CDS spreads. Fong et al. (2009) applies CoVaR to the Hong Kong financial system. Arias et al. (2010) apply CoVaR to the Colombian banking system analysing the systemic market risk contributions of banks, pension funds, and between different types of financial institutions. A comparison of different sets of systemic risk measures is performed by Rodriguez-Moreno and Pea Snchez de Rivera (2010). The authors argue that simple indicators are better suited for analysing systemic risk and find that the best indicators are the first Principal Component of the single-name CDSs and the LIBOR-OIS or LIBOR-TBILL spreads, respectively. According to Rodriguez-Moreno and Pea Snchez de Rivera (2010), the least reliable indicators are the Co-Risk measures and the systemic spreads extracted from the CDO indexes and their tranches.

Huang et al. (2009a) propose a framework for measuring and stress testing the systemic risk of a group of major financial institutions. They construct an hypothetical insurance premium against systemic risk, called the *distress insurance premium* (DIP). The DIP is based on on ex ante measures of default probabilities of individual banks and forecasted asset return correlations. In order to construct the proability of default of individual banks and asset return correlations are calculated from CDS spread data. Huang et al. (2009a) applys the DIP to 12 major U.S. banks during a sample period 2001-08 and are able to show a substantial increase in the indicator after the onset of the subprime crisis. Huang et al. (2009b) furthermore applys the DIP methodology to twenty-two major banks in Asia and the Pacific and illustrate the dynamics of the spillover effects of the financial crisis into the region. Brownlees and Engle (2010) construct the Marginal Expected Shortfall (MES) as a measure of the systemic risk of an individual financial institution. The MES of a financial firm is based on market data and describes the expected loss of an equity investor should the overall market decline substantially. It depends on the volatility of a firm equity price and is determined by using advanced econometric models. Acharya et al. (2010b) define the contribution of a financial institution to overall systemic risk as the institution's systemic expected shortfall (SES). The systemic expected shortfall of an institution increases with the leverage of this institution and with it's MES. The authors demonstrate how SES can be used to predict the outcome of stress tests, decline in equity valuations of large firms during the financial crisis and the increase in their CDS spreads. Both papers are the building blocks of the NYU Stern systemic risk ranking[4] that measures the systemic risk contributions of the largest U.S. financial institutions.

Integrated Measurements of Systemic Risk. Besides attributing systemic risk to individual financial institutions, it is also possible to derive measurements of overall systemic risk in a financial system. These approaches have in common, that they use more than one indicator of systemic risk, typically based on market data (i.e. CDS spreads) and network data (i.e. about the interbank network structure). Gauthier et al. (2010) compare different methods of attributing systemic importance to individual institutions using data from the Canadian banking system. The authors find that macroprudential capital requirements can reduce the risk of a systemic crisis by 25% and that the macroprudential capital requirements can differ from the observed capital levels by up to 50%. This difference is furthermore not trivially related to a banks size or it's default probability. Schwaab et al. (2010) propose an econometric framework for the measurement of global financial and credit risk conditions based on state space methods. Furthermore, they propose a coincident indicator for unobserved default stress as a

[4] http://www.systemicriskranking.stern.nyu.edu/

measure for overall financial system risk. They find that credit risk conditions can significantly and persistently decouple from business cycle conditions due to e.g. unobserved changes in credit supply and that such decoupling can be an early warning signal for macro-prudential policy.

Chan-Lau (2010) proposes to base additional capital charges for systemically important financial institutions on their incremental contribution to systemic risk. The proposed framework to measure a financial institution's contribution to systemic risk uses CoRisk, network analysis and one-factor credit risk portfolio models. Chan-Lau uses the expected societal loss as a proxy for the systemic importance of a financial institution. In contrast to Tarashev et al. (2009) and Gauthier et al. (2010), Chan-Lau also factors in the increase in default risk of other institutions triggered by the failure of one institution. Aikman et al. (2009) develop a model that uses macro-credit risk, income risk, network interactions, feedback effects and funding risk to assess the impact of macroeconomic and financial shocks on the banking system. Their "Risk Assessment Model for Systemic Institutions" (RAMSI) is based on detailed balance sheet data and can be used to assess the impact on shocks on individual financial institutions and the financial system as a whole. One particular interesting point about the RAMSI model is, that it incorporates a mechanism to model informational contagion. Three indicators, solvency concerns, liquidity position and confidence are used to describe a banks ability to refinance on funding markets.

1.2 Structure of this Thesis

This thesis builds on six consecutive papers that develop a flexible framework to analyze different aspects of systemic risk with a special focus on interbank markets and financial networks. The chapters are designed to be self-contained, even though Chapter (2) goes somewhat beyond the main scope of this thesis and applies the microfoundations developed in this chapter to a model of endogenous money creation. In Chapter (3) various aspects of the network structure of interbank markets are analyzed and the South African interbank market is analyzed as a real-world example. This chapter develops an index to measure the systemic importance of individual financial institutions that can be used as a tool for macroprudential oversight of the financial system. Chapter (4) draws on Chapter (2) and uses the simple banking behaviour to develop a dynamic model of a banking system. One of the key results of this chapter is that systemic risks in the form of common shocks can be more severe than systemic risk that emerges in the form of interbank contagion. This result is further analyzed in Chapter (5), where we develop a general equilibrium model of a banking system and combine two formerly distinct strands of systemic risk literature in a unified model. Chapter (6) draws policy conclusions on the recently endorsed Basel III framework, based on all previous chapters and key results outlined in this thesis.

Chapter (2) develops the microfoundations of bank and non-bank behaviour in order to study the endogenous process of money creation, which is determined by the interaction of banks, non-banks, and the central bank on the interdependend markets for reserves, loans, and bonds. It has previously been published as Georg and Pasche (2008).[5] Our model extends the approach of Bernanke and Blinder (1988) and models the risk and return preferences of banks by using portfolio theory. We then introduce Value at Risk as a tool for banks to manage their liquidity preferences. The model of banking behaviour is then combined with the model of Bofinger (2001), who develops a model of the macroeconomic loans market in order to explain the money creation process endogenously. Bofinger derives the demand for central bank reserves as a function of the interest rate on the loans market, the main refinancing rate, and the required reserve rate. We use the Bofinger model, where the demand for reserves is explicitely derived, and combine it with the Bernanke and Blinder approach, which models the behaviour of a commercial bank using portfolio theory in a richer setting with

[5] The results in Georg and Pasche (2008) have been presented at the conference *"Managing Financial Instabilities in Capitalist Economies 2009"* in Reykjavik.

loans and bonds markets.

We extend this combined approach and develop a model of banks, non-banks and the central bank, where money supply is truly endogenous. The endogeneity of money supply in the model is twofold: The structure of the portfolio, driven by risk and liquidity preferences, determines the money multiplier, while the portfolio volume determines the demand for reserves and hence the money base. For the non-banks (households and firms) we apply a similiar logic that makes it possible to derive their behaviour from portfolio considerations as well. The approach is related to the structuralist approach in Post Keynesian macroeconomics, but can also be used as a building block for New Keynesian and other type of models. We determine the influence of the central bank on the money base in the short- and long-run.

The model enables us to derive credit multipliers under the assumption that the interest rate on the loans and bonds market are given exogenously. We derive the money multiplier for open market operations in the short- and long-run and show that open market operations are less effective in the long-run due to portfolio restructuring of commercial banks. When calculating the money multiplier for a change in the main refinancing rate, we find that the central banks' refinancing policy may fail due to binding liquidity and solvency constraints. We again find a smaller impact of monetary policy in the long-run, which raises the question how effective central bank policy can be in a dynamic model of a banking system. This question will be further analyzed in Chapter (4).

In Chapter (3), which has previously been published as Brink and Georg (2011a). we introduce network theory as a tool to assess systemic risk in interbank markets.[6] This chapter serves two purposes. First, it analyzes the network structure

[6]The results of this chapter will also appear as Brink and Georg (2011b) and have been presented at seminars at the South African Reserve Bank and the University of Pretoria.

of the South African overnight interbank market with tools from network theory. A financial network is described by a set of nodes, which represent banks, and a set of edges, which represent connections between the banks. In our example, these connections will be overnight interbank loans. Using a unique dataset of interbank transactions from the South African Multiple Options Settlement (SAMOS) system between Februar 2005 and June 2010, we introduce basic network measures, such as the shortest average path length, and the clustering coefficient to analyze the network topology. Like most interbank networks, the South African overnight interbank market is characterized by a few large, highly interconnected, money center banks and a large number of small, less interconnected banks at the periphery of the network. We show that the network was largely stable, both by the number of banks that participated in the interbank market and their high level of interconnectedness. Liquidity provision was ensured even during times of high uncertainty on international capital markets.

The second purpose of this chapter is to introduce a measure for the systemic importance of individual financial institutions. This measure, the Network Systemic Importance Index (NSII) is based on three quantities that characterize the relevance of a bank in the interbank network: size, interconnectedness and betweenness. While the first two are easily understood, betweenness is used as a proxy for a banks' substitutability. A high betweenness indicates that the bank is on many shortest paths of liquidity flows and will thus be larger and more complex to manage and hence harder to substitute. Even though the NSII can only be one building block of a larger set of macroprudential tools necessary to assess systemic risk, it captures many features of the impact that the network structure has on systemic risk. One particular relevant feature of the NSII is that it is a relative measure in the sense, that it does not attribute absolute values of systemic importance to individual banks. Rather, it measures the systemic importance of one bank with respect to all other banks in the network. This is of particular importance, as measures of systemic importance are prone to generate moral hazard. Due to implicit and explicit bail-out guarantees, banks might try to gain systemic importance in order to benefit from these guarantees. The NSII circumvents this effect, as it takes the whole network structure into account. Banks themselves cannot be totally certain about their ranking in terms of systemic importance within the interbank market, as they cannot fully anticipate the behaviour of the other banks in the system. Hence, the NSII is a useful tool to measure the systemic importance of individual banks and can be used to impose additional measures on SIFIs that are commensurate with their systemic importance.

The recent financial crisis has highlighted the necessity to understand systemic risk both qualitatively and quantitatively in order to safeguard financial stability. It became apparent, that the structure and dynamics of interbank markets have to be taken into account when assessing the resilience of the financial system. In Chapter (4) we therefore develop a dynamic multi-agent model of systemic risk in a banking system with interbank linkages. The results of this chapter have been previously published as Georg and Poschmann (2010) and Georg (2010).[7] This chapter extends the static banking behaviour of Chapter (2) into a dynamic setting and proposes an algorithm for the time-evolution of the system. It draws on earlier works of Iori et al. (2006) and Nier et al. (2007), but extends those models in various aspects.

Iori et al. (2006) develop a network model of a banking system, where agents (banks) can interact with each other via interbank loans. The balance sheet of banks consits of risk-free investments and interbank loans as assets, and deposits, equity and interbank borrowings as liabilities. Banks channel funds from

[7] I wish to thank Jenny Poschmann, Marcus Guenther, Markus Pasche, Christoph Ohler, Monika Bucher, Peter Burgold, Virginie Kemter, Natlia Kohtamäki, Esti VanWykdeVries, and seminar participants at Deutsche Bundesbank, University of Leipzig, University of Halle, University of Pretoria, South African Reserve Bank and ETH Zürich for helpful comments and discussions. Part of this research was conducted at Deutsche Bundesbank and the South African Reserve Bank.

depositors towards productive investment. They receive liquidity shocks via deposit fluctuations and pay dividends if possible. Nier et al. (2007) describe the banking system as a random graph where the network structure is determined by the number of nodes (banks) and the probability that two nodes are connected. The banks' balance sheet consists of external assets (investments) and interbank assets on the asset side and net worth, deposits, and interbank loans as liabilities. Net worth is assumed to be a fixed fraction of a banks total assets and deposits are a residual, designed to complete the banks liabilities side. Shocks that hit a bank and lead to its default are distributed equally amongst the interbank market. Nier et al. (2007) find, that (i) the banking system is more resilient to contagious defaults if its banks are better capitalized and this effect is non-linear; (ii) the effect of the degree of connectivity is non-monotonic; (iii) the size of interbank liabilities tend to increase the risk of a knock-on default; and (iv) more concentrated banking systems are shown to be prone to larger systemic risk. More recently, Ladley (2011) analyzes the impact of the interbank network heterogeneity on systemic risk in a multi-agent setting. The balance sheet of banks consists of equity, deposits, cash reserves, loans to the non-bank sector and interbank loans. Ladley considers risky investment opportunities and explicitely models how banks attract deposits by choosing their offered deposit interest rates. Banks determine the optimal structure of their portfolio via a genetic algorithm. He finds that that for small shocks, high interconnectivity helps stabilizing the system, while for large shocks high interconnectivity amplifies the initial impact.

In this chapter, we develop a dynamic model of a banking system, where banks optimize a portfolio of risky investments and riskless excess reserves. Risky investments are long-term investment projects that fund an unmodelled firm sector while riskless excess reserves are short-term and held at the deposit facility of the central bank. Banks face a stochastic supply of household deposits and stochastic returns from risky investments. This gives rise to liquidity fluctuations and initiates the dynamic formation of an interbank loan network. Banks have furthermore access to central bank liquidity if they can provide sufficient collateral.

This model is used to first analyze the impact that the provision of central bank liquidity has on financial stability. It is shown that the central bank can stabilize the financial system in the short-run. This result is in line with the results of Chapter (2), where the efficiency of central bank policy in the long-run is smaller than in the short-run. Possible network structures will be given at the beginning of each simulation. They reflect contractual agreements amongst banks and determine the set of possible interbank loans. The realized network structure at each point in time is a subset of the possible network structure (i.e. the set of existing edges at any point in time is a subset of the set of possible edges). This closely resembles the situation in reality, where the day-to-day topology of interbank networks also varies from the monthly or quaterly aggregated network structures that are analyzed in the literature. This chapter thus extends the analysis of Chapter (3) from static to dynamic interbank networks. Different possible network structures are compared, and it is shown that in random graphs, the relationship between the degree of interconnectivity and financial instability is non-monotonic. Scale-free networks are seen to be more stable than small-world networks, which in turn tend to be more stable than random networks. Thus, the effect of contagion is exagerrated in the literature, as most papers assume random networks and most real-world interbank networks are scale-free. The model captures key effects of the dynamics of interbank networks and can thus be used to analyze the impact of different externalities on financial stability. The counterparty risk externality is compared to the correlation externality and it is shown that, contrary to their importance in the literature, common shocks are not subordinate to interbank contagion.

While the mdoel developed in chapter (4) allows for a comparison of different forms of systemic risk in a multi-agent setting, chapter (5) develops a general equilibrium model that aims to better understand the interaction effect the different manifestations of systemic risk have. The results of this chapter have been published as Ahnert and Georg (2011).[8] There exists a large and growing liter-

[8]The results in this chapter have been presented at the New York University and the Federal

ature on individual forms of systemic risk, starting with the seminal paper on bank-runs by Diamond and Dybvig (1983). This setup has been extended by i.e. Allen and Gale (2000) and Freixas et al. (2000) in order to analyze contagion in interbank markets. Dasgupta (2004) uses the setup of Allen and Gale and calculates the optimal level of interconnectedness. However, as has been argued in chapter (4), common shocks are not subordinate to interbank contagion and thus have to be taken into account. A model of common shocks in a banking system is developed by Acharya (2009), while Acharya and Yorulmazer (2003) show that the fear of informational spillovers lead to endogenous portfolio correlation amongst banks. What is missing, however, is a unified model of systemic risk that incorporates all relevant forms and analyzes their complex interplay. Such a model is developed this chapter.

Our model consists of three periods and two regions, each with a representative bank and a number of depositors that deposit at their regional bank only. Banks invest into risky securities with long maturity and a riskless storage technology with short maturity, while households have access to the storage technology only. Households are either early or late consumers that value consumption in period one or period two only. The type of the household is private information and revealed to the households in period one. Early consumers will always withdraw in period one, while late consumers might misrepresent their type and withdraw prematurely. The strategic withdrawal decision is based upon signals that the households receive about the long assets' return of their own bank and the bank in the other region. This can lead to the insolvency of the bank. Contagion through interbank markets arises as banks are unaware of a counter-party externality and thus over-insure themselves against regional liquidity shocks. The default of the borrowing bank can lead to the default of the lending bank in

Reserve Bank of Philadelphia. I wish to thank Viral Acharya, Christian Aulepp, Sudipto Bhattacharya, Francesco Caselli, Amil Dasgupta, Elizabeth Foote, Douglas Gale, Marcus Guenther, Yaron Leitner, Friederieke Niepmann, Cecilia Parlatore Siritto, Markus Pasche, and Elu von Thadden for fruitful discussions and comments.

this situation. Common shocks arise from a correlation externality that leads to banks having strongly correlated portfolios and thus being prone to common shocks. Informational spillovers are introduced where depositors become aware of this externality and extract information about the health of their own bank by receiving signals about the return of the other bank. Examining the probability of systemic crisis, we find a non-trivial interaction effect between the different forms of systemic risk. This interaction effect is pro-cyclical and increases with increasing asset volatility. Thus, our findings not only highlight the importance of incorporating different forms of systemic risks, but also have strong implications for capital requirements. In particular, in order to effectively reduce the probability of a systemic crisis, it is necessary to counterveil all forms of systemic risk.

While a number of policy conclusions are drawn at the end of each chapter, the new Basel III framework deserves special attention, as it captures the key policy lessons from the crisis. Therefore, in chapter (6), the Basel III framework is reviewed in the light of the results in this thesis and the literature on systemic risk. This chapter has been previously published as Georg (2011) where also section (1.1) from this chapter has been included.[9] Besides substantial increases in the requirements for capital quality and quantity, Basel III introduces two liquidity ratios. A net stable funding ratio targets long-term liquidity requirements, while the liquidity coverage ratio aims at short-term liquidity. In addition to that, Basel III proposes the implementation of a leverage ratio on bank debt. These measures, however, suffer from a number of shortcomings that are outlined in this chapter. In order to describe a way forward with systemic risk regulation, the chapter concludes with a proposal of three measures that can enhance the design of financial regulation. Counter-cyclical risk-weights can alleviate the time-dimension of systemic risk while a dynamic asset value correlation can counteract the cross-sectional dimension of systemic risk. Most importantly, however, is the

[9]The results in this chapter have been presented at the University of Erfurt. I wish to thank Christian Fahrholz, Markus Pasche and Sebastian Voll for helpful discussions and comments.

conclusion that financial regulation should emphasize the third pillar of Basel III and enhance transparency requirements in order to counteract systemic risk that emerges via common shocks and informational spillovers.

Chapter 2

Microfoundations of Bank and Non-Bank Behaviour

This chapter develops the microfoundations of banking and non-bank behaviour that will be used in the multi-agent simulation in chapter (4). The motivation for the model stems from New and Post Keynesian macroeconomics, where money supply is assumed to be endogenous. In this chapter, we explicitly derive the behaviour of the banking sector regarding the loan supply, bonds demand, and demand for reserves from portfolio and liquidity considerations. The microeconomic foundations have an impact on the process of money creation, which is determined by the interaction of banks, non-banks, and the central bank on the interdependent markets for reserves, loans, and bonds. Although the microeconomics of bank behaviour is modelled quite simply, interest rates as well as monetary aggregates depend on policy variables in a non-linear and non-monotonous way. The contents of this chapter have been previously published as Georg and Pasche (2008).

2.1 Introduction

The endogeneity of money supply is a widely discussed topic, especially in New and Post Keynesian macroeconomics. It can be taken as a common conviction that individual behaviour regarding credit demand and supply as well as holding currency and deposits has an impact on the money creation process. These issues are often neglected in Neoclassical and Monetarist type models. There are, however, very different approaches how endogeneity of money originates (for an extensive review see e.g. Palley (2002), Palley (2008a)). New Keynesian economics (see e.g. Mankiw and Romer (1991), Romer (2000), Woodford (2003)) is dominated by the *"New Consensus"* where the exogenously determined money supply of the central bank (LM curve) is replaced by the Taylor rule (Taylor (1993)). The monetary policy targets inflation and output gap by controlling the real interest rate, while there is no explicit theory about the creation of credit and money.

In Post Keynesian economics money is endogenous by its nature (Lavoie (1992), Lavoie (2006), Rochon (1999)). There have been two distinct approaches developed which are usually denoted as the *"accomodationist"* (or horizontalist) and the *"structuralist"* (or verticalist) approach (see Moore (1988), Pollin (1991), Fontana (2004), Wray (2007), Palley (2008b)). Both schools have in common that the money creation process is determined by the behaviour of commercial banks and non-banks on the credit market. The process starts with credit demand, and credit creates deposits. The accomodationist approach argues that an increase in credit demand leads to a need for additional reserves. In order to ensure the liquidity of the banking sector, the central bank has to respond by increasing the money base and hence to accomodate the credit demand. In this view the microeconomic considerations of the commercial banking sector play a minor role. In contrast, the structuralist approach argues that commercial banks respond to an increase in credit demand with structural changes of their portfolio on the asset and the liability side. This may lead to a change in the demand for reserves and hence in the interaction with the central bank. However, there is no monotone relationship between credit demand and the response of the central bank, but complex structural effects on the interest rates and portfolio composition. While the accomodationists see the central bank's behaviour as a reflex to the non-bank public (which hence determines solely the money supply), the structuralists see a certain degree of autonomous central banking policy. Hence, money is endogenously generated by the interaction of the public, the central bank, and the commercial banks.

We argue that it is important to investigate these complex interactions to understand how monetary policy impulses are transmitted to the real sphere via the credit and bonds market. We further argue that it is important to understand how the real sphere affects the money creation process. Therefore, our approach is related to the structuralist view. We will not consider any strategic policy implications like the Taylor rule since such rules make sense only in the context of a full-fledged macroeconomic model. It is important to understand how commercial banks behave on credit, bond and reserve markets, and how they respond to changes on these markets, as well as to changes in the central bank policy. As we will see, open market operations and changes in interest rates for borrowed reserves have – depending on the parametrization – complex and sometimes countervailing effects on variables like credit supply or bonds demand. Therefore, it is more reasonable to combine such a building block of the financial sector, as outlined in this chapter, with a complete macroeconomic model, and then – if possible – to derive a rationale for monetary policy rules.

In contrast to most Post Keynesians who assume simple markup pricing for determining the loans interest rate, we develop a model of banking behaviour which is in some sense neoclassical: the (representative) bank has preferences regarding risk, return, and liquidity, and it manages its assets and liabilities via portfolio and Value at Risk techniques. A single commercial bank operates in competitive markets and responds to changes in market conditions as well as to changes in central bank policy. This allows for a detailed analysis of some spillover effects between credit and bonds market, the market for reserves, and the real sector (via income). Although the microeconomics of banking are portrayed in a very simplified way the results are not trivial.

This chapter is organized as follows: Before developing our model, we briefly discuss two sources of endogeneity by means of two approaches in the literature. In section (2.2) we review the model of Bernanke and Blinder (1988) who introduce the idea how portfolio considerations of the commercial bank affect the money multiplier. Section (2.3) discusses the less common approach of Bofinger (2001) where changes on the credit market affects the bank's demand for central bank loans. This establishes a close relation between the interest rates on the market for credit and the market for central bank money via an optimization calculus of the commercial bank. Section (2.4) incorporates both ideas in a consistent framework and extends them with liquidity considerations. These liquidity issues are twofold: When the bank's capital is fixed, the volume of risky assets has to be restricted. On the liability side there is a risk of unperceived outflows of deposits which requires to hold a sufficient volume of liquid assets like excess reserves. All portfolio- and Value at Risk decisions are calculated explicitly and exhibit nonlinear relationships between the central variables (e.g. loans (bonds) demand (supply)) and the interest rates. The money creation process is analysed in section (2.5). It starts with some multiplier considerations, then develops a model of the financial sector which includes also non-bank behavior, and discusses the interdependency with the real sector of the economy. Finally, section (2.6) concludes.

2.2 The Approach by Bernanke and Blinder

In the approach by Bernanke and Blinder (1988), the commercial bank's simplified balance sheet contains reserves (R), loans (L^s), and bonds (B^b) as assets, while deposits (D) are the unique liability. There are no currencies and no central bank loans to commercial banks. The reserve requirements are rD, hence the balance sheet can be written as $E + L^s + B^b = (1 - r)D$, where E are the excess reserves at the central bank with a zero interest rate. Since loans and bonds have both expected returns and a certain risk (credit failure and bonds price volatility) the commercial bank has portfolio considerations about its assets. The structure of the portfolio is given by:

$$\begin{aligned} E(i) &= \lambda_E(i)(1-r)D \\ L^s(i,\rho) &= \lambda_L(i,\rho)(1-r)D \\ B^b(i,\rho) &= (1-\lambda_E(i)-\lambda_L(i,\rho))(1-r)D \end{aligned} \tag{2.1}$$

where i is the interest rate of the bonds, and ρ is the interest rate of loans. Obviously λ_L depends positively on ρ, negatively on i, and vice versa for λ_B. For simplicity, Bernanke and Blinder assume that variations in ρ only affect the shares of L^s and B^b in the portolio. The balance sheet of the central bank is given by

$$R = rD + E = rD + \lambda_E(i)(1-r)D = (r + \lambda_E(i)(1-r))D \tag{2.2}$$

Hence the money multiplier is $m(i) = [r + \lambda_E(i)(1-r)]^{-1}$. In contrast to the exogenous multipliers in common textbook models there is now a dependency of the multiplier on the behaviour of the commercial bank, i.e. the multiplier depends on the endogenously determined bonds interest rate i.

The equilibrium in the loans market is determined by $L^d(i,\rho,y) = L^s = \lambda_L(\rho,i)(1-r)D$. The demand for loans depends positively on i and income y, and negatively on ρ. The bonds market is not explicitely modelled in the Bernanke/Blinder approach. While the loans and the bonds market determine the money supply $D^s = m(i)R$, the money demand $D^d = D^d(i,y)$ follows the standard assumptions (positive dependency on y and negative dependency on the bonds interest rate i). Money market equilibrium is given by $D^d(i,y) = m(i)R$ which is the conventional LM curve. From these results Bernanke and Blinder construct a so-called CC curve as a substitute for the IS curve where the goods and credit markets are in equilibrium. Together with the LM curve they study the impact of monetary impulses on the real sector.

For the purpose of this chapter we are not interested into the CC-LM macro model but we pick up the idea that the commercial bank's behaviour is driven by portfolio considerations, which have important implications for the loans market and the money market. The mechanistic exogenous money multiplier is modified to an endogenous money multiplier, based on the behaviour in the loans market and on portfolio considerations of the commercial bank. There are, however, some shortcomings which deserve an extension of the framework (for further critical remarks see Bajec and Graf Lambsdorff (2006)).

First, there are no central bank loans to the commercial bank, even though the interest rate policy plays a prominent role in central banking. Changes in the central banks interest rate ρ_c for refinancing commercial banks is an important component of monetary policy. If we allow central bank credits L_c with interest rate ρ_c, the commercial bank has not only to decide on the portfolio structure of a given volume, but also on the volume itself.

Second, the bonds market is not modelled explicitely. Bernanke and Blinder implicitly assume that the non-bank's demand for bonds is a residual from net financial wealth plus loans demand minus desired deposits (Bajec and Graf Lambsdorff (2006), p.10). Since firms and households face budget constraints it is more reasonable to argue that they decide on the desired structure of financial assets like deposits and bonds, and then decide on the volume of the assets, financed also by loans. Thus, the loans demand L^d is not properly derived. Furthermore, if we assume that open market operations are conducted by buying or selling bonds, this also affects the bonds interest rate i and henceforth the portfolio decisions of non-banks.

Third, the bank's portfolio considerations are reduced to risk and return decisions. However, banking management also addresses solvency and liquidity issues. These shape the loan supply, bonds demand, and the extent of refinancing the operations with central bank loans.

Fourth, there are neither domestic nor foreign currencies, and there is no market for equities and derivative financial contracts. It is clear that a model cannot include too many items without losing the ability to derive clear analytical results. For the sake of simplicity it is admissible to neglect these things. However, the market for financial contracts apart from loans and bonds becomes of growing importance as the recent financial crisis indicates. Since the observed fragility of the inter-related markets challenges monetary policy, it may be worth to include them in the framework.

Fifth, all markets are assumed to be perfect. Starting from Stiglitz and Weiss (1981) there is a broad literature on credit rationing based on asymmetric information which plays a role also in equity markets (see e.g. Hellmann and Stiglitz (2000)). From Neo Keynesian theory we know that rationing changes the agent's calculus. They will adapt their plans so that e.g. rationing on the loans market probably has spillovers to other financial markets as well as to the real sphere. As a result, the macroeconomic effective demand may depend on rationing effects.

It is not possible, of course, to address all mentioned shortcomings. This chapter concentrates on the first three mentioned issues. Regarding the central bank loans for commercial banks we first summarize a model by Bofinger (2001).

2.3 The Approach by Bofinger

In Bofinger (2001) (pp. 53) a model of the macroeconomic loans market is presented, where commercial banks are able to refinance their credit supply by central bank loans L_c, i.e. by the demand for reserves. The aim of the model is to explain the money creation process endogenously by the interaction of the market for loans and the market for reserves. There are no bonds, no excess reserves, and we neglect currency in this model. Hence, the simplified commercial bank's balance sheet is $R + L^s = L_c + D$. The loan supply is explicetly derived from a profit maximizing calculus:

$$\max_{L^s} \ \pi = \rho L^s - \rho_c L_c - \beta(L^s)^2 \tag{2.3}$$

where the term $\beta(L^s)^2$ describes the increasing risk of debt failures. This can be justified by assuming that with an expanding loan volume, the bank finances more and more risky projects, or more debitors have limited soundness. However, it is more reasonable to assume that the debt failure probability depends on ρ rather than L. Since a central bank loan L_c extends the balance sheet of the bank and increases the reserves, the credit expansion follows the multiplier process. When $R = rD$ is subtracted from the balance sheet we have:

$$L^s = L_c + (1-r)D = L_c + (1-r)mL_c \tag{2.4}$$

Because for the money multiplier $m = 1/r$ holds true in absence of currency and excess reserves, a simple rearrangement leads to $L^s = mL_c$. Substituting $L_c = m^{-1}L^s$ into the profit function the first order condition yields the supply function:

$$L^s = L^s(\rho, \rho_c, \beta) = \frac{1}{2\beta}\left(\rho - \rho_c/m\right) \tag{2.5}$$

which is increasing in ρ. The demand for loans is given by $L^d(\rho, y)$. From the market equilibrium condition $L^d = L^s$ we obtain an equilibrium interest rate $\rho^*(\rho_c, \cdot)$. Of course ρ^* also depends on demand parameters. The loans market equilibrium implies a profit maximizing demand for reserves, i.e. central bank loans. Substituting $L^s = mL_c$ into the profit function and maximizing with respect to L_c yields the reserve demand function:

$$L_c(\rho, \rho_c, \beta) = \frac{1}{2m\beta}\left(\rho - \rho_c/m\right) \tag{2.6}$$

On the market for reserves the central bank acts as a monopolist. The central bank chooses a point on the demand function L_c^d according to monetary policy goals instead of profit maximization. A change in the interest rate ρ_c for reserves and therefore a shift of the reserve demand changes the loan supply curve L^s and

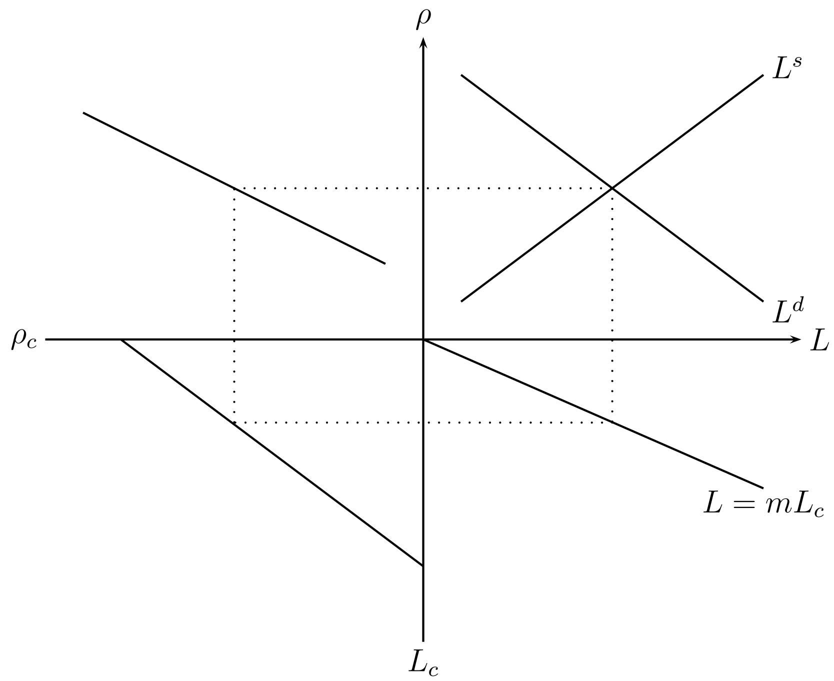

Figure 2.1: The Bofinger model as described in Bofinger (2001).

has therefore an impact on the loan interest rate $\rho^*(\rho_c, \cdot)$.

Assuming a linear loan demand $L^d = \gamma y - \alpha\rho$ it is an easy task to derive the resulting equilibrium interest rates. Figure 2.1 shows the complete model for the linear case. The upper right quadrant depicts the loans market, the lower right quadrant shows the money multiplier. The loans market equilibrium hence determines the demand for reserves (lower left quadrant) via the multiplier. The relation between the interest rates for loans and reserves ($\rho^*(\rho_c, \cdot)$) is depicted in the upper left quadrant. The interest rate based transmission of monetary impulses works as usual: An increasing ρ_c shifts the loan supply curve upwards. This results in a raise of the market intrerest rate ρ (depending on supply and demand elasticities), and a decrease of the demand for central bank money L_c. However, the money supply is no longer a policy variable, the money (credit) creation process is also determined by the loans demand.

Obviously, the Bofinger model has some shortcomings. As in the Bernanke/Blinder approach, there are no equity markets, no currencies, and no rationing effects due to market imperfections. Moreover, there is neither a bonds market nor excess reserves. So the commercial bank has no asset portfolio and therefore no portfolio considerations (which implies risk aversion while the profit function in the Bofinger model implies risk neutrality). As a consequence, the multiplier is constant. Nevertheless, the money creation process is determined by the behaviour of the commercial banks and the debitors.

Our aim is now to combine Bofinger's idea of an analytically derived demand for reserves, depending on the interest rate policy of the central bank with the Bernanke/Blinder approach which includes a bonds market and portfolio considerations of a (risk averse) commercial bank. Furthermore we extend the framework by liquidity and solvency considerations.

2.4 An Aggregated Model of Banking Behaviour

Starting from the balance sheet of the aggregated banking sector, we derive the decision of a single representative commercial bank regarding the structure and volume of its portfolio. These decisions are driven by considerations about risk, return and liquidity.

2.4.1 The Balance Sheet of the Aggregated Banking Sector

The balance sheet of a commercial bank contains three liabilities: deposits D, central bank loans L_c, and bank capital $\overline{BC}$, and the three assets: loans L, bonds B and excess reserves E. The required reserves rD are subtracted from both sides of the sheet. The balance sheet of the commercial bank thus reads:

$$L + B + E = (1 - r)D + L_c + \overline{BC} \tag{2.7}$$

where the bank capital is assumed to be fixed for simplicity. Since we look at the aggregated banking sector, all inter-bank loans are subtracted from the sheet.

Therefore, the market for reserves consists of the aggregated banking sector on the demand side and the central bank on the supply side. All types of reserves demanded by commercial banks which have to pay interest rates to the central bank are subsumed to L_c.

The portfolio considerations of the commercial bank are now twofold. First, the bank has to decide about the portfolio *structure*, which is determined by the shares λ_L, λ_B and λ_E which give the fractions of L, B and E in the full portfolio (with $\lambda_L + \lambda_B + \lambda_E = 1$). The second decision a commercial bank has to make is about the *volume* of the portfolio. The portfolio volume is defined by:

$$V = (1 - r)D + L_c + \overline{BC}. \tag{2.8}$$

A single bank is seen as not being able to determine the outcome of the macroeconomic deposit creation process. Although an additional credit creates additional deposits, the volume of deposits of a single bank is determined by a process of inflows and outflows of deposits due to the payment behavior of non-banks which cannot be controlled by the beank's behavior. Hence, in a competitive market the single bank will take D as given. Therefore the volume of the portfolio is determined solely by L_c which hence is a policy variable of the bank.

2.4.2 Management of Risk and Return

From the three assets L, B and E, there is one riskless asset E with expected return $\mu_E = 0$, and two risky assets L and B. For L, the expected return per unit and the variance are

$$\begin{aligned} \mu_L &= p\rho - (1 - p) \\ \sigma_L^2 &= p(\rho - \mu_L)^2 + (1 - p)(-1 - \mu_L)^2 \end{aligned} \tag{2.9}$$

where p is the probability for a successfully returned credit and ρ is the loans interest rate, collaterals have been neglected. As Stiglitz and Weiss (1981) argue, the probability $(1-p)$ of a complete credit failure may be assumed to be a positive function of ρ. In this section, however, we take p as exogenously given. The expected return and variance for bonds is

$$\begin{aligned} \mu_B &= i \\ \sigma_B^2 &= const \end{aligned} \tag{2.10}$$

For the sake of simplicity we assume that covariances are not present.

The optimal portfolio structure for one riskless and two risky assets is determined in two steps (for details see Huang and Litzenberger (1988)). In the first step, the efficient portfolio frontier for a mix of the two risky assets has to be derived. The risky portfolio R is given by the shares $\tilde{\lambda}_L$ and $\tilde{\lambda}_B = (1-\tilde{\lambda}_L)$ which implies:

$$\begin{aligned} \mu_R &= \tilde{\lambda}_L\mu_L + \tilde{\lambda}_B\mu_B = \tilde{\lambda}_L(p\rho - (1-p)) + (1-\tilde{\lambda}_L)i \\ \sigma_R^2 &= \tilde{\lambda}_L^2\sigma_L^2 + \tilde{\lambda}_B^2\sigma_B^2 = \tilde{\lambda}_L^2(p^2(\rho-\mu_L)^2 + (1-p)^2(-1-\mu_L)^2) + (1-\tilde{\lambda}_L)^2\sigma_B^2 \end{aligned} \tag{2.11}$$

Hence, $\tilde{\lambda}_L$ determines all possible (μ_R, σ_R)-combinations, which define the portfolio frontier. In order to find the optimal risky portfolio, which is then mixed with the riskless asset E, we have to determine the tangential point of the efficient portfolio frontier with the capital allocation line (CAL) being defined as:

$$\mu_P = \mu_E + \left(\frac{\mu_p - \mu_E}{\sigma_R}\right)\sigma_P = \left(\frac{\mu_R}{\sigma_R}\right)\sigma_P \tag{2.12}$$

Standard portfolio methods provide the solution:

$$\tilde{\lambda}_L = \frac{\mu_L\sigma_B}{\mu_L\sigma_B + \mu_B\sigma_L} \quad \text{and} \quad \tilde{\lambda}_B = 1 - \tilde{\lambda}_L = \frac{\mu_B\sigma_L}{\mu_B\sigma_L + \mu_L\sigma_B} \tag{2.13}$$

as there is no covariance present. As μ_L may become negative due to total debt failure, $\tilde{\lambda}_L$ has to be truncated at zero. In the second step, the bank decides how to mix the riskless asset E with the risky portfolio R according to its preferences. To determine the optimal proportion λ_R, the bank maximizes its utility function. We assume a Power function with constant relative risk aversion since this function allows for a separate determination of optimal portfolio structure and optimal portfolio volume, i.e. λ_R is independent from V. The realized value of the portfolio after the investment period is $\tilde{V} = V(1 + \lambda_R r)$ with r as the realized return and $E[r] = \mu_R, Var[r] = \sigma_R^2$. The agent subjectively expects a mean wealth $E[\tilde{V}] = V(1 + \mu_P)$ and a variance $Var[\tilde{V}] = V^2\sigma_P^2$. The Power utility function is $u(\tilde{V}) = \tilde{V}^{(1-\theta)}/(1 - \theta)$ where $\theta > 0$ is the constant Arrow-Pratt measure for relative risk aversion. Maximizing $E[u(\tilde{V})]$ with respect to λ_R leads to the well established result from portfolio theory (see appendix):

$$\lambda_R = \min\left\{\frac{\mu_R}{\theta\sigma_R^2}, 1\right\} \tag{2.14}$$

Note, that λ_R changes as soon as additional constraints from Value at Risk are introduced. Now the bank's optimal portfolio structure is completely determined by:

$$\lambda_L = \tilde{\lambda}_L\lambda_R, \quad \lambda_B = (1 - \tilde{\lambda}_L)\lambda_R, \quad \lambda_E = 1 - \lambda_R \tag{2.15}$$

where the explicit form is not further revealing and thus have been omitted here.

The next task is to determine the optimal portfolio volume V which is given by (2.8). By assumption V could be adapted solely by changing reserve demand L_c. Optimality requires that the portfolio volume is expanded by L_c until the expected marginal utility equals the marginal cost ρ_c. In this case it is neccessary to interpret $u(\cdot)$ as a cardinal utility function. To obtain numerically reasonable results, the marginal utility has to be scaled with a scaling parameter $\xi > 0$. For our purposes we set $\xi = 1$, i.e. the scaling is omitted. The calculus $\max_{L_c \geq 0} E[u(\tilde{V})] - \rho_c L_c$ leads to:

$$L_c = \left(\frac{(1 + \lambda_R\mu_R - \frac{1}{2}\theta\lambda_R^2\sigma_R^2)^{(1-\theta)}}{\rho_c}\right)^{1/\theta} - (1 - r)D - \overline{BC} \tag{2.16}$$

Observe, that the effect of an increasing portfolio performance μ_R on L_c is negative (positive) for $\theta > 1$ ($\theta < 1$) as it can seen by differentiating (2.16) with respect to μ_R. Increasing portfolio performance leads to higher *total* expected utility, accelerated by an increase of λ_R, but this implies a lower *marginal* utility due to the concavity of $u(\cdot)$. Hence the portfolio will be sized down. Only in case of low risk aversion ($\theta < 1$) the marginal utility of the last portfolio unit and therefore borrowed reserves increase. Inserting (2.14) for λ_R and (2.11) for μ_R and σ_R^2 into (2.16), the demand for central bank loans L_c is given by:

$$L_c = L_c(\rho, i, \underset{-}{\rho_c}, \underset{-}{D}) \tag{2.17}$$

which determines the volume V.

With the optimal shares λ_L, λ_B and λ_E and the optimal portfolio volume V, we obtain the demand for bonds B, the excess reserves E, and the supply of loans L:

$$L = \lambda_L V, \quad B = \lambda_B V, \quad E = \lambda_E V \tag{2.18}$$

Again, the explicit form is omitted here. For two reasons the dependencies on ρ and i may be not clear: First, since σ_L^2 depends on ρ, an increase in ρ may have ambiguous effects on λ_R, the share of the risky assets. Second, the marginal utility of the portfolio changes with increasing i or ρ which may have a negative effect on L_c and hence L and B (depending on θ). Then the shares λ_L, λ_B and L_c may have different signs in their derivatives with respect to i and ρ. The structural and the volume effects may be countervailing, thus the total effect depends on the parametrization.

2.4.3 Mangement of Liquidity by Value at Risk

In the last section the commercial bank's goal was to balance risk and expected returns. But banks are also interested to keep a certain level of capital in order to stay solvent. Loans may fail and the bonds position in the portfolio is also volatile. Only the excess reserves E are risk-free. Depending on the probability distributions of μ_L, μ_B and the optimal shares λ_L, λ_B it is possible to derive a probability distribution for the losses of the portfolio. With a certain probability the losses could exceed the bank's capital $\overline{BC}$. In this case the bank would be insolvent.

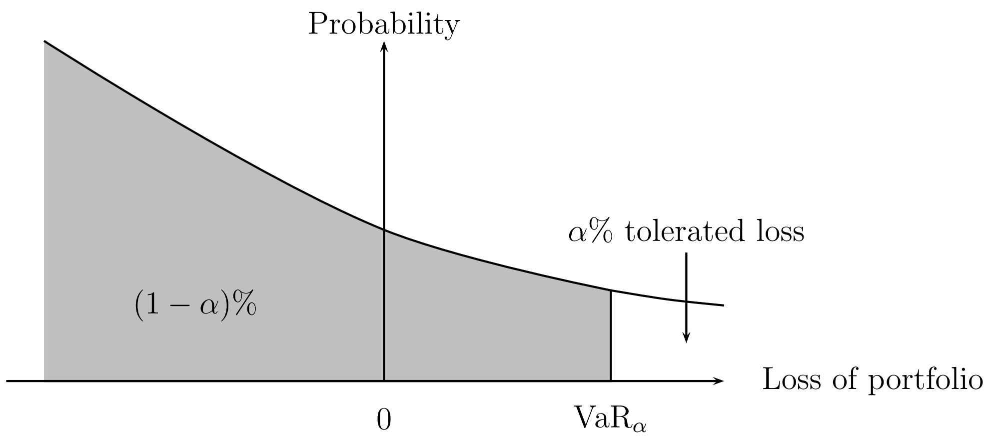

Figure 2.2: Loss distribution with Value at Risk.

We assume that the bank's management addresses this problem with the Value at Risk (VaR) approach (for details see e.g. Wahl and Broll (2003)). Let α be the probability that the losses exceed the bank's capital, then

$$\mathrm{VaR}_\alpha = q_\alpha V \tag{2.19}$$

determines the capital requirement to ensure solvency with probability $1-\alpha$ in a given period. Here V is the portfolio volume and $-q_\alpha$ is α-fractile of the probability distribution (see Figure (2.2)).

The VaR approach requires that the capital $\overline{BC}$ covers at least the VaR at the level α, i.e. $\overline{BC} \geq \mathrm{VaR}_\alpha = q_\alpha V$. The more risky the portfolio and the higher the desired probability $(1-\alpha)$ of staying solvent – either determined by the bank's management or by bank regulation policy – the more capital $\overline{BC}$ is required. It can be shown that, for a given VaR_α, the bank chooses an optimal structure of V and BC. In our approach, however, we take $\overline{BC}$ as a given constant. Hence, VaR_α is a constraint for the portfolio volume V, leading to:

$$\begin{aligned} \overline{BC} &\geq \mathrm{VaR}_\alpha = q_\alpha V = q_\alpha((1-r)D + L_c + \overline{BC}) \qquad (2.20) \\ \Rightarrow \quad L_c &\leq \frac{1-q_\alpha}{q_\alpha}\overline{BC} - (1-r)D \end{aligned}$$

This is an additional restriction for determining the optimal portfolio volume via L_c as discussed in the previous section. In case that the restriction is binding, the equality sign holds true in (2.20) and the marginal utility of the portfolio exceeds the marginal cost ρ_c. As a consequence, the money creation process is eventually limited by the bank's solvency policy.

The liquidity management also affects the portfolio structure. If we consider the deposits D not to be a given deterministic value, but a stochastic variable with a given distribution (with D as the expected value), the bank faces the risk of deposit volatility and sudden deposit outflows (bank runs). If depositors wish to draw their deposits, the bank needs immediately liquid assets. We assume that only excess reserves E have the required liquidity (see e.g. Mishkin (2006), pp. 208). Then the VaR approach also applies to the probability to be a victim of bank runs, i.e. to become illiquid. Let β be the probability that sudden outflows of deposists exceed the excess reserves E. Then the bank avoids illiquidity with probability $1-\beta$ if for excess reserves

$$\begin{aligned} & E & \geq & \; \mathrm{VaR}_\beta = q_\beta D \\ \Rightarrow \quad & \lambda_E & \geq & \; q_\beta \frac{D}{(1-r)D + L_c + \overline{BC}} \equiv \underline{\lambda}_E \end{aligned} \tag{2.21}$$

holds true. Again, we have an additional constraint for the portfolio calculus as discussed in the previous section. The structure of the risky portfolio $\tilde{\lambda}_L, \tilde{\lambda}_B$ is obviously not affected by the VaR approach. But if (2.21) is binding then we have $\lambda_R = 1 - \underline{\lambda}_E$ which determines λ_L and λ_B.

Summing up, the VaR approach can be used on the one hand to ensure solvency by balancing V and $\overline{BC}$. This eventually has an impact on the chosen portfolio volume. On the other hand the approach is used to avoid illiquidity in case of deposit outflows by balancing E and D. This eventually has an impact on the chosen portfolio structure. In this chapter we do not investigate these effects analytically.

2.5 Endogenous Money Supply

2.5.1 Some multiplier considerations

Up to now, this chapter addresses only the behavior of commercial banks. Therefore we could only analyse their influence on the endogenous money creation process. It is clear, however, that the behavior of non-banks regarding the credit demand L^d, the bonds demand, and the demand for money (deposits D) play a crucial role because this directly or indirectly affects the bank's decisions about portfolio structure and reserve demand. As we will take D as well as the interest rates on credit and bonds market as given, the analysis must be incomplete. Nevertheless, we are able to highlight the behavior of banks as a hinge between central bank policy and the financial markets. In a framework of endogenous money, monetary policy is about how the central bank *influences* the interactions on the credit and bonds market rather than *determining* their outcome (see also Chick and Dow (2002)).

The multiplier analysis treats D as an outcome of a mechanistic process. In a first step, we derive a money multiplier under the assumption that i and ρ are given exogenous variables. Let $e = E/D = \lambda_E((1-r)D + L_c + \overline{BC})/D$, then the central bank's balance sheet can be expressed as:

$$(MB =) \quad S + L_c = (r + e)D \tag{2.22}$$

with MB as the money base and S as the securities held by the central bank (e.g. bonds). It is assumed that S is determined by purchases and sales of the central bank on the market for securities. Note again, that in this chapter we neglect any currency. The ratio e depends on D and on endogenously determined values of λ_E and L_c. Inserting e into (2.22) and solving for D we obtain:

$$D = \frac{S + (1-\lambda_E)L_c - \lambda_E \overline{BC}}{r + (1-r)\lambda_E} \tag{2.23}$$

The central bank could conduct open market operations on the market for securities, which leads c.p. to the multiplier:

$$\left.\frac{dD}{dS}\right|_{L_c=const} = \frac{1}{r+(1-r)\lambda_E} > 0 \tag{2.24}$$

where λ_E is endogenously determined but is assumed to have a given value throughout the multiplier process. The result is essentially the same as the multiplier derived by Bernanke and Blinder (1988). This is a conventional view of the multiplier process which is slightly enriched by the assumption that the fraction of excess reserves is endogenously determined by portfolio considerations. The multiplier is very sensitive to changes in λ_E. In the 2008 financial crisis most central banks decided for a very expansive policy, but with very modest effects on monetary aggregates. This is partly due to the fact that excess reserves have increased drastically (von Hagen (2009)) as a result of the interbank market failure. Also the Fed's decision to pay interest on excess and required reserves increased the incentives for banks to hold more excess reserves.

Commercial banks will manage the portfolio volume by adjusting borrowed reserves L_c. As eq. (2.16) shows, a change in D leads to an adjustment of L_c which also determines the money base. The multiplier (2.24) is therefore valid only in case of a fixed L_c. Otherwise an expansion of the money base by $dS > 0$ induces a decrease of L_c because the bank attempts to keep its portfolio volume on an optimal level. In an equilibrium ("long run") perspective the values of D and L_c are determined by the solution of the linear equation system (2.16) and (2.23):

$$D^{\text{long}} = \begin{cases} (S-\overline{BC}) + (1-\lambda_E)\left(\frac{(1+\lambda_R\mu_R-\frac{1}{2}\theta\lambda_R^2\sigma_R^2)^{(1-\theta)}}{\rho_c}\right)^{1/\theta} & \text{for } L_c^{\text{long}} > 0 \\ \frac{S-\lambda_E\overline{BC}}{r+(1-r)\lambda_E} & \text{for } L_c^{\text{long}} = 0 \end{cases} \tag{2.25}$$

where L_c^{long} is given as:

$$L_c^{\text{long}} = \arg\max\left\{(r+(1-r)\lambda_E)\left(\frac{(1+\lambda_R\mu_R-\frac{1}{2}\theta\lambda_R^2\sigma_R^2)^{(1-\theta)}}{\rho_c}\right)^{1/\theta}, 0\right\} \tag{2.26}$$

When the commercial bank is able to keep the portfolio volume at the chosen optimal level, the required reserve rate r does not play a role anymore. The central bank is then able to enforce an increasing money supply D but it is not able to initiate a multiplier process since we have:

$$\frac{dD^{\mathrm{long}}}{dS} = 1$$

The conventional multiplier (2.24) holds true only if the banks are not willing or able to adjust L_c. If L_c is determined endogenously by optimal banking behavior, then outright purchases of securities seem to be an ineffective way for initiating a money multiplier process and should therefore be considered for finetuning operations only.

The second policy variable of the central bank are the refinancing conditions ρ_c. A change in ρ_c affects the demand for L_c and therefore the money base. We do not distinguish different types of borrowed reserves like standing facilities and open market operations on the market for reserves – all reserves where commercial banks have to pay interest rates to the central bank are subsumed to central bank loans L_c. It is easy to derive money multipliers for changes in the rate ρ_c in the same mechanistic way as before. In the short run L_c is assumed to respond only to changes in ρ_c. Ceteris paribus we have from (2.16) and (2.23):

$$\frac{dD}{d\rho_c} = \frac{dD}{dL_c}\frac{dL_c}{d\rho_c} = -\frac{1-\lambda_E}{\theta\rho_c(r+\lambda_E(1+r))} \cdot \left(\frac{(1+\lambda_R\mu_R - \frac{1}{2}\theta\lambda_R^2\sigma_R^2)^{(1-\theta)}}{\rho_c}\right)^{1/\theta} < 0 \tag{2.27}$$

In the long run, ρ_c affects the equilibrium values D^{long} and L_c^{long} which yields the multiplier:

$$\frac{dD^{\mathrm{long}}}{d\rho_c} = -\frac{1-\lambda_E}{\theta\rho_c} \cdot \left(\frac{(1+\lambda_R\mu_R - \frac{1}{2}\theta\lambda_R^2\sigma_R^2)^{(1-\theta)}}{\rho_c}\right)^{1/\theta} < 0 \tag{2.28}$$

in case of $L_c^{\mathrm{long}} > 0$ in the long run and, of course, $dD^{\mathrm{long}}/d\rho_c = 0$ otherwise. Note, that also in case of a fixed L_c due to VaR restrictions the multiplier becomes zero. Comparing (2.27) and (2.28), it can be seen that in the long run the impact of monetary policy is lower than in the short run.

2.5.2 The Impact of the Non-Banking Sector

The previous analysis has shown that the impact of monetary policy on monetary aggregates is strongly influenced by bank's decision on portfolio structure and reserve demand. A severe shortcoming of a mechanistic multiplier analysis is that interest artes i, ρ are taken as given. However, they will change as a result of changed loans supply L and bonds demand B. Therefore the analysis is incomplete. Furthermore, multiplier analysis presumes that deposits are automaticcally created by loans rather than being an autonomous decision of non-banks. Since holdung deposits D and demanding loans L are driven by different micro-motives of households and firms, a mechanistic multiplier analysis is not very informative.

We will now consider the behavior of non-banks, following the same logic as in section (2.4). To obtain a consistent framework of balance sheets we assume that central bank's securities are bonds: $S = B^{cb}$. The upper index denotes the sector or institution which holds the bonds. Hence, the balance sheets of the central bank, the commercial bank, and their aggregated balance sheets reads:

$$
\begin{array}{lrcl}
\text{central bank} & B^{cb} + L_c & = & E + rD \\
\text{commercial banks} & B^b + L + E & = & (1-r)D + L_c + \overline{BC} \\
\hline
\text{aggregated} & B^{cb} + B^b + L & = & D + \overline{BC}
\end{array}
$$

The non-bank sector consist of firms and households. We assume that firms hold physical capital PC and money D^f as assets, and loans L^f, bonds $\bar{B}$, and capital $\bar{C}$ as liabilities. Households hold bonds B^h, firm and bank capital, and money D^h. On the liability side we have the net financial wealth NFW and loans L^h. Thus we have:

$$
\begin{array}{lrcl}
\text{firms} & PC + D^f & = & \bar{B} + \bar{C} + L^f \\
\text{households} & \bar{C} + \overline{BC} + B^h + D^h & = & NFW + L^h \\
\hline
\text{aggregated} & PC + D + \overline{BC} & = & NFW + (\bar{B} - B^h) + L
\end{array}
$$

with $D = D^h + D^f$ and $L = L^d = L^f + L^h$ (loans demand) and $\bar{B} = B^{cb} + B^b + B^h$. Therefore, adding all balance sheets of the bank and non-bank sector leads to the identity of physical capital goods and net financial wealth, implying that investments equals savings. Observe, that in case of subtracting $PC = NFW$ from the aggregated non-bank balance sheet, L is not neccessarily equal to D since banks and non-banks are connected also by equity and bonds contracts. Holding deposits D and demanding loans L are based on different motives. It is then not reasonable anymore to consider a “money market”. The focus has to be on the credit and bonds market (see Palley (2008a)).

Without going into details of the micro-motives of households and firms, we consider

$$\begin{aligned} B^h &= B^h(\underset{-}{\rho}, \underset{+}{i}) \\ D &= D(\underset{-}{\rho}, \underset{-}{i}, \underset{+}{y}) \\ L^d &= L^d\underset{-}{\rho}, \underset{+}{i}, \underset{+}{y}) \end{aligned} \tag{2.29}$$

which is in line with standard economic literature.

Note, that all *plans* of banks, firms, and households about their asset and liability side could be consistently realized only in case of equilibrium interest rates. On the loans market we have in a partial equilibrium

$$L(\rho^*, i, \rho_c) = L^d(\rho^*, i, y)$$

and therefore $\rho^*(i, \rho_c, y)$. On the bonds market we have in partial equilibrium

$$\bar{B} = B^{cb} + B^b(\rho, i^*, \rho_c) + B^h(\rho, i^*)$$

and therefore $i^*(\rho, \rho_c, B^{cb})$. Due to this interdependency of the two markets, both interest rates are positively related and the total equilibrium values are $\rho^{**}(\rho_c, y, B^{cb}), i^{**}(\rho_c, y, B^{cb})$. The partial derivatives for ρ_c and y are positive, and negative for B^{cb}. Observe, that $i^{**}(\cdot, y)$ is a kind of LM curve which is parametrized by central bank policy variables.

Instead of relying on a mechanistic multiplier process, the central bank is only able to influence credit and deposit volume by affecting the interest rates. Contrary to some Post Keynesian views where money is endogenous but the interest rate is exogenously determined by the central bank, we take money *and* interest rates as endogenous. Interest rates determine the decisions about holding bonds or deposits, and the supply and demand of loans. If the real sector is taken into account, things become more complicated: Assume a negative relationship between income y and the interest rate i according to the IS curve. Then monetary policy has a *direct* influence on money demand $D(y, i)$ via the changed interest rates, but also an *induirect* influence via real effects on y. An appropriate analysis of monetary policy effects on monetary aggregates has to replace the mechanistic multiplier approach by

$$\frac{dD}{d\rho_c} = \frac{\partial D}{\partial i}\frac{\partial i^{**}}{\partial \rho_c} + \frac{\partial D}{\partial y}\frac{\partial y}{\partial i}\frac{\partial i^{**}}{\partial \rho_c} \tag{2.30}$$

and

$$\frac{dD}{dB^{cb}} = \frac{\partial D}{\partial i}\frac{\partial i^{**}}{\partial B^{cb}} + \frac{\partial D}{\partial y}\frac{\partial y}{\partial i}\frac{\partial i^{**}}{\partial B^{cb}} \tag{2.31}$$

where the first terms on the r.h.s. include all direct effects within the fiancial sector as discussed in this section, while the second terms denote indirect effects from the real sector. It is a priori not clear which of both effects dominates the results.

The influence of the real sector on the monetary aggregate D runs as follows: Increasing income y leads to an increased loans demand. This affects the loans interest rate and via portfolio adaptations also the bonds interest rate which dampens money demand. A change in deposits as well as changed interest rates have an effect on the reserve demand. It is a matter of the monetary policy strategy how the central bank responds to such a shock (e.g. by accomodation). This will not be analysed in this chapter since the purpose has been to demonstrate how the monetary aggregate is determined endogenously be the behavior of banks and non-banks, and how these processes are influenced by policy variables B^{cb} and ρ_c.

2.5.3 Numerical Examples

From simple optimization considerations we obtain functions which depend in a non-linear and partially non-monotonous way on the variables. The explicit form of the behavioral equations for optimal loans supply L, bonds demand B^b, and demand for borrowed reserves L_c are too complicated to show them here. They consist of optimal structural variables $\tilde{\lambda}_L, \lambda_R$ (determining $\lambda_L, \lambda_B, \lambda_E$) and optimal reserve demand L_c which determines the volume.

Figure (2.3) shows the relevant structural variables which have slopes that could be expected intuitively. The underlying values are $p = 0.95, \sigma_B^2 = 0.2, r = 0.05, \theta = 1.5, D = 5, \overline{BC} = 1, \rho_c = 0.02$. They are truncated to the interval $[0, 1]$, neglecting any VaR constraints. Note that for very small interest rates ρ the expected return could be negative due to the possibility of total debt failure. Therefore $\tilde{\lambda}_L$ may have a zero border value. Such truncations also affect λ_L, λ_B and hence L_c, L, B, E, causing the kinks in the 3D-plots.

Figure (2.4) shows L_c and the resulting functions for L, B, E. Observe, that the bonds demand depends non-monotonously on ρ. For low loans interest rates the portfolio will consist only of bonds. When ρ increases, the portfolio will be restructured in favor of loans. But also the fraction λ_R will increase because the risky part of the portfolio becomes more attractive. Therefore the bonds demand increases. With high values of ρ we have $\lambda_R = 1$ so that the restructuring effect within the risky part of the portfolio dominates and the bonds demand will decrease again, causing a non-monotonicity. Another non-monotonous dependency is possible, though not observed with these parameter values: If i (ρ) increases, bonds (loans) become more attractive, but we may have countervailing effects because the marginal utility of the portfolio and hence the portfolio volume decreases. If the latter effect dominates, bonds demand (loans supply) could decrease although interest rates increase.

2.6 Discussion

In this chapter we presented a simple model of the aggregated commercial banking sector. The bank is assumed to manage its assets and liabilities according to risk, return, and liquidity considerations. This is done by the portfolio as well as by the Value at Risk methodology. Although each loan creates deposits by the initial accounting record, the non-bank sector decides due to different motives about demanding loans and holding deposits. The existence of other financial contracts than loans (here: bonds and equity) allows for distinct decisions about loans demand and holding deposits and a inequality of L and D.

From the banking side the endogeneity of money supply is hence twofold: The *structure* of the portfolio, driven by risk and liquidity preferences, determines the money multiplier, while the acchieved portfolio *volume* determines the demand for reserves and hence the money base. Nevertheless we made clear that multiplier analysis is of very limited use because it neglects the behavior of the non-bank sector. An analysis of money endogeneity has to abandon the multiplier view.

The commercial banking sector is a hinge between the central bank policy and the non-banking sector. As we have outlined in section (2.4.2) the demand for money D and for loans L is determined by the dispositions of non-banks, not by a multiplier. This part of the endogenous money creation process will be studied in more detail in a subsequent paper. We haven't made any assumptions about central bank behavior. The central bank has to respond to shocks from the banking and non-bank sector in some way, e.g. by accomodating positive credit demand shocks. It is also possible to incorporate fixed policy rules like the Taylor rule into this framework. However, it has to be clarified that the central bank's decision variable is not *the* interest rate, but ρ_c which has an *influence* on ρ and i in a non-linear way. Such a monetary policy analysis deserves further investigation.

As an extension of the framework different types of liabilities may be considered. Deposits D have been assumed to have no interest rate and a high risk of outflows and (therefore) a requirement for holding excess reserves. However, there are other types of liabilities where the bank has to pay interest rates but has no reserve requirements. This enriches the strategic possibilities to attrract deposits in order to enhance the portfolio volume and is hence a substitute for the central bank loans demand L_c. Since these liabilities have no reserve requirement, this may have substantial effects on the money multiplier – the abilities of the central bank to manage the expansion process are much more restricted as they are anyway.

A further extension would be to endogenize the bonds supply since bonds are an imperfect substitute to loans. For a more dynamic perspective it would be desirable to include expectations explicitely into the calculus and to consider the different maturities of the liabilities and assets. Thus the banks are prevented from an instantanous adaption of their portfolio when the environment changes.

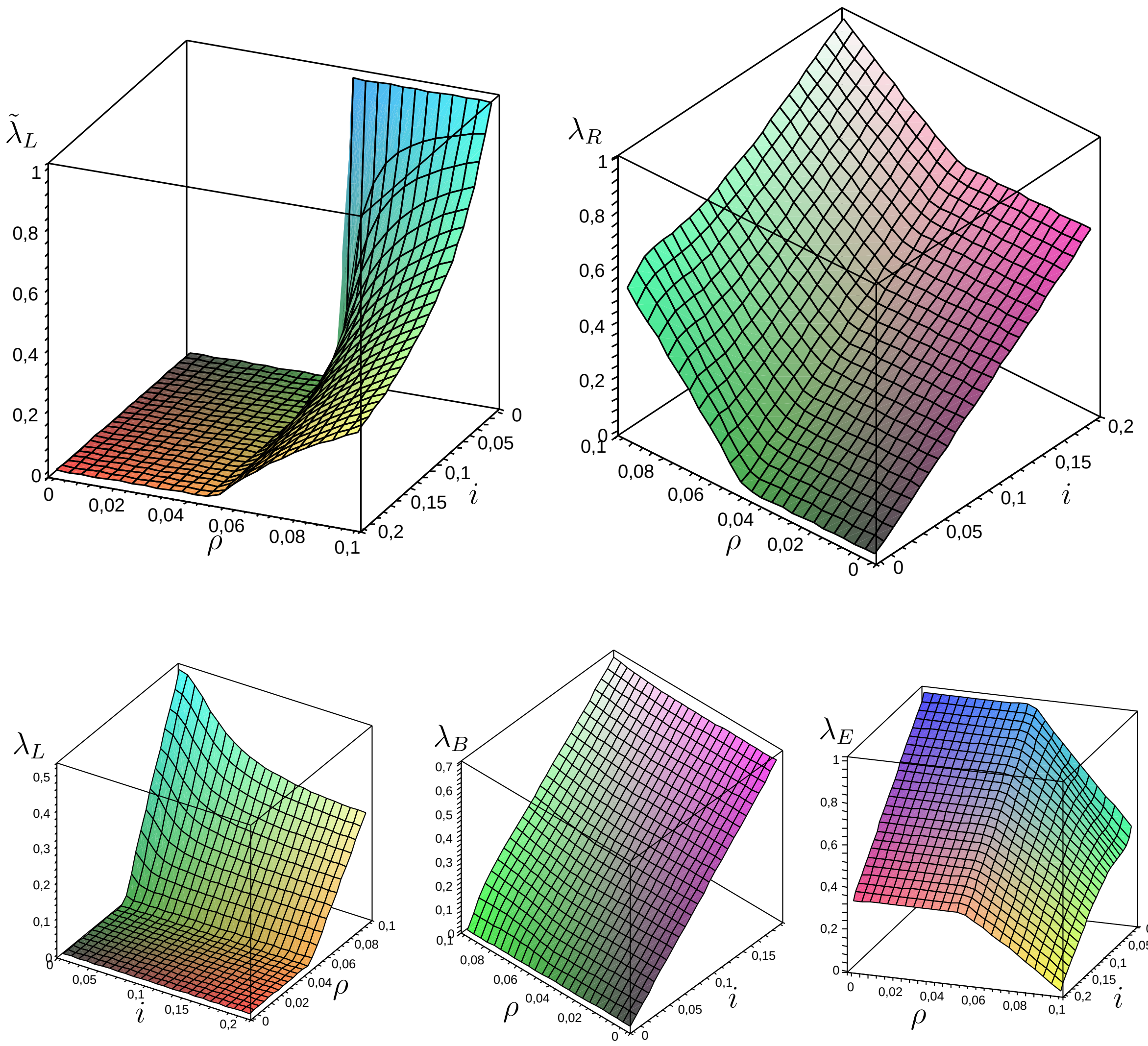

Figure 2.3: Structural variables: structure of the risky portfolio $\tilde{\lambda}_L$ and share of the risky portfolio λ_R (first row), resulting shares $\lambda_L, \lambda_B, \lambda_E$ of the total portfolio (second row)

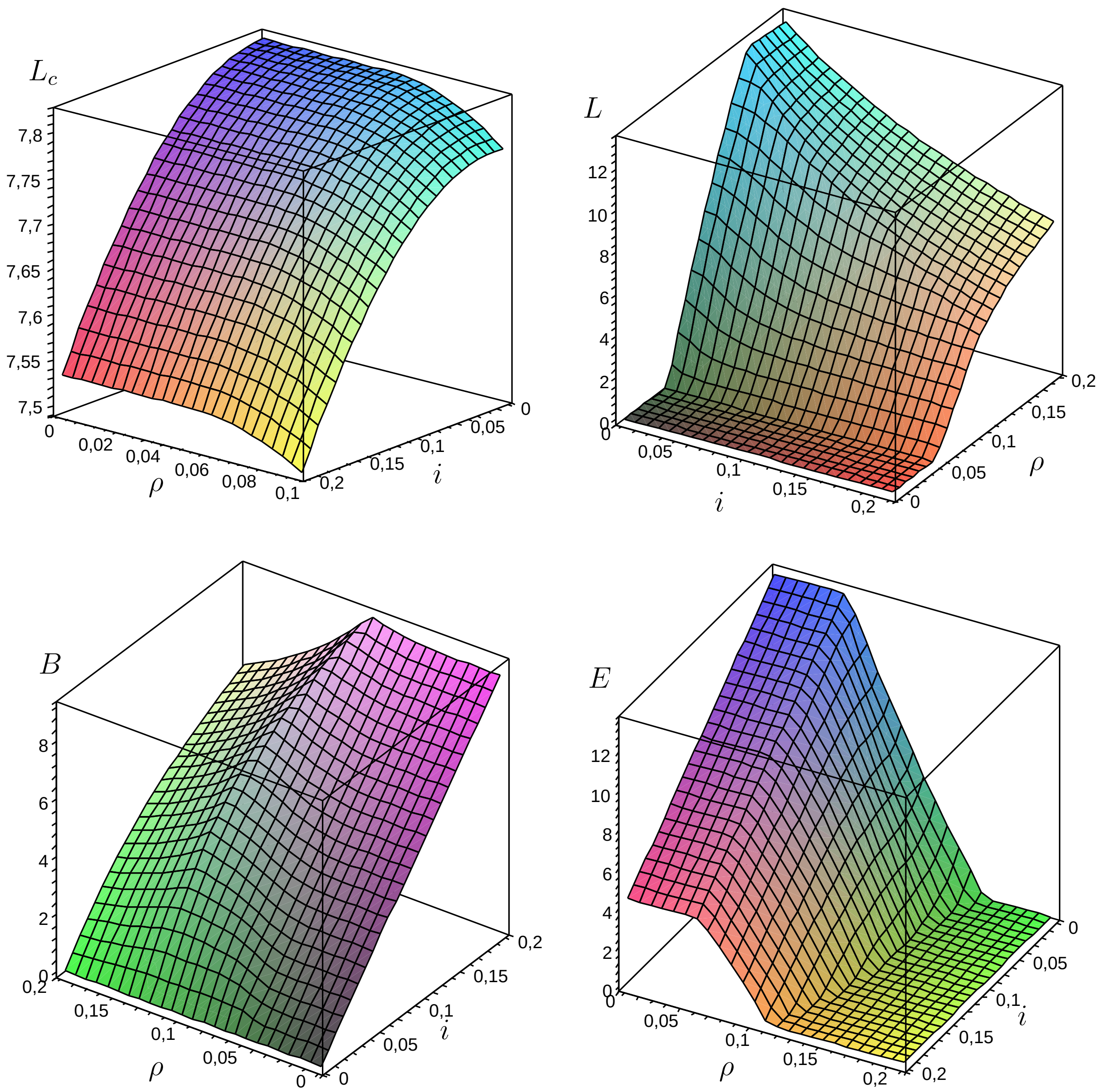

Figure 2.4: Behavioral functions: Reserve demand L_c, credit supply L, bonds demand B, excess reserve demand E (with fixed deposits D)

Chapter 3

Financial Networks and Systemic Risk

3.1 Introduction

The financial crisis of 2007/08 highlighted, among other things, the necessity of macroprudential oversight of the financial system in addition to the existing microprudential supervision. To ensure the stability of the financial system, it is important to not only monitor the strength of individual financial institutions themselves, but also to analyse the network structure that they form due to their various interlinkages. Because of the banks dependency on access to liquidity, interbank loans are amongst the most vital interconnections between banks. In normal times, banks with excess liquidity provide loans to banks with a liquidity shortage, usually on a short-term basis and without underlying collateral. These interconnections between banks can enhance liquidity allocation and risk sharing in the banking system.

There is, however, a downside to the interconnectedness of the banking system. As was seen in September 2008, interbank markets display a *"robust-yet-fragile behaviour"* - the very same interconnections that lead to an enhanced liquidity allocation in normal times, can amplify shocks in times of a crisis. Central banks around the world were forced to undertake unprecedented non-standard measures to reduce money-market spreads and ensure liquidity provision to and distribution within the banking system. Even though the direct effects of the crisis on the South African financial system were very modest and the South African interbank market escaped the problems experienced in some other countries, systemic risk and contagion in interbank markets are a continuous concern for central banks. The urgency of addressing systemic risk and the soundness of systemically important financial institutions was emphasized by the Group of Twenty (G20) leaders at the Pittsburgh Summit, where it was agreed that *"the prudential standards for systemically important institutions should be commensurate with their systemic importance"*.

The purpose of this chapter is twofold. Firstly, it analyses the interbank network structure of the South African banking system from April 2005 until June 2010 with measures from network theory and thereby provides a useful tool for macroprudential oversight. The analysis shows that the South African interbank market was stable both according to the number of participants and according to the level of their interconnectedness. This result is confirmed by the high clustering coefficient that has been observed and the low average path length, both indicating the high availability of liquidity in the period under investigation.

Secondly, an index to measure the systemic importance of South African banks from a network perspective is proposed. This index can be used as a building block to impose prudential requirements on firms commensurate with their systemic risk. Such prudential requirements would help to further strengthen the trust in the stability of the South African interbank market. The proposed index is a relative measure in the sense that the systemic importance of one bank depends not only on the properties of that bank, but also on properties of the whole network. This makes a particular banks systemic significance less predictable and less constant. Banks themselves cannot be totally certain at any given point in time about their ranking in terms of systemic significance within the interbank market. As a result, the index is less prone to moral hazard, which is a major concern in the discussion of systemically important financial institutions (SIFIs).

This chapter is organized as follows: After a short introduction, section (3.2) gives an overview of attempts to define systemic risk in the international context. Section (3.3) motivates the use of network theory to assess systemic risk in interbank markets while section (3.4) shows the results of various measures from network theory in the South African interbank market. Section (3.5) introduces the Network Systemic Importance Index (NSII) and shows the result for three groups of South African banks. In section (3.6) it is argued that the NSII is less prone to moral hazard, while section (3.7) concludes.

3.2 Systemic Risk

In the literature there are a large number of definitions of systemic risk, each emphasizing a certain aspect of it. The International Monetary Fund et al. (2009) states that most G20 countries do not have a formal definition of systemic risk either. Most commonly accepted, however, is the distinction between a broad and a narrow sense of systemic risk, as described by Bandt et al. (2009). In this classification, contagion effects on interbank markets pose a systemic risk in the narrow sense, whereas in the broad sense it is characterised as a common shock to many institutions or markets. This distinction is followed by the Financial Stability Board (FSB) who defines systemic risk as *"a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy"*. The European Central Bank (ECB) suggests that systemic risk can be described as the risk of experiencing a strong systemic event that adversely affects a number of systemically important intermediaries or markets (see

European Central Bank (2009)). The trigger of the event could either be a shock from outside or from within the financial system. The systemic event is strong when the intermediaries concerned fail or when the markets concerned become dysfunctional. Since all these different dimensions of a systemic event interact with each other, it is clear that systemic risk is a highly complex phenomenon. In its analysis, the ECB focuses on three main forms of systemic risk namely contagion risk, the risk of macroeconomic shocks causing simultaneous problems at many financial institutions or markets and the risk of an abrupt unravelling of imbalances that have built up over time.

According to Acharya and Yorulmazer (2003) as well as Nier et al. (2008), informational contagion is another form of systemic risk that has to be taken into account. Especially in times of crises financial markets exhibit a herding behaviour. The insolvency of a bank can increase the cost of borrowing for the remaining banks quite drastically in these situations. The insolvency of the US investment bank Lehman Brothers in September 2008 led to a breakdown of interbank markets not only because of the direct losses that were associated with it, but mainly because it was a signal to financial market participants that their own risk perceptions were incorrect. This led to a surge in riskawareness and risk-aversion and ultimately to the breakdown of interbank money markets. While informational contagion clearly deserves more attention, currently there exists no model to properly assess it.

Following the approach of the European Central Bank (2010a), it is possible to distinguish between four broad analytical approaches to assess the different dimensions of systemic risk. Firstly, financial stability indicators can measure the current state of instability in the financial system. Secondly, early warning models can help assess the likelihood and severity of systemic crises. Thirdly, stress-tests of the financial system can be used to analyze the impact of macro-shocks. Lastly, contagion and spillover models can be employed to analyze how initial shocks spread throughout the financial system. While central banks today have to employ all four types of models to properly assess systemic risk, the academic literature is at different stages in the development of those tools.

It was recently emphasized by e.g. Borio (2010) that the distinction between the time- and cross-sectional dimensions of aggregate risk is critical. In the time-dimension leading indicators of financial distress are needed, while in the cross-sectional dimension a robust quantification of the contribution of each institution to systemic risk is necessary. There exists a growing literature on cross-sectional measures to assess systemic risk (see e.g. Tarashev et al. (2009), Huang et al. (2009a), Acharya et al. (2010b), Adrian and Brunnermeier (2009), or Segoviano Basurto and Goodhart (2009)). The NSII proposed in this chapter falls into the second strand of models as it contributes the systemic risk in the interbank to individual institutions.

3.3 Network Theory

A new approach to assess systemic risk in financial markets originates from network theory and has been widely applied to ecology, neuroscience, biochemistry, epidemology, social sciences and computer science. The neural network of the worm C-Elegans, the structure of the world-wide-web, the power grid of the United States and the spreading of the HI virus have all been analysed using network theory. The increase in computing power in recent years has led to a vast increase in the research of large and complex systems and some of the results, especially from Epidemology, can be applied to the analysis of financial networks. A financial network consists of a set of banks (nodes) and a set of relationships (edges) between the banks. Even though many relationships exist between banks, this chapter focuses on relationships that stem from interbank lending. For the originating (lending) bank the loan will be on the asset side of its balance sheet, while the receiving (borrowing) bank will hold the loan as a liability.

3.3.1 Financial Networks and Systemic Risk

As for example Allen and Babus (2008) argue, linkages between financial institutions can stem from both the asset side (through holding similiar portfolios) and the liabilities side (by sharing the same mass of depositors). These linkages can be direct (as in the case of interbank loans) and indirect (as in the case of similiar portfolios). The authors investigate the resilience of financial networks to shocks and the formation of financial networks. Network theory has also been successfully applied in the analysis of payment systems (see e.g. Soramäki and Galbiati (2008) or Markose et al. (2010)). Castrén and Kavonius (2009) apply network theory to study accounting-based balance sheet interlinkages at a sectoral level. Canedo and Jaramillo (2009) propose a network model to analyse systemic risk in the banking system and seek to obtain the probability distribution of losses for the financial system resulting both from the shock/contagion process. Nier et al. (2007) construct a network model of banking systems and find that (i) the banking system is more resilient to contagious defaults if its banks are better capitalized and this effect is non-linear; (ii) the effect of the degree of connectivity is non-monotonic; (iii) the size of interbank liabilities tend to increase the risk of a knock-on default; and (iv) more concentrated banking systems are shown to be prone to larger systemic risk. In Gai and Kapadia (2009) the authors investigate systemic crises with a network model and show that on the one hand the risk of systemic crises is reduced with increasing connectivity on the interbank market. On the other hand, however, the magnitude of systemic crises increases at the same time. Georg and Poschmann (2010) employ network theory to analyze contagion and common shock effects in a model of interbank markets with central bank activity. They show that common shocks are not subordinate to contagion, but pose instead a greater threat to systemic stability.

Contagion in interbank markets emerges if, for example, Bank A, which has an interbank loan from Bank B, is hit by a shock and goes into insolvency. Bank B then suffers a loss on its assets and might itself become insolvent if it does not have enough bank capital. If Bank C now has an exposure to Bank B, this could also cause solvency problems for Bank C. Now Bank C faces problems, even though it had no immediate interconnection with Bank A, which was the root of the shock. Even from this very simple example one can see that microprudential supervision and regulation is inadequate on its own to identify potential routes of contagion and assess the stability of a financial system.

The situation is even more complex when other interlinkages between banks are taken into account, caused for example by investing into a similar class of assets. To illustrate this form of systemic risk Whelan (2009) considers three banks - Bank A, B and C whose balance sheets are shown in Table (3.1). Now assume that Bank A makes an initial loss of 5 on its loan book. This will reduce its equity capital to 5 and increase its leverage ratio from $200/10 = 20$ to $195/5 = 39$, putting it close to, or below, the capital adequacy ratio. This very modest initial loss then forces A to sell some of its securities. Originally its securities were worth 40 but since Bank A has to do away with them in a fire-sale, the bank sells half of them and recoups only 18 instead of their original value of 20. The reduced value of Bank As securities will reduce its equity capital to 1, as it suffers a loss of 2 on the securities it sold and a mark-to-market loss of 2 on the remaining securities. Now Banks B and C are hit with two problems: since Bank A has been selling its securities in a fire-sale, the securities of Bank B and Bank C are now worth only 36. This reduces their equity capital from 10 to 6. Needing to shrink their balance sheets and worried about Bank As solvency, they decide to not roll-over their loans to A. Bank A now has to repay the loans to Bank B and Bank C but with almost no equity and the value of its securities falling, it fails to do so. Banks B and C now suffer losses on their own loan book as well as on their securities and are then just as vulnerable as Bank A, even without directly suffering the initial loss.

There are various attempts to assess systemic risk in a broad context. Lehar

Assets		Liabilities	
Loans to Customers	100	Retail Deposits	130
Loans to B	30	Borrowing from B	30
Loans to C	30	Borrowing from C	30
Other Securities	40	Equity Capital	10
Total	200	Total	200

Table 3.1: Example balance sheet of bank A. Banks B and C analogous. Source: Whelan (2009).

(2005) estimates the risk of a common shock by the correlation between institutions asset portfolios. Brunnermeier et al. (2009) propose to apply leverage, maturity mismatch or the rate of expansion to measure systemic risk. Acharya et al. (2009) recommend to measure an institution's contribution to aggregate risk based on its marginal VaR and its marginal expected shortfall. Acharya et al. (2010b) proposes to assess the systemic expected shortfall, which indicates how much an institution is prone to undercapitalize when the financial system is also undercapitalized. Haldane (2009) suggests to measure contagion based on the interconnectedness of each institution within the financial system, whereas Adrian and Adrian and Brunnermeier (2009) focus on CoVaR, which is the value at risk of the whole financial sector in times of crisis. They argue to interpret the difference between CoVar and the institution's specific value at risk as the institution's contribution to systemic risk. Tarashev et al. (2009) propose to apply the Shapley value methodology to asses this contribution. Thomson (2009) provides a scoring model to categorize each institution according to its contribution to systemic risk. Eligible criteria are size, contagion, correlation, concentration and economic conditions.

3.3.2 Data Gaps

Despite the importance of macroeconomic shocks to financial stability, policy makers and academia are faced with huge information and data gaps. A number of suggestions on how to close these gaps have been made in the past two years Financial Stability Board et al. (2009a), but the issue is far from resolved. The unavailability of data makes it impossible, for all practical purposes, to properly measure the systemic risk that is associated with cross-correlations amongst banks portfolios. Yet, it is clear that structured finance and derivatives have increased the number of cross-correlations between different portfolios. In South Africa, the fraction of derivative financial instruments to the total balance sheet volume is much smaller than in the United States, the United Kindom or the Euro-area, for example. This is not to say that there are no cross-correlations amongst the portfolios of the South African banks. Especially the large banks all depend heavily on short-term wholesale funding, which effectively introduces cross-correlations between their portfolios that have to be taken into account when assessing the vulnerability of the South African banking system to macroeconomic shocks.

3.3.3 The Structure of Interbank Networks

Even with the aforementioned limitations, network theory can provide valuable information about the health and stability of the banking system. This is underlined by the large number of countries that have employed network theory to assess systemic risk. Basically there are two strands of literature. One strand follows Eisenberg and Noe (2001) who develop a liabilities matrix for a financial system and show that it has a unique clearing payment vector. Sheldon and Maurer (1998) construct a matrix of interbank loans for Switzerland based on known marginal loan distributions and the principle of entropy maximisation. Blåvarg and Nimander (2002) construct the matrix of interbank exposures from the reports of Swedish banks to the Riksbank. Upper and Worms (2004) analyze the risk of contagion in the German interbank market using data from banks submitted to the Bundesbank. They apply the principle of entropy maximisation to construct the matrix of interbank exposures. Wells (2004) constructs the matrix of bilateral exposures by using data on UK banks money market loans and deposits with other UK-resident banks. Degryse and Nguyen (2007) use detailed information on aggregate interbank exposures of individual banks and on large bilateral interbank exposures of the Belgian banking system to construct the matrix of interbank exposures. They analyse the years 1993 - 2002 and find that the structure of the Belgian banking system has changed from a complete structure to a "multiple-money-centre" structure. van Lelyveld and Liedorp (2004) use several data sources, including monthly balance sheet data, large exposures and survey data from an ad hoc survey obtained from the largest ten banks in the Netherlands to construct the matrix of interbank exposures. Boss et al. (2004) study the Austrian interbank market with a combination of actual interbank exposures (for large loans) and an estimation technique, and were able to show that the degree distribution of the interbank network shows two different power law exponents, relating to two different sub-network structures, differing in the degree of hierarchical organization. They identified the Austrian interbank network to be a small-world network.

Another strand of literature uses payment system data and actual interbank exposures to analyze systemic risk. Furfine (1999) examines the likelihood that a failure of one bank would cause the subsequent collapse of a large number of other banks in the US using the Federal Reserve's large-value transfer system Fedwire. Mistrulli (2007) uses actual interbank exposure data from the Bank of Italy Supervisory Reports database to analyze the risk of contagion in the Italian interbank market. The results are compared to the analysis of contagion in the Italian interbank market if the maximum entropy method is used. It is shown that the maximum entropy method leads to an overvaluation of the severity of contagion, which is in contrast with the common view that complete markets are more resilient to financial contagion. Memmel and Stein (2008) use data from the German credit register and of the regulatory reports filled in by the banks, to analyze contagion risk in the German interbank market. Gabrieli (2010) and Gabrieli

(2011) analyzes the functioning of the overnight unsecured euro money market during the ongoing crisis in terms of operational efficiency of monetary policy implementation, efficient reallocation of banking systems reserves and developments in the pricing of interbank loans using data on unsecured euro-denominated loans executed through the e-MID platform (which represents roughly 17% of the total turnover of the overnight segment). The results suggest that monetary policy implementation has been hampered by the crisis, particularly after the end of September 2008. Becher et al. (2008) examine the broad network topology of interbank payments in the United Kingdom and show that the UK financial system exhibits a tiered structure, making it distinctly different from the United States' financial system. They use data from the Clearing House Automated Payment System (CHAPS) 2003 data survey, which includes intraday data for 5 days in February 2003.

Chang et al. (2008) analyze the market structure and degree of completeness and heterogeneity in order to assess the financial fragility of the Brazilian financial system. They apply the Hirschman-Herfindahl index (HHI) which was used by Nissan (2004) and Geldos and Roldós (2004) to evaluate the concentration of banking systems in developing countries, as well as the dual HHI that was analyzed by Tabak et al. (2009). They analyze the concentration, heterogeneity and completeness of the Brazilian banking system. Cajueiro and Tabak (2007) analyze the topology of the Brazilian interbank market. They introduce different measures, such as (weighted) degree, (weighted) efficiency, domination and the minimal spanning tree to analyze the topology of the interbank network. They could show that the Brazilian interbank market employs a scale-free toplogy and is characterized by money-center banks. Manna and Iazzetta (2009) use network theory to analyze monthly data on deposit exchanged by banks on the Italian interbank market from 1990 to 2008. They find that there is no direct connection between interconnectedness and volume of banks, leading to the question which of the three by International Monetary Fund et al. (2009) proposed criteria (volume, interconnectedness, and substitutability) gives the largest contribution to systemic risk.

We follow the second strand of literature and use actual exposures of banks obtained from the South African Multiple Option Settlement (SAMOS) system. Unlike Europe and the United States, the majority of interbank payments in South Africa are made via the SAMOS system, giving a uniquely accurate overview of the actual payments between banks. In total, there were nearly 13 million transactions taken into account over the period March 2005 to June 2010. Interbank loans were identified by the matching algorithm of Furfine (1999) where for each transaction from Bank A to BankB, the algorithm searches for a matching transaction in the opposite direction. We focussed on interbank loans that are overnight, as these loans are the most prominent type of interbank loans and also represent the most rapid contagion channel for interbank systemic risk. We further required the loans to be larger than 10 Million Rand in order to enhance the probability that a transaction is indeed an interbank loan and not a retail transaction. The data set used in this analysis is one of the most extensive ones ever used to assess the stability of an interbank system on the basis of actual exposures. The analysis therefore can contribute to strengthening the trust in the long-term stability of the South African interbank system.

3.3.4 Network Measures

To analyze the structure of the South African interbank system, we make extensive use of tools and notions from network theory. We therefore give a brief overview of network and graph theory to introduce the necessary measures. We follow the notation by Manna and Iazzetta (2009) and start by defining what a graph is:

Definition 1 *A (un)directed graph $G(V, E)$ consists of a nonempty set V of vertices and a set of (un)ordered pairs of vertices E called edges. If i and j are vertices of G, then the pair ij is said to join i and j.*

One sometimes speaks of graphs as networks and the two terms are often used interchangably. Since the focus of this chapter is on interbank markets, the nodes of a network are (commercial) banks and the edges are interbank loans between two banks. For every graph a matrix of bilateral exposures which describes the exposure of bank i to bank j can be constructed.

Definition 2 *The matrix of bilateral exposures $W(G) = [w_{ij}]$ of an interbank market G with n banks is the $n \times n$ matrix whose entries w_{ij} denote bank i's exposure to bank j. The assets a_i and liabilities l_i of bank i are given by $a_i = \sum_{j=1}^{n} w_{ij}$ and $l_j = \sum_{j=1}^{n} w_{ji}$.*

Closely related to the matrix of bilateral exposures is the adjacency matrix that describes the structure of the network without referring to the details of the exposures.

Definition 3 *The entries a_{ij} of the adjacency matrix $A(G)$ are one if there is an exposure between i and j and zero otherwise.*

One can define the interconnectedness of a node as the in- and out-degree of the node.

Definition 4 *The in-degree $d_{in}(i)$ and out-degree $d_{out}(i)$ of a node i are defined as:*

$$d_{in}(i) = \sum_{j=1}^{n} a_{ji} \quad , \quad d_{out}(i) = \sum_{j=1}^{n} a_{ij} \tag{3.1}$$

and give a measure for the interconnectedness of the node i in a directed graph $G(V,E)$. The two degrees are equal for directed graphs.

One can define the size of a node i analogously to its interconnectedness in terms of the value in- and out-degree.

Definition 5 *The value in- and out-degree of a node are defined as:*

$$vdc_{in}(i) = \frac{\sum_{j=1}^{n} w_{ji}}{\sum_{k=1}^{n} \sum_{j=1}^{n} w_{kj}} \in [0,1] \tag{3.2}$$

$$vdc_{out}(i) = \frac{\sum_{j=1}^{n} w_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} w_{jk}} \in [0,1] \tag{3.3}$$

and give a measure for the size of the node. The value in-degree is a measure for the liabilities of a node while the value out-degree is a measure for its assets.

A quantity that can be used to characterise a network is its average path length. The average path length of a network is defined as the average length of shortest paths for all pairs of nodes $i, j \in V$. Another commonly used quantity to describe the topology of a network is the clustering coefficient, introduced by Watts and Strogatz (1998) in their seminal work on small-world networks. Given three nodes i, j and k, with i lending to j and j lending to k, then the clustering coefficient can be interpreted as the probability that i lends to k as well. For $i \in V$, one define the number of opposite edges of i as:

$$m(i) := |\{j,k\} \in E : \{i,j\} \in E \text{ and } \{i,k\} \in E| \tag{3.4}$$

and the number of potential opposite edges of i as:

$$t(i) := d(i)(d(i) - 1) \tag{3.5}$$

where $d(i) = d_{in}(i) + d_{out}(i)$ is the degree of the vertex i. The clustering coefficient of a node i is then defined as:

$$c(i) := \frac{m(i)}{t(i)} \tag{3.6}$$

and the clustering coefficient of the whole network $G = (V, E)$ is defined as:

$$C(G) := \frac{1}{|V'|} \sum_{i \in V'} c(i) \tag{3.7}$$

where V' is the set of nodes i with $d(i) \geq 2$. The average path length of the whole network can be defined for individual nodes. The single source shortest path length of a given node i is defined as the average distance of this node to every other node in the network.

It is possible to distinguish between a number of networks by looking at their average path length and clustering coefficient. One extreme type of networks are regular networks which exhibit a large clustering coefficient and a large average path length. The other extreme are random networks which exhibit a small clustering coefficient and a small average path length. Watts and Strogatz (1998) define an algorithm that generates a network which is between these two extremes. They could show that the so-called *"small-world networks"* exhibit both, a large clustering coefficient and small average path length. A large number of real networks like the neural network of the worm Caenorhabditis elegans, the power grid of the western United States, and the collaboration graph of film actors are small-world networks. From a systemic risk perspective, small-world networks are interesting, as it is reasonable to assume that the short average path length and high clustering of small-world networks make them more vulnerable to contagion effects than random or regular networks. Small-world networks can be created by using the algorithm defined in Watts and Strogatz (1998). Starting point is a regular networks of N nodes where each node is connected to its m neighbours. The algorithm now loops over all links in the network and rewires each link with a probability β. For small values of β (about 0.01 to 0.2) the average path length drops much faster than the clustering coefficient so one can have a situation of short average path length and high clustering. On the left side of Figure 3.1 is a small-world network with $N = 100$, $m = 4$ and $p = 0.05$ shown.

Another interesting class of networks are scale-free networks. They are characterized by a logarithmically growing average path length and approximately algebraically decaying distribution of node-degree (in the case of an undirected network). They were originally introduced by Barabási and Albert (1999) to describe a large number of real-life networks as e.g. social networks, computer networks and the world wide web. To generate a scale-free network one starts with an initial node and continues to add further nodes to the network until the total number of nodes is reached. Each new node is connected to k other nodes in the network with a probability that is proportional to the degree of the existing node. When thinking about financial networks, this preferential attachment resembles the fact that larger and more interconnected banks are generally more

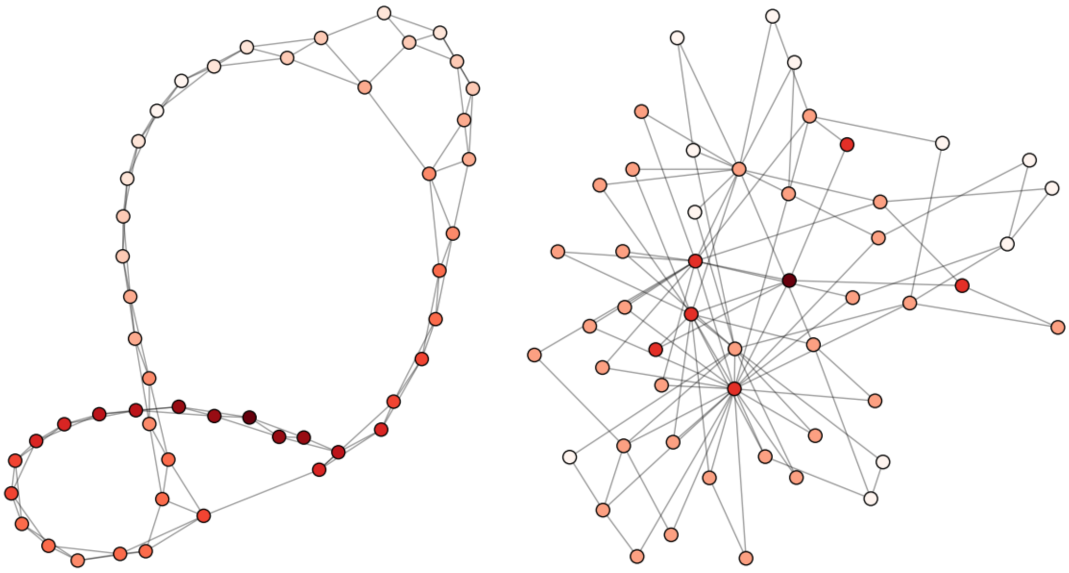

Figure 3.1: On the left: a small-world network that was created using the algorithm of Watts and Strogatz (1998) with $N = 50$, $k = 4$ and $\beta = 0.05$. On the right: a scale-free network that was created using the methodology introduced in Barabási and Albert (1999) with $N = 50$ and $m = 2$. The colour is an indication for the single source shortest path length of the node and ranges from white (large) to red (short).

trusted by other market participants and therefore form central hubs in the network. On the right side of Figure 3.1 a scale-free network with $N = 50$ and $k = 2$ is shown.

A typical feature of scale-free networks is their degree-distribution, as it typically follows a power-law. The exponent of the power-law can be measured and characterises the network topology for different networks. Boss et al. (2004) show that the degree distribution of the Austrian interbank market follows a power law with an exponent of $\gamma = -1.87$. Cajueiro and Tabak (2007) analyze the topology of the Brazilian interbank market. They show that the Brazilian interbank market employs a scale-free toplogy and is characterized by money-center banks. Iori et al. (2008) and Manna and Iazzetta (2009) report that the Italian interbank market shows a similiar scale-free behaviour. Cont and Moussa (2009) show that a scale-free interbank network will behave like a small-world network when Credit Default Swaps (CDS) are introduced. In this sense a CDS acts as a “short-cut” from one part of the network to another. This chapter therefore focuses on these three classes of networks (random, scale-free and small-world) to analyze their effect on systemic risk through contagion effects.

3.4 Network Measures of the South African Interbank System

In order to describe the network topology of the South African interbank system, one can resort to measures from network theory. Four properties were used to describe a network in this note. The first one is the size of the network, given by the number of nodes in the network and shown in Figure 1 on the left axis. The second measure is the connectivity of the interbank market. This is defined as the fraction of actual edges to possible edges between nodes and called the connection level. It can range from 0 (no interconnections) to 1 (every bank is connected to every other bank) and shown in Figure (3.2) on the right axis. In normal times a high connection level will lead to a more stable system as banks can access liquidity from more sources.

In the South African system, the number of banks (nodes) that participate in interbank lending varied between 15 and 18, while the connection level varied between 0,33 and 0,50. It can be seen that the system is largely stable both by looking at the fairly stable number of banks that participate in interbank lending and the relatively high level of connections between the banks. The large number of banks actively participating in the interbank market also indicates the availability and reliability of the SAMOS system.

The third quantity that is used to determine the structure of the interbank system is the average path length, which is defined as the average number of connections that is needed to transfer liquidity from one bank to another. In normal times a small average path length indicates a well connected system, where liquidity

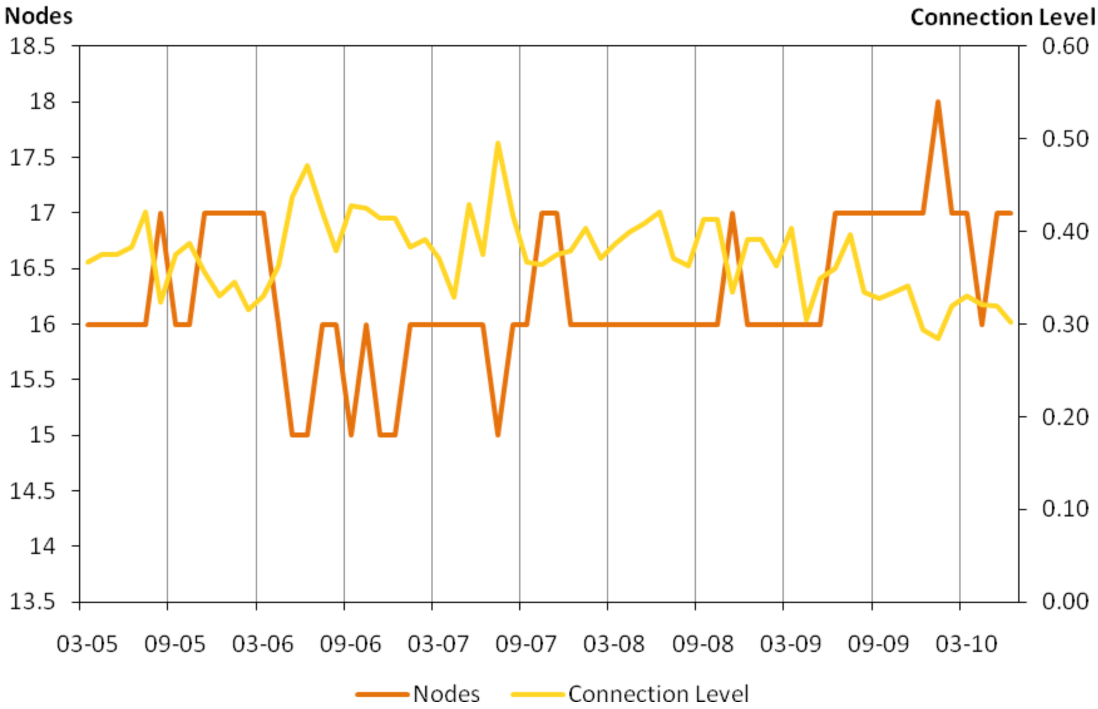

Figure 3.2: Network properties of the South African interbank market. Source: South African Reserve Bank, SAMOS Data.

can easily be transferred from one bank to another. In times of crises, however, a short average path length also implies that contagion can spread faster through the system. Note that the average path length does not give any indication of the probability of an initial knock-on default but rather describes how such an exogenous event can spread in the system.

The fourth measure of the network topology is the clustering coefficient, which is defined as the probability of two banks being exposed to each other, if both of them are exposed to a common third bank. A high clustering coefficient, similar to the average path length, indicates a well connected interbank system where banks distribute liquidity widely in the system. In times of crises, however, a high clustering coefficient increases the risk of joint failure of banks. In Figure (3.3) the results for average path length (left axis) and clustering coefficient (right axis) are shown.

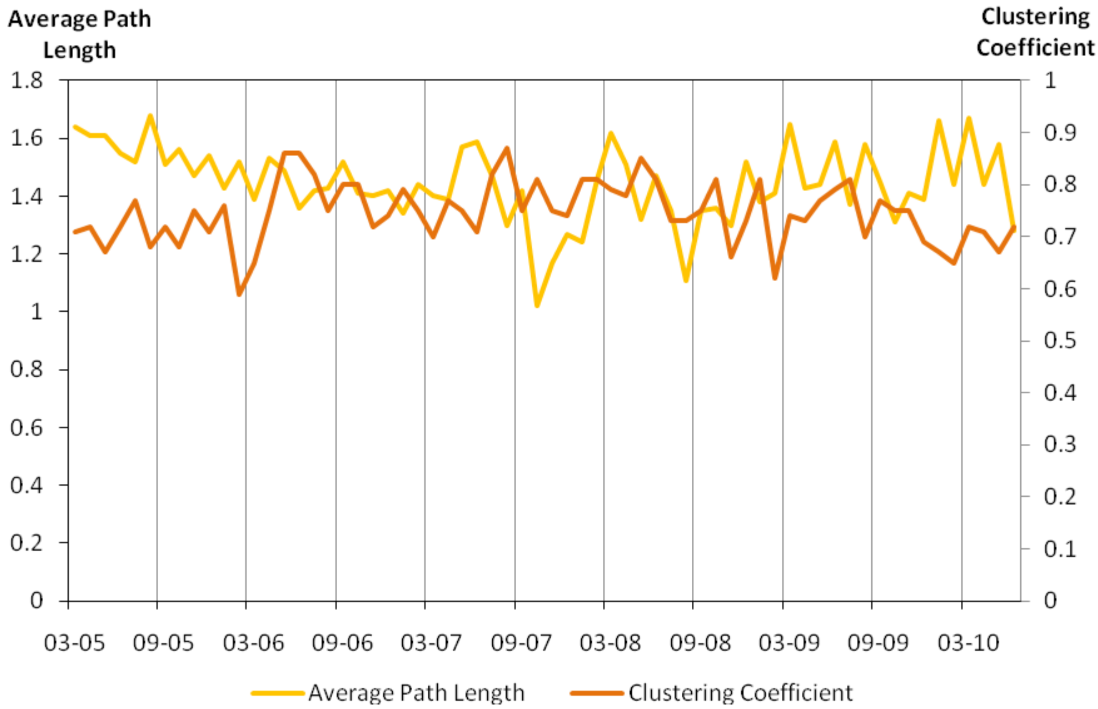

Figure 3.3: Clustering and Average Path Length of the South African Overnight Interbank market. Source: South African Reserve Bank, SAMOS Data.

The short average path length and high clustering coefficient of the South African interbank system vary little over time, indicating a stable network structure even in times of distress such as the crisis on the international financial markets in September and October 2008. These results are in line with the findings of Brink (2009) stating that the direct impact of the financial crisis of 2007/08 on the South African interbank market were modest.

3.5 The Systemic Importance Index for South African Banks

While the results above are measures of the global network topology, a more detailed view of individual banks is needed in order to assess their individual systemic importance. The FSB proposes three key criteria to determine the systemic importance of markets and institutions namely size (the volume of financial services provided by the individual component of the financial system), substitutability (the extent to which other components of the system can provide the same services in the event of a failure) and interconnectedness (linkages with other components of the system).

These measures can be translated into measures from network theory. To assess the systemic risk that is associated with a given bank, one has to look at the impact that a default of this bank would have on the rest of the system. In case of insolvency it will be the banks liabilities that determine its size for the purpose of this note. The impact of a shock that originates from this bank will increase the larger its interbank liabilities. The second variable to assess the systemic risk associated with a given bank is its interconnectedness. As in the case for interbank liabilities, the impact of a shock will be larger if the bank is more connected to the rest of the system. In terms of a network measure it is therefore the number of edges that originate from somewhere in the system and end at the given bank that depict its systemic importance. In network theory this is referred to as the node in-degree of the bank. The third and most complicated measure is a banks substitutability. A bank will be difficult to substitute if it receives and originates a lot of interbank funding. It will therefore be harder to substitute if it is in the middle of many interbank payment flows and its systemic importance will increase the harder it is to substitute. The network measure that can be associated with this property is a nodes betweenness. It measures the number of shortest paths between any other two nodes in the network, which pass through the node in question. The higher the number of shortest paths that pass through a given node, the more interbank funding flows through this bank and the harder it will be to substitute.

In order to construct the systemic importance index from these three measures, every measure was normalized to be between zero and one. This normalisation was done by taking each variable and dividing it by the maximal variable in the

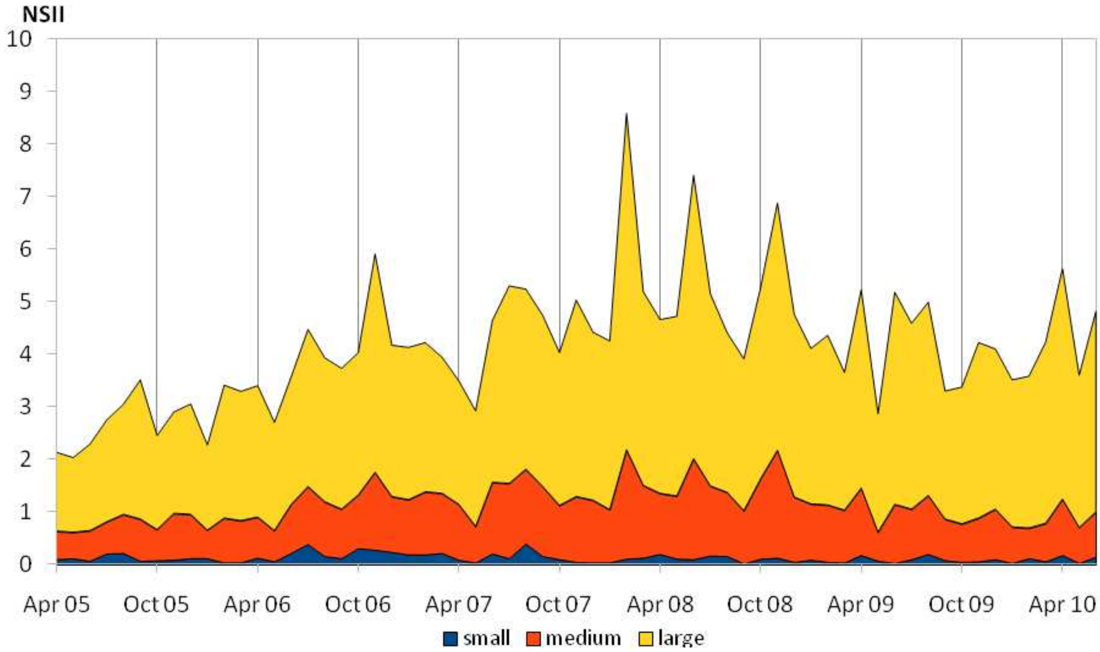

Figure 3.4: Network Systemic Importance Index (NSII) for South African banks. Source: South African Reserve Bank, SAMOS Data.

network. The network systemic importance index (NSII) of any given bank is then the sum of the three submeasures. To account for the fact that the total interbank volume changes over time, the NSII was multiplied with the actual volume of interbank exposures and normalized by the total exposures for the first measurement point, which is March 2005. The NSII will thus measure the systemic importance of individual banks for every month from March 2005 to June 2010. Note, however, that it is a relative measure and will only give the systemic importance of one bank in comparision to other banks in the system.

The results for the NSII of three groups of South African banks are shown in Figure (3.4). The first group consists of "large" banks, comprising all banks that had a network systemic importance index of NSII≥ 2 in June 2010. The groups of "medium" banks consists of all banks with $0.5 \leq$ NSII < 2. All other banks are defined to be "small". The NSII shown in Figure (3.4) is normalized by the number of banks in each of the three groups.

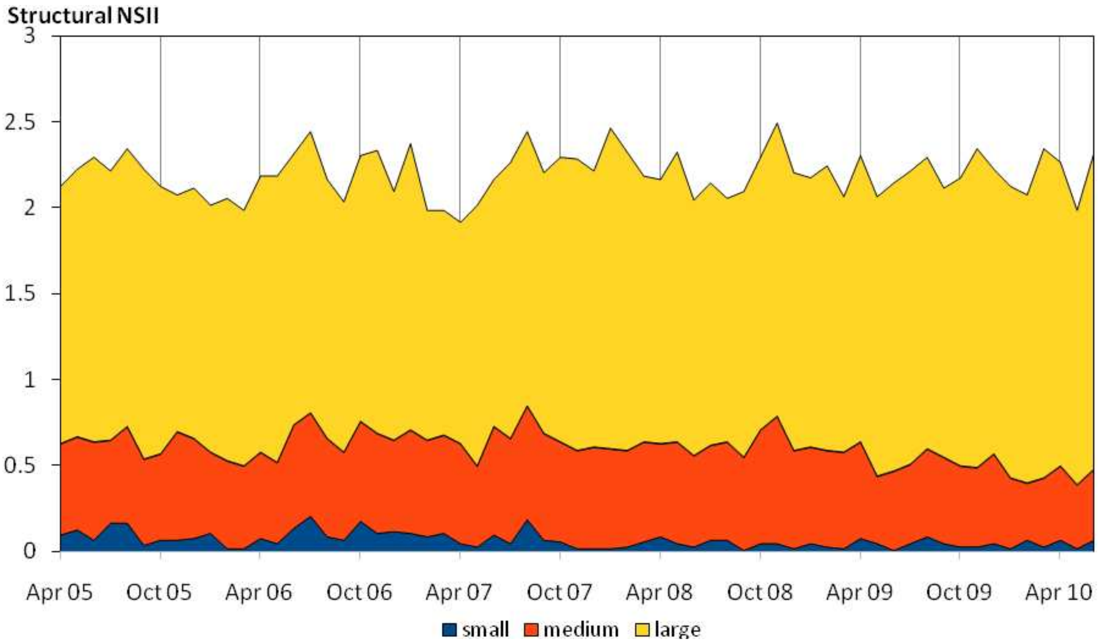

Figure 3.5: Structural component of the NSII for South African banks. Source: South African Reserve Bank, SAMOS Data.

As can be seen in Figure (3.4), the main contribution to systemic importance comes from large banks, while almost no contribution comes from small banks. It is illustrative to look at the structural component of the network systemic importance index, as an increase in the total NSII of a group of banks can also stem from an increase in total market volume. In Figure (3.5) this structural component of the NSII for the South African banks is shown.

It can be seen, that the structural NSII has remained approximately constant over the period under investigation. This indicates a stable network structure during the whole period where the large banks contribute about two third to overall network systemic importance.

In order to properly assess systemic risk of the three groups of banks, one has to analyse which of the three criteria (size, interconnectedness and substitutability) contributes most to the overall NSII of each group. In Figures (3.6)-(3.8) the results for the individual measures are shown for all three groups. They all range

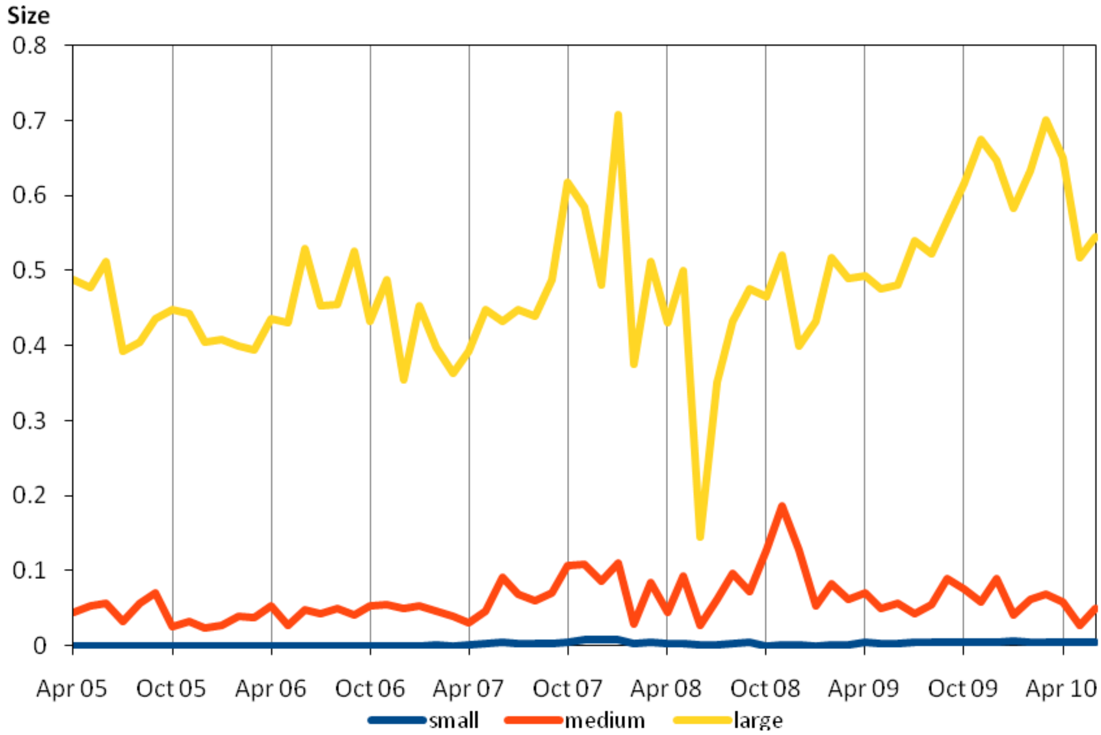

Figure 3.6: Size of South African Banks in the interbank market by bank groups. Source: South African Reserve Bank, SAMOS Data.

from 0 to 1 as they were normalized by first calculating each measure for every individual bank, then dividing them by the maximum value and finally adding them and dividing them by the number of banks in the respective group.

It can be seen from Figure (3.6) that the contribution of size to overall network systemic importance is the largest for large banks, while there is almost no contribution for small banks. The results also indicate that size is a key factor that accounts for the large difference in the systemic importance of large and medium banks and that size is a key difference between medium and small banks.

In Figure (3.7) the connectedness of South African banks in the interbank market is plotted for the three groups of banks. One can see that for all banks a large part of their overall systemic importance stems from their interconnectedness. This holds true for small banks, as their interconnectedness is the only quantity

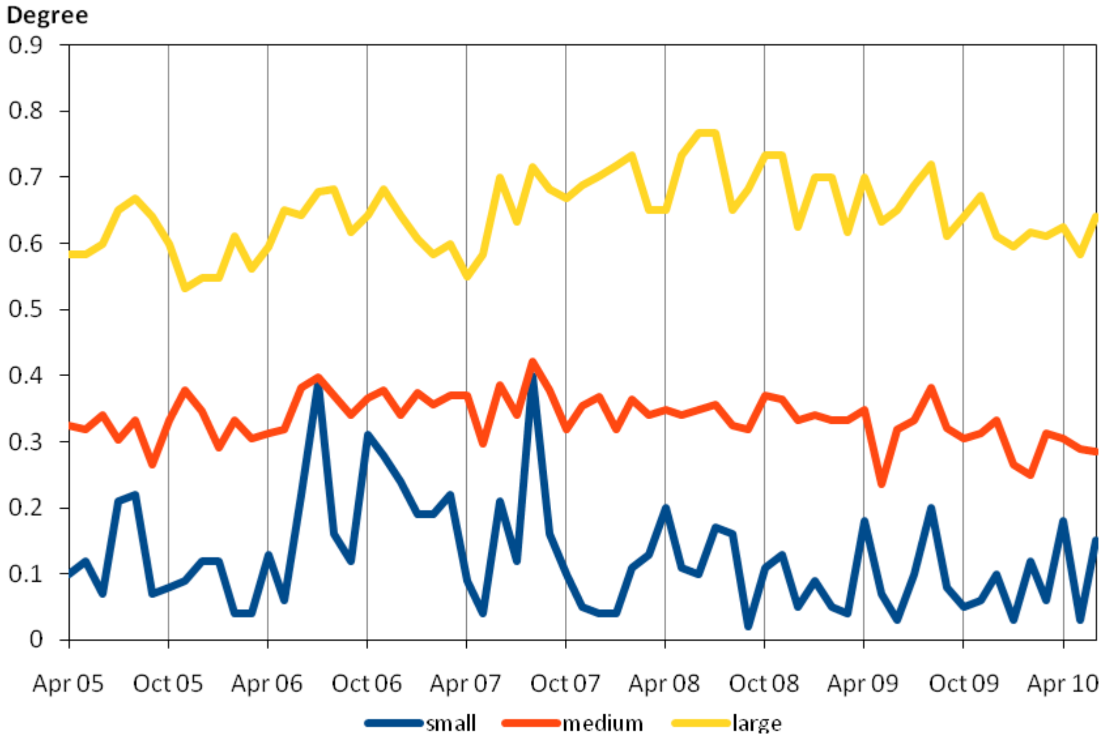

Figure 3.7: Connectedness of South African banks in the interbank market by bank groups. Source: South African Reserve Bank, SAMOS Data.

that contributes to their systemic importance on a relevant level. The medium banks have a contribution from interconnectedness which is significantly larger than for the small banks. The results show that the high interbank transaction volume of large banks goes hand in hand with a large interconnectedness, making them the central hubs of funding flows.

In Figure (3.8) the betweenness of the three groups of banks is shown and it can be seen that the small banks have virtually no betweenness. The betweenness is the quantity that ultimately distinguishes medium from large banks. While the large banks are high in size, interconnectedness and betweenness, the medium banks are moderate in size, moderate in interconnectedness and low in betweenness. Small banks are low in size and betweenness and moderate in interconnectedness. These structural differences between large, medium and small banks should be taken into account when prudential requirements are proposed.

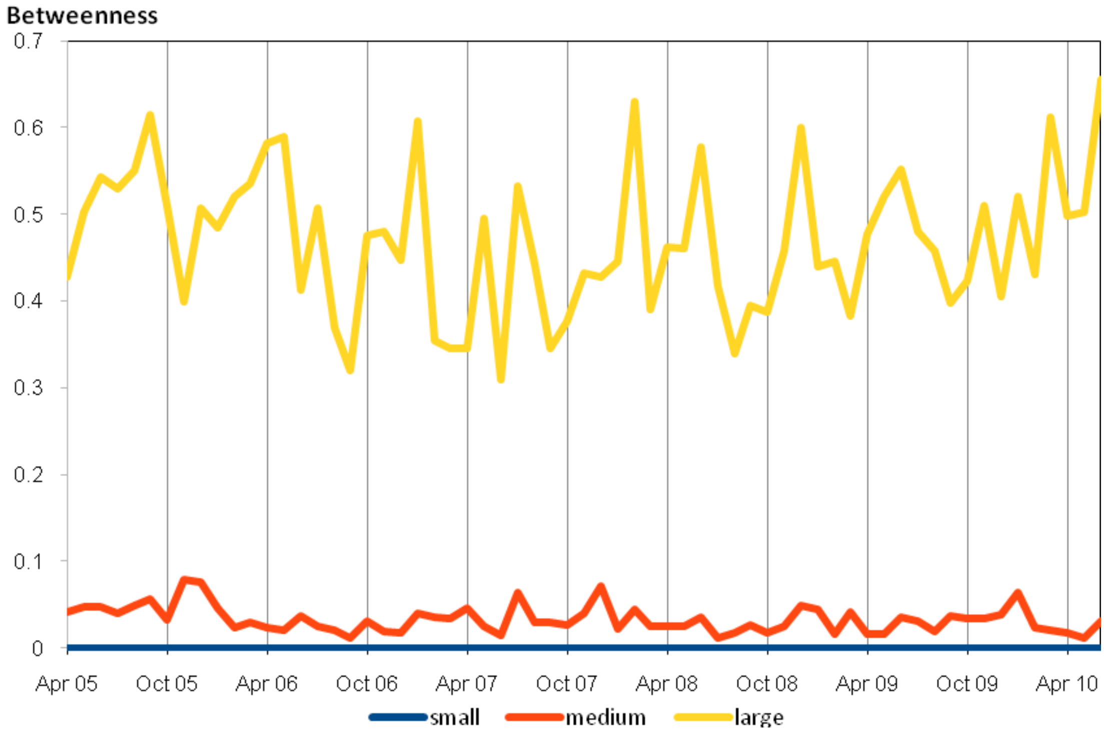

Figure 3.8: Betweenness of South African banks in the interbank market by bank groups. Source: South African Reserve Bank, SAMOS Data.

The overall network systemic importance index is a very volatile quantity that changes on a real-time basis. To interpret this index, one has to look at how the interbank network changes over time. The network structure for overnight and longer-term interbank loans is a structure that is fixed every morning and varies from day to day. This volatile nature of the interbank system does not in itself threaten the stability of the financial system as it indicates a well-functioning interbank system where liquidity is readily distributed amongst its participants.

It is illustrative to display the interbank network structure in order to get a better understanding what a low/high network systemic importance means. The structure of the interbank market is displayed for the period of August 2008 (top left) to January 2009 (bottom right) when the turmoil on the international financial markets was at its highest. The size of each node in the network corresponds to the size of the node in terms of interbank exposure. In the centre of the graph are the largest node (in terms of interbank exposure) and all nodes that are at least half its size, while all other nodes are grouped on the outside. The colour of the nodes is an indication for their interconnectedness and ranges from blue (little interconnectedness) to red (highly interconnected). The size of the edges is a measure for the exposure between two banks, a thicker line indicates higher exposure. The thick end of an edge is an indicator for the direction of the edge. Edges go from the small end to the thick end.

It can be seen that during the whole period there was one bank that had a significantly high systemic importance in terms of size, interconnectedness and betweenness. However, during the whole crisis period there was a well connected interbank system with large liquidity flows inside the system are a signal of trust amongst the South African banks as well as a signal of mistrust of South African banks to foreign banks. This situation is not alarming since the systemic importance of a bank itself is not related to the default probability of this bank. It is nonetheless desirable to have a situation with a low network systemic importance index since this situation will be even more resilient should a shock hit the South African interbank market.

3.6 Moral Hazard

One of the main concerns of attributing systemic importance to individual banks is related to moral hazard and implicit bail-out guarantees. A bank that knows that it will be bailed out, should it default, will be more likely to take on excess risks. The issuance of implicit or explicit bail-out guarantees therefore might increase the risk that the guarantees could actually be needed. While insolvencies are an important part of any healthy market economy, the insolvency of a bank might lead to a breakdown of the financial system as a whole and can have devastating effects on the real economy. These effects can be even more severe in a developing country with a relatively concentrated banking system, like South Africa. It is therefore necessary to keep moral hazard issues in mind when constructing measures for the systemic importance of a bank.

The network NSII is an index that does not solely depend on the properties of an individual bank. It rather depends on the properties of all banks in the interbank system. Even if a bank knows its network systemic importance index at a given point in time, its importance could change very quickly due to the interactions of the other banks. Every bank knows that it can increase its systemic importance by taking on larger risks and more connections in the interbank market. Banks can, however, not be sure that other banks are not doing the same. Since the network systemic importance index is a relative index, there are no guarantees for a bank that increasing exposures will lead to higher systemic importance. It is precisely that relative nature of the NSII that makes it less vulnerable to moral hazard.

In some countries the systemic importance of financial institutions is assessed in a discretionary manner by the central bank, the banking supervision authority and the government. Such a discretionary assessment, however, fails to take the volatile nature of systemic risk into account. And even worse, it creates major moral hazard problems. Banks that are deemed to be systemically relevant according to the discretionary assessment might correctly guess that they are and are therefore directly affected by moral hazard. The implicit bail-out guarantee that has been issued for systemically relevant banks by bailing them out in the financial crisis of 2007/2008 creates incentives for those banks to take on excessive risk. The situation is even worse for banks that are not deemed to be systemically important but assume they are. Those banks also have the incentive to take on excessive risks, but are not covered by a bail-out guarantee. Their insolvency might lead to informational contagion and an increase in the refinancing cost of the remaining banks, which in turn can trigger further defaults. To prevent such a situation, it is strongly desirable to have a transparent measure for the systemic importance of individual financial institutions and markets.

3.7 Conclusion

The NSII defined in this chapter gives valuable insight into the structure of the South African interbank system, thereby representing one of the measures with which to assess systemic significance. With the index it is possible to measure the systemic importance of individual banks on an ongoing, day-to-day, month-to-month or even longer basis. In combination with other measures of systemic significance, this information could be used to impose prudential requirements on firms commensurate with their systemic importance. However, one has to take into account that systemic importance of the different groups of banks is driven by different criteria. Banks in the group of large banks are usually high in size, interconnectedness and betweenness, while medium banks are moderate in size, moderate in interconnectedness and low in betweenness. Small banks are low in size and betweenness and moderate in interconnectedness. It is argued that these structural changes have to be taken into account when further prudential requirements for firms are discussed. The South African banking system has been shown to be stable in terms of structure and number of participants, even in times of high transactional volumes and great distress in the international financial markets.

It is argued that moral hazard is less pressing when the network systemic importance index is taken into account and therefore preferable in this regard to having a secret list of banks that are considered to be systemically important. Moral hazard is less pressing, since the systemic importance of each bank depends not only on its own behaviour, but also on the behaviour and structure of the rest of the banking system.

While the South African interbank system has been proven to be resilient to shocks in the international financial markets, a continuous monitoring of the interbank network structure can help alleviate future stress and provide a tool for cross-section analysis of systemic risk. The network systemic importance index can therefore contribute to further strengthen the stability of the South African financial system.

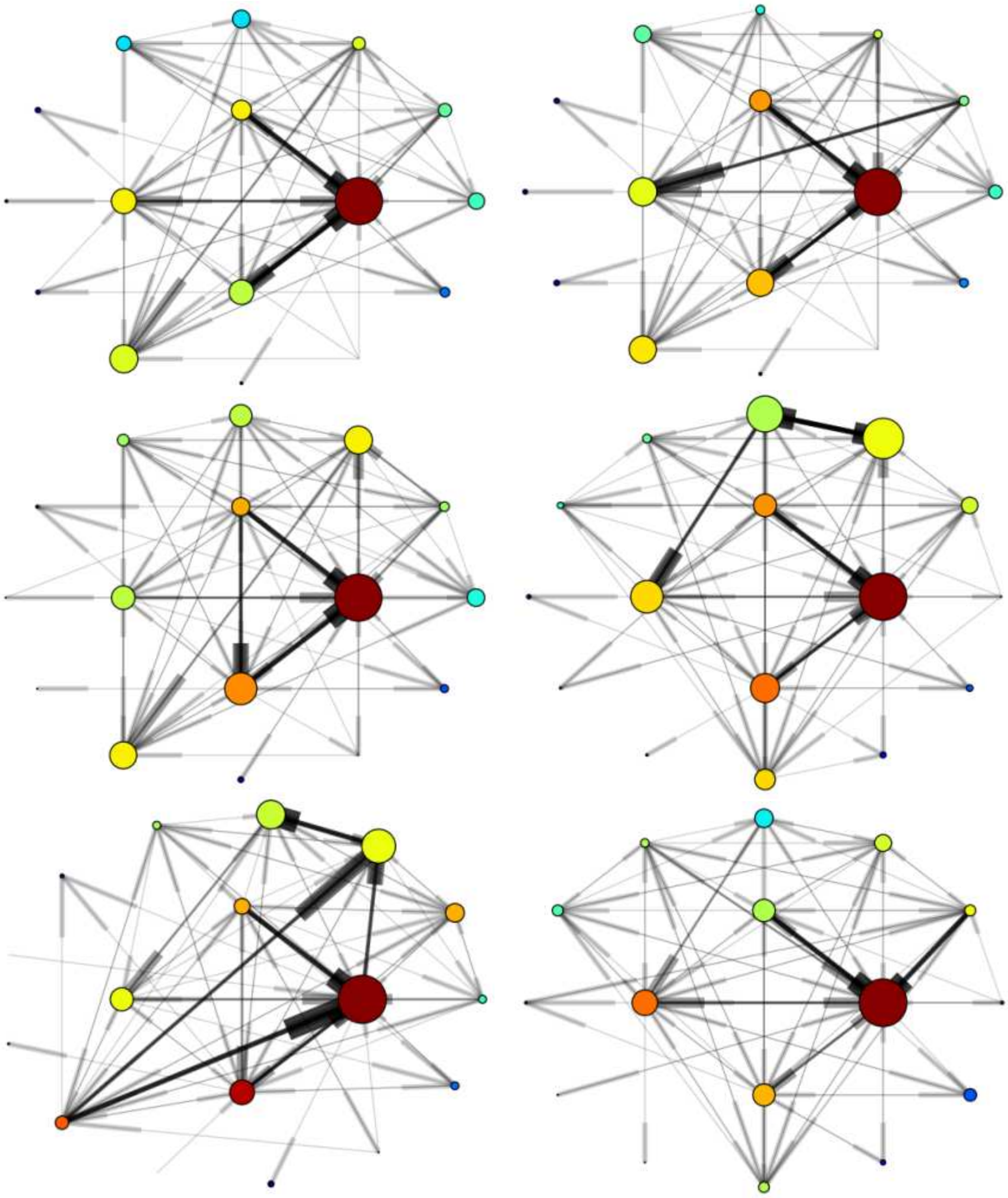

Figure 3.9: Network topology of the South African interbank system from July 2008 (top left), to December 2008 (bottom right). Source: South African Reserve Bank, SAMOS Data.

Chapter 4

A Dynamic Network Model of Systemic Risk

As the recent financial crisis has shown, the structure and dynamics of interbank markets have to be taken into account when assessing the resilience of the financial system. Network- and multi-agent models of banking systems are particularly useful for this task. This chapter proposes a dynamic multi-agent model of a banking system where banks optimize a portfolio of risky investments and riskless excess reserves according to their risk and liquidity preferences. They are endogenously linked via interbank loans and face a stochastic supply of household deposits. The banking behaviour was developed in chapter (2), but is now extended to a dynamic setting. The goal of this chapter is to use this model to answer three key questions about the impact of the network structure on financial stability. First, how efficient is the central bank in stabilizing interbank markets with different network structures during a crisis? Second, which network structures are most resilient to financial distress and thus most desirable from a financial stability point of view? And third, given a specific network structure, what form of systemic risk poses a greater threat to financial stability: interbank contagion or common shocks?

4.1 Introduction

The recent financial crisis has highlighted the necessity to understand systemic risk both qualitatively and quantitatively in order to safeguard financial stability. Bandt et al. (2009) provide a categorization of systemic risks, distinguishing between a broad and a narrow sense. In their nomenclature, contagion effects on interbank markets pose a systemic risk in the narrow sense, whereas the broad sense of systemic risk is characterized as a common shock that affects many institutions at once. The crisis has shown that systemic risk not only can take many forms, but is also highly dynamic: slowly building up in normal times, but rapidly emerging during times of distress. The insolvency of the US investment bank Lehman Brothers in September 2008 marked the tipping point between the build up and rapid manifestation of systemic risks and lead to a freeze in interbank markets. As a consequence, the risk premia for unsecured interbank loans increased drastically, which resulted in a massive impairment of banks' liquidity provision. Governments and central banks were forced to undertake unprecedented non-standard measures to reduce money market spreads and ensure liquidity provision to the banking system.[1] This shows that central banks are key actors for the functioning of interbank markets, even though they do not directly participate in them. To motivate central bank interventions, already Goodfriend and King (1988) could show that open market operations enhance the liquidity provision in the financial system. More recently, Allen et al. (2009) and Freixas et al. (2010) show that central bank intervention can increase the efficiency of interbank markets. Lenza et al. (2010) argue that quantitative and qualitative easing acted mainly through their effect on money market spreads, effectively reducing them. It is thus clear, that every realistic model of interbank markets has to feature the central bank as one key actor.

[1] For an overview of the immediate crisis reaction of governments and central banks, see i.e. Cecchetti (2009) for the United States and Petrovic and Tutsch (2009) for the European Union. See also Heider et al. (2009), and Brunnermeier (2008) for an analysis of the liquidity crunch of 2007/2008.

Interbank markets exhibit what Haldane (2009) denotes as a knife-edge, or robust-yet-fragile property. In normal times, the connections between banks lead to an enhanced liquidity allocation and increased risk sharing amongst financial institutions. This was shown by Allen and Gale (2000) who extend the classical bank-run model by Diamond and Dybvig (1983) and show that highly interconnected banking systems are less prone to bank-runs. Dasgupta (2004) confirms this result and determines the optimal level of interconnectedness in a banking system. In times of crisis, however, the same interconnections can amplify shocks that spread through the system. This was shown i.e. by Gai and Kapadia (2008), who investigate systemic crises with a network model and show that on the one hand, the risk of systemic crises is reduced with increasing connectivity on the interbank market. On the other hand, however, the magnitude of systemic crises increases at the same time.[2] This knife-edge property of interbank markets can be attributed to a counterparty risk externality.[3] Acharya and Bisin (2010) compare over-the-counter (OTC) and centralized clearing markets in a general equilibrium model. They show that the intransparency of OTC markets is ex-ante inefficient and attribute this to a counterparty risk externality.[4] This externality can best be illustrated in a small example. Assume a simple banking network that consists of three banks (A,B, and C) where bank A has issued uncollateralized interbank loans to banks B and C. The interest rate on the interbank loans will include a risk premium to capture counterparty risk. Now assume that B has issued another interbank loan to C. This will increase the counterparty risk of bank B, as B is now vulnerable to a default of bank C. However, bank A is not aware of this increase and will thus underprice the counterparty risk. Thus, the structure of financial networks and especially interbank networks is relevant for the analysis of systemic risk. Taking this into account, the question arises, if there exist network structures that are less prone to the counterparty externality and hence

[2] See also Fernando (2003), and Cifuentes et al. (2005).

[3] Furthermore, Rochet and Tirole (1996), Furfine (2001), or Freixas and Holthausen (2005) argue that interbank markets are characterized by asymmetric information, which poses another form of market incompleteness.

[4] The importance of transparency in contracting has also been analyzed in Leitner (2009).

more resilient to financial distress.

The counterparty risk externality makes it clear that the network structure of financial system plays an important role when assessing systemic risk. An overview of the existing literature on financial networks can be found i.e. in Allen et al. (2010) and European Central Bank (2010b). The network structure of interbank markets can be best captured in an exposure matrix where the issuance of a loan from bank i to bank j is denoted as the loan size in row i and column j. Using such a matrix, Eisenberg and Noe (2001) show that a unique clearing payment vector exists and analyze the spreading of contagious defaults in general network topologies. The difference to this chapter is that we develop a dynamic model of cascading bank defaults, while Eisenberg and Noe (2001) calculate the impact of a default in a static network structure. Empirical analyses of the interbank network structure exist for for a number of countries.[5] It is shown that interbank networks often exhibit a scale-free topology, i.e. they are characterized by few money center banks with many interconnections and many small banks with few connections. Sachs (2010) follows the static approach of Eisenberg and Noe, but also compares contagion effects in scale-free networks and random networks and finds that contagion is more pressing in scale-free networks. What is missing in the literature, however, is a dynamic analysis of the financial stability properties of different network topologies.

The crisis revealed that there also exist other externalities besides the counterparty risk externality. One of them being a correlation externality between banks'

[5]The topology of the interbank has been analyzed i.e. in the United States (Furfine (1999)), the Euroarea (Gabrieli (2010), Gabrieli (2011)), the United Kingdom (Wells (2004), Becher et al. (2008)), Brazil (Cajueiro and Tabak (2007), Chang et al. (2008)), Italy (Mistrulli (2007), Iori et al. (2008), Manna and Iazzetta (2009)), Switzerland (Sheldon and Maurer (1998)), Sweden (Blåvarg and Nimander (2002)), Belgium (Degryse and Nguyen (2007)), the Netherlands (van Lelyveld and Liedorp (2004)), Austria (Boss et al. (2004)) and South Africa (Brink and Georg (2011a)).

portfolios. Securitization was designed to distribute risks from within the banking system to investors outside the banking system. A thorough analysis, however, shows that a significant part of the securitized risk was still residing within the banking system at the peak of the crisis (see i.e. Krishnamurthy (2008)). As a consequence, a strong correlation between banks' assets arised. As banks are unaware of the portfolio of competing banks, they cannot assess this correlation and choose non-optimal levels of correlation for their portfolios. This externality could thus be best described as a correlation externality. A large extend of the literature on systemic risk in interbank markets has focused on the analysis of contagion effects (i.e. studying the counterparty risk externality). Recently, more attention has been given to the correlation externality and the analysis of common shocks as sources of systemic risk. Acharya and Yorulmazer (2008) point out how banks are incentivized to increase the correlation between their investments and thus the risk of an endogenous common shock in order to prevent costs arising from potential information spillovers. The increasing correlation in the financial sector is also verified empirically. De Nicolo and Kwast (2002) analyze the increase in the correlation between large and complex financial organizations during the 1990s, a development that was further fueled by securitization. The new insights on common shocks give rise to the question which form of systemic risk poses the greater threat to financial stability: interbank contagion caused by the counterparty externality, or common shocks caused by the correlation externality. Thus far, no comparison of the different systemic risk manifestations in a single model has been conducted in the literature. This chapter aims to close this gap by explicitely comparing the impact of different shocks resulting from the two externalities.

One particularly useful class of models to analyze the above mentioned questions are multi-agent simulations. Iori et al. (2006) develop a network model of a banking system, where agents (banks) can interact with each other via interbank loans. The balance sheet of banks consits of risk-free investments and interbank loans as assets, and deposits, equity and interbank borrowings as liabilities. Banks channel funds from depositors towards productive investment. They receive liquidity shocks via deposit fluctuations and pay dividends if possible. Nier et al. (2007) describe the banking system as a random graph where the network structure is determined by the number of nodes (banks) and the probability that two nodes are connected. The banks' balance sheet consists of external assets (investments) and interbank assets on the asset side and net worth, deposits, and interbank loans as liabilities. Net worth is assumed to be a fixed fraction of a bank's total assets and deposits are a residual, designed to complete the bank's liabilities side. Shocks that hit a bank and lead to its default are distributed equally amongst the interbank market. The authors find, that (i) the banking system is more resilient to contagious defaults if its banks are better capitalized and this effect is non-linear; (ii) the effect of the degree of connectivity is non-monotonic; (iii) the size of interbank liabilities tend to increase the risk of a knock-on default; and (iv) more concentrated banking systems are shown to be prone to larger systemic risk. More recently, Ladley (2011) analyzes the impact of the interbank network heterogeneity on systemic risk in a multi-agent setting. The balance sheet of banks consists of equity, deposits, cash reserves, loans to the non-bank sector and interbank loans. Ladley considers risky investment opportunities and explicitely models how banks attract deposits by choosing their offered deposit interest rates. Banks determine the optimal structure of their portfolio via a genetic algorithm. He finds that that for small shocks, high interconnectivity helps stabilizing the system, while for large shocks high interconnectivity amplifies the initial impact.

This chapter wants to answer the aforementioned questions about the impact of the network structure on financial stability by developing a dynamic model of a banking system. Banks optimize a portfolio of risky investments and riskless excess reserves. Risky investments are long-term investment projects that fund an unmodelled firm sector while riskless excess reserves are short-term and held at the deposit facility of the central bank. Banks face a stochastic supply of household deposits and stochastic returns from risky investments. This gives rise to liquidity fluctuations and initiates the dynamic formation of an interbank loan network. Banks have furthermore access to central bank liquidity if they can provide sufficient collateral. This model is used to first analyze the impact that the provision of central bank liquidity has on financial stability. It is shown that the central bank can stabilize the financial system in the short-run. In the long-run, however, the system always converges to the equilibrium state. This result is in line with the results of chapter (2) on the effectiveness of monetary policy and its impact on money multipliers. Possible network structures will be given at the beginning of each simulation. They reflect contractual agreements amongst banks and determine the set of possible interbank loans. The realized network structure at each point in time is a subset of the possible network structure (i.e. the set of existing edges at any point in time is a subset of the set of possible edges). This closely resembles the situation in reality, where the day-to-day topology of interbank networks also varies from the monthly or quaterly aggregated network structures that are analyzed in the literature. Different possible network structures are compared, and it is shown that in random graphs, the relationship between the degree of interconnectivity and financial instability is non-monotonic. Scale-free networks are seen to be more stable than small-world networks, which in turn tend to be more stable than random networks. Thus, the effect of contagion is exagerrated in the literature, as most papers assume random networks and most real-world interbank networks are scale-free. The model captures key effects of the dynamics of interbank networks and can thus be used to analyze the impact of different externalities on financial stability. The counterparty risk externality is compared to the correlation externality and it is shown that, contrary to their importance in the literature, common shocks are not subordinate to interbank contagion. Finally, a number of policy conclusions for the optimal reaction to financial crises, as well as for the monitoring and regulation of systemic risk are drawn from the model.

The remainder of this chapter is organized as follows. After this introduction, section (4.2) describes the dynamic model that has been used to analyze the aforementioned questions. Section (4.3) will present the main results, while section

(4.4) derives some policy implications and concludes. In the appendix section (4.5), additional results that were obtained from the model are discussed. As these results do not fall within the main scope of this chapter, they were put into a separate appendix that is concluded by a brief discussion of the additional results.

4.2 The Model

This section wants to outline some key features that all models of systemic risk should incorporate and develop a dynamic model of a banking system that can be used to analyze the impact of the interbank network structure on financial stability. Firstly, deposit fluctuations have to be included for two reasons: (i) Because of the maturity transformation that banks perform and since deposits usually have a short maturity, deposit fluctuations can lead to illiquidity. Banks that become illiquid will have to liquidate their long-term investments at steep discounts (for a model that describes this mechanism, see i.e. Uhlig (2010)). Due to marked-to-market accounting, these steep discounts will lead to losses in banks' trading books and have to be compensated by banking capital. Thus, illiquidity can lead to insolvency. (ii) As deposit fluctuations are generally considered to be one of the reasons why banks engage in interbank lending (see i.e. Allen and Gale (2000), Dasgupta (2004)), they have to be included into all models of systemic risk. Without deposit flucutations as a driving force for the formation of interbank networks, it is impossible to describe the counterparty risk externality in a dynamic setting. Secondly, as fluctuations in investment returns have to be compensated by banking capital, risky investments are a major cause of bank insolvencies. Without risky investments, it is impossible to model the correlation externality as it arises precisely in a situation when the returns of risky assets of a number of banks have negative realizations at the same time. In order to model common shocks, risky investments have thus to be taken into account.

Iori et al. (2006) and Nier et al. (2007) develop multi-agent models of a banking system, but assume a risk-free investment opportunity. Nier et al. (2007) further assume deposits to be residual. We follow both papers in some aspects and develop a network model of interbank markets. However, we explicitely allow the possibility of risky investments and deposit fluctuations. We furthermore include a central bank in the model, since it is evident from the literature that monetary policy has a large influence on the stability of interbank markets. This model allows the investigation of direct contagion effects as well as common shocks. This is another difference to the existing literature, which exclusively focuses on individual forms of systemic risk.

4.2.1 Balance Sheets

The balance sheet of a bank k holds risky investments I^k and riskless excess reserves E^k as assets at every point in (simulation-) time $t = 1 \dots \tau$. The investments of bank k have a random maturity[6] $\tau_I^k > 0$ and we assume that each bank finds enough investment opportunities according to its preferences. The bank refinances this portfolio by deposits D^k (which are stochastic and have a maturity of zero), from which it has to hold a certain fraction rD^k of required reserves at the central bank, fixed banking capital BC^k, interbank loans L^k and central bank loans LC^k. Interbank loans and central bank loans are assumed to have a maturity of $\tau_L^k = \tau_{LC}^k = 0$. The maturity mismatch between investments and deposits is the standard maturity transformation of commercial banks. Interbank loans can be positive (bank has excess liquidity) or negative (bank has demand for liquidity), depending on the liquidity situation of the bank at time t. The same holds for central bank loans, where the bank can use either the main refinancing operations to obtain loans, or the deposit facility to loan liquidity to the central bank. The balance sheet of the commercial bank therefore reads as:

$$I_t^k + E_t^k = (1 - r)D_t^k + BC_t^k + L_t^k + LC_t^k \tag{4.1}$$

[6]Maturity τ implies that the asset matures in $\tau + 1$ update steps.

The interest rate for deposits at a bank is r^d and the interest rate for central bank loans is r^b. Note that there is no distinction between an interest rate for the lending and deposit facility and therefore the interest rate on the interbank market will be equal to the interest rate for central bank loans.

The banks decide about their portfolio structure and portfolio volume. A constant relative risk aversion (CRRA) utility function is assumed to model the bank's preferences:

$$u^k = \frac{1}{1-\theta^k}\left(V^k(1+\lambda^k\mu^k - \frac{1}{2}\theta^k(\lambda^k)^2(\sigma^2)^k)\right)^{(1-\theta^k)} \tag{4.2}$$

where λ^k is the fraction of the risky part of the portfolio, μ^k is the expected return of the portfolio and θ^k is the banks risk aversion parameter. $V_t^k = I_t^k + E_t^k$ denotes the bank's portfolio volume. The risky part of the portfolio follows from utility maximisation and reads as:

$$(\lambda^k)^* = \min\left\{\frac{\mu^k}{\theta^k(\sigma^2)^k}, 1\right\} \quad \in [0,1] \tag{4.3}$$

The portfolio volume can be obtained by similar measures as:

$$(V^k)^* = \left[\frac{1}{r^b}\left(\left(1+\lambda^k\mu^k - \frac{1}{2}\theta^k(\lambda^k)^2(\sigma^2)^k\right)^{(1-\theta^k)}\right)\right]^{1/\theta^k} \tag{4.4}$$

where r^b denotes the refinancing cost of the portfolio. Since banks obtain financing on the interbank market and at the central bank at the same interest rate, this refinancing cost is equal to the main refinancing rate. It is possible to introduce a spread between the lending and deposit facility and therefore allowing the interest rate on the interbank market to stochastically vary around the main refinancing rate. If a bank now plans its optimal portfolio volume, it calculates with a planned refinancing rate. This refinancing rate follows from the banks plan about how much interbank loans it wants to obtain on the interbank market at a planned refinancing rate and how much central bank loans it plans to obtain at the main refinancing rate. If this plan cannot be realized (e.g. if a bank's liquidity demand is unsatisfied on the interbank market), banks make a non-optimal

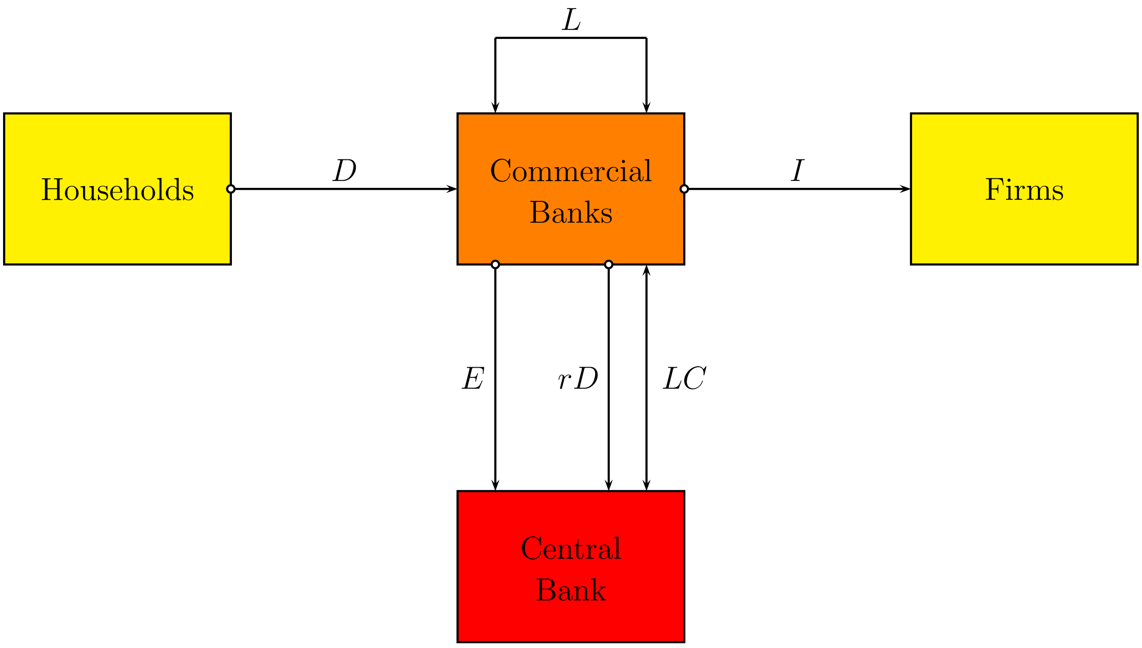

Figure 4.1: Interaction dynamics of the model. The private sector (household/firms), the banking sector (commercial banks) and the central bank interact via the exchange of deposits, investments, loans, excess- and required reserves and central bank loans. Arrows indicate the direction of fund flows.

portfolio choice. This possibility is excluded for the sake of simplicity. Note, that a market for central bank money is not explicitely modelled. The central bank rather accomodates all liquidity demands of commercial banks, as long as they can provide the necessary securities. This assumption is not unrealistic in times of crises, as for example the full allotment policy of the ECB shows.

4.2.2 Update Algorithm

In the simulation, we have implemented an update algorithm that determines how the system evolves from one state to another. The algorithm is divided up into three phases that are briefly described here. Every update step is done for all banks for a given number of sweeps. At the beginning of phase 1 the bank holds assets and has liabilities from the end of the previous period:

$$\underline{I}^k_{t-1} + \underline{E}^k_{t-1} + r\underline{D}^k_{t-1} = \underline{D}^k_{t-1} + \underline{BC}^k_{t-1} + \underline{L}^k_{t-1} + \underline{LC}^k_{t-1} \tag{4.5}$$

where an underline denotes realized quantities. In period 0 all banks are endowed with initial values. The update step starts with banks getting the required reserves $r\underline{D}^k_{t-1}$ and excess reserves $\underline{E}^k_{t-1}$ plus interest payment from the central bank (it is assumed that for both required and excess reserves an interest of r^b is paid). The banks obtain a stochastic return for all investments $\underline{I}^k_{t-1}$ which might be either positive or negative. The firms furthermore pay back all investments $\underline{I}^k_f$ that were made in a previous period and have a maturity of $\tau^k_I = 0$. The banks then pay interest for all deposits that were deposited in the previous period. After that, the banks can either receive further deposits from the households, or suffer deposit withdrawings ΔD^k_t. At the end of the first period, all interbank and central bank loans plus interests are paid either to, or by bank k.

At the beginning of phase 2, the bank's liquidity $\widehat{Q}^k$ is therefore given as:

$$\begin{aligned} \widehat{Q}^k_t \;=\;& (1+r^b)\left[r\underline{D}^k_{t-1} + \underline{E}^k_{t-1}\right] + \mu^k \underline{I}^k_{t-1} + \underline{I}^k_f - r^d \underline{D}^k_{t-1} \pm \Delta D^k_t \\ & -(1+r^b)\left[\underline{L}^k_{t-1} + \underline{LC}^k_{t-1}\right] + \underline{BC}^k_{t-1} \end{aligned} \tag{4.6}$$

All banks with $\widehat{Q}^k_t < 0$ are marked as illiquid and removed from the system. Banks that pass the liquidity check now have to pay required reserves $r\underline{D}^k_t$ to the central bank.

In phase 3 the bank k determines it's planned level of investment $I^k_t = (\lambda^k)^*(V^k)^*$ and excess reserves $E^k_t = (1-(\lambda^k)^*)(V^k)^*$ according to equations (4.3) and (4.4). From this planned level and the current level of investments (all investments that were done in earlier periods and have a maturity $\tau^k_I > 0$), as well as the current liquidity (4.6) the bank determines its liquidity demand (or supply). If a bank has a liquidity demand, it will go first to the interbank market, where it asks all banks i that are connected to k (denoted as $i : k$), if they have a liquidity surplus. In this case the two banks will interchange liquidity via an interbank loan. The convention is adpotet that a negative value of L denotes a demand for liquidity and therefore the interbank loan demand of bank k is given by:

$$L_t^k = \widehat{Q}_t^k - I_t^k \tag{4.7}$$

From this, one can obtain the realized interbank loan level, via the simple rationing mechanism:

$$\underline{L}_t^k = \min \begin{Bmatrix} L_t^k & , & -\sum_{i:k} L_t^i & \mid & L_t^i \cdot L_t^k < 0 & ; & \text{if } L_t^k > 0 \\ -L_t^k & , & \sum_{i:k} L_t^i & \mid & L_t^i \cdot L_t^k < 0 & ; & \text{if } L_t^k < 0 \end{Bmatrix} \tag{4.8}$$

Now there are three cases, depending on the bank's liquidity situation. If a bank has neither a liquidity demand nor excess liquidity, it will not interact with the central bank and this step is skipped. However, if the bank still has a liquidity demand, it will ask for a central bank loan:

$$LC_t^k = \underline{L}_t^k - L_t^k \tag{4.9}$$

The central bank then checks if the bank has the neccessary securities and if so, it will provide the loan:

$$\underline{LC}_t^k = \max\left(LC_t^k, -\alpha^k \underline{I}_{t-1}^k\right) \tag{4.10}$$

where $\alpha^k \in [0,1]$ denotes the fraction of investments of bank k that are accepted as securities by the central bank. If a bank has insufficient securities, the central bank will not provide the full liquidity demand and the bank has to reduce the planned investment and excess reserve level. If the bank has no securities (no investments $\underline{I}_{t-1}^k$), it cannot borrow from the central bank. This rationing mechanism maps planned investment levels to realized ones.

The second case is that a bank has a large liquidity surplus even if all planned investments can be realized. In this case, the bank is able to pay dividends A_t^k and the dividend payment is determined by:

$$A_t^k = \min\left\{LC_t^k, \beta^k \underline{I}_t^k\right\} \tag{4.11}$$

where $\beta^k \in [0, 1]$ is the dividend level of bank k. The dividend level will typically be close to 1 as shareholders will push the bank to rather pay dividends than use the money to deposit it at the central bank at low interest rates. The remaining:

$$\underline{LC}_t^k = LC_t^k - A_t^k \tag{4.12}$$

is transferred to the central bank's deposit facility. Finally the realized investments are transferred to the firm sector and the realized excess reserves are transferred to the central bank.

These steps are done for all $k = 1 \dots N$ banks in the system for $t = 1 \dots \tau$ time steps. As there are two stochastic elements in the simulation (the return of investments and the deposit level) two channels for a banks insolvency are modelled. The first channel is via large deposit withdrawals. As deposits are highly liquid and investments are illiquid for a fixed, but random investment time, this maturity transformation might lead to illiquidity and therefore to insolvency. The second channel for insolvency is via losses on investments. If the banks banking capital is insufficient to cover losses from a failing investment, this bank will be insolvent. If a bank fails, all the banks that have loaned to this bank will suffer losses, which they have to compensate by their own banking capital. This is a possible contagion mechanism, where the insolvency of one bank leads to the insolvency of other banks, that would have survived if it was not for the first bank's insolvency. The impact of the contagion effect will depend on the precise network structure of the interbank market at the time of the insolvency.

4.2.3 Model Parameters

There are eighteen model parameters that control the numerical simulation. If not stated otherwise, numerical simulations were performed with the parameters given in this section. The simulations were perfomred with $N = 100$ banks and $\tau = 1000$ update steps each. Every simulation was repeated `numSimulations=100` times to average out stochastic effects. The interest rate on the interbank market was chosen to be $r^d = 0.02$ and the main refinancing rate as $r^b = 0.04$. The required reserve rate is $r = 0.02$. The interbank connection level for random graphs is denoted as `connLevel`$\in [0, 1]$. At a `connLevel=0` there is no interbank market and at `connLevel=1` every bank is connected to every other bank. For scale-free networks the parameters $m = 1, 2, 4, 10$ and for small-world networks the parameters $\beta \in [0.001, 0.1]$ were used.

Two sets of parameters are used to describe the influence of the real economy on the model. The first set is the probability that a credit is returned successful, $p_f = 0.97$. The return for a successful returned credit is $\rho_f^+ = 0.09$ and in case a credit defaults, the negative return on the investment is $\rho_f^- = -0.05$. This set of parameters will sometimes be referred to as "normal" parameters. As "crisis" parameters $\rho_f^+ = 0.97$ and $\rho_f^- = -0.08$ were used. To plan their optimal portfolio, the banks have an expected credit success probability p_b and expected credit return ρ_b^+. It is assumed that these expected values correspond to the true values from the real economy. The optimal portfolio structure and volume of a bank depends also on its risk aversion parameter θ. For each bank, $\theta \in [1.67, 2.0]$ was chosen randomly to account for heterogeneity in the banking sector.

Deposit fluctuations ΔD_t^k were modelled as:

$$\Delta D_t^k = (1 - \gamma^k + 2\gamma^k x)\underline{D}_{t-1}^k \tag{4.13}$$

with $\gamma^k = 0.02$ (in "normal" times) and $\gamma^k = 0.1$ (during a "crisis" period) can be interpreted as a scaling parameter for the level of deposit fluctuations and x being a random variable with $x \in [0, 1]$. The fraction of a banks investments that the central bank accepts as securities is set to $\alpha^k = 0.8$, assuming that banks invest only in assets which have a good rating. The level of dividends β^k that a bank pays to its shareholders was chosen as $\beta^k = 0.99$.

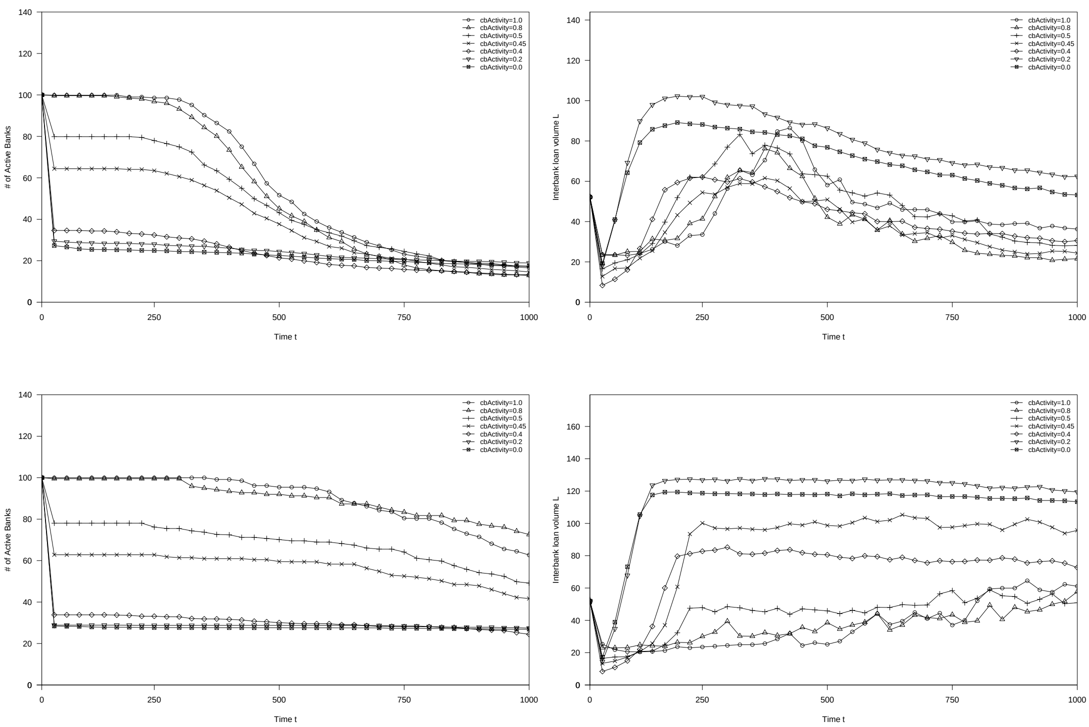

Figure 4.2: The effect of central bank activity for different scenarios. Top: crisis scenario. Bottom: normal scenario. Left: number of active banks over simulation time. Right: interbank loan volume over simulation time. The central bank activity α^k varied between $\alpha^k \in [0.0, 1.0]$.

4.3 Results

To answer the question which impact central bank activity has on financial stability, we first varied the level of collateral α^k that is accepted by the central bank in order to provide liquidity to banks. For $\alpha^k = 1$ the central bank will accept all assets of commercial banks as collateral, while for $\alpha^k = 0$, no assets will be accepted. Thus, α^k is used as a parameter to determine the fraction of assets that are of high enough quality to be accepted as collateral. Banks will obtain liquidity for the amount of collateral that they can deposit at the central bank. In Figure (4.2) it can be seen, that a significant stabilizing effect from the liquidity provision by the central bank is obtained from $\alpha^k \sim 0.45$. However, this effect is non-linear in α^k which implies that, on the one hand, even slight changes in the collateral requirements can have significant stabilizing effects if performed

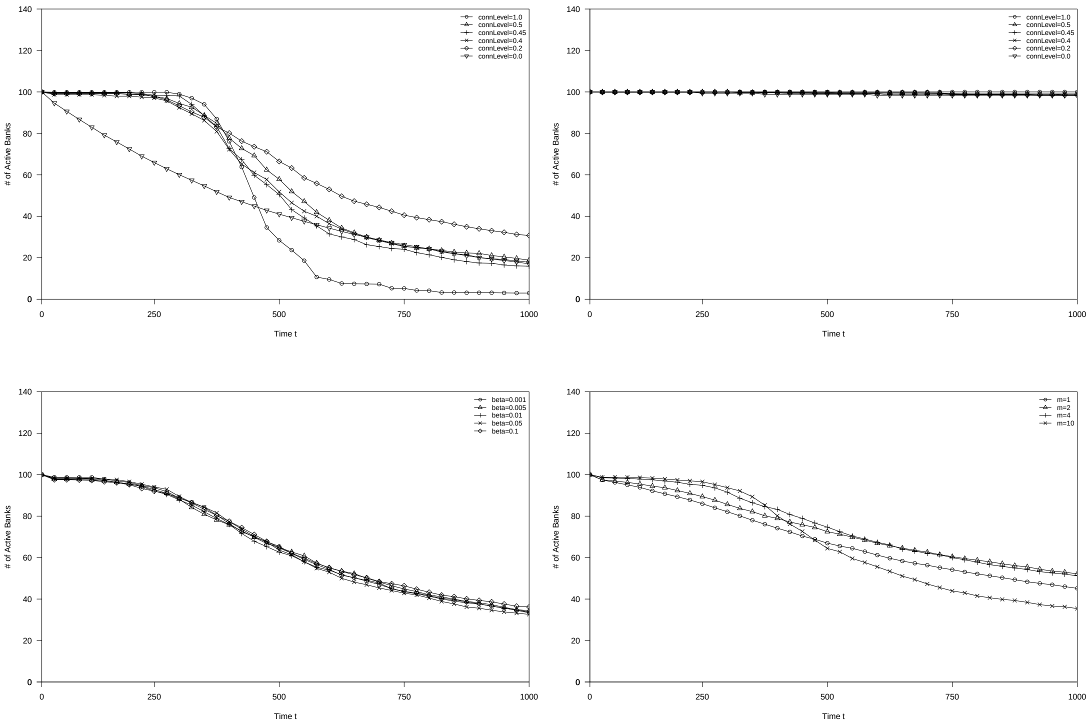

Figure 4.3: The effect of different network topologies on financial stability. Left top: crisis scenario and random topology. Right top: normal scenario and random topology. Connection levels of `connLevel`= $0.0, 0.2, 0.4, 0.45, 0.5, 1.0$ were used. Bottom left: crisis scenario and small-world network with $\beta = 0.001, 0.005, 0.01, 0.05, 0.1$. Bottom right: crisis scenario and scale-free network with $m = 1, 2, 4, 10$.

around the critical value. On the other hand, even large changes can have very little effect, if performed away from the critical value. The effect on the number of active banks is similar for both, the normal and the crisis scenario. On the right hand side of Figure (4.2) the impact of the collateral requirements on the volume of interbank loans is displayed. It can be seen, that in both scenarios an abundant provision of central bank liquidity will lead to a crowding-out effect on interbank liquidity. It can further be seen, that a high amount of interbank liquidity is correlated with high financial instability. This is precisely the knife-edge property of interbank markets: if the exposures amongst banks are too large, an initial knock-on effect will be amplified in the system.

In Figure (4.3) the impact of different network topologies on financial stability in times of crisis and normal times is shown. When comparing the results for random networks, it can be seen that the difference in network topology is not significant during normal times.[7] In times of crisis, however, the different levels of interconnectedness come into play. Figure (4.3) also confirms the result of Nier et al. (2007), who show that the relationship between the level of interconnectedness on interbank markets and financial contagion is non-monotonic. It can furthermore be seen, that contagion effects tend to be larger in random networks than in small-world networks, where in turn contagion effects tend to be larger than in scale-free networks. This implies that analyses that are conducted with static random networks can overestimate contagion effects when a dynamic model of systemic risk is used.

For increasing levels of interconnectedness in random networks, it can be seen from Figure (4.3) that there exists a "tipping" point, where the networks become endogenously instable. To better understand this, the interbank loan volume is depicted in Figure (4.4). As Ladley (2011) argues, the knife-edge property of interbank markets requires shocks to be small, in order to exihibt a stabilizing effect. Figure (4.4) shows an increase in interbank market volume until a tipping point, where the amount of interbank loans becomes large and contagion effects dominate. This in turn leads to an increasing number of insolvencies that spread easier in the system if the level of interconnectedness increases. It can also be seen from Figure (4.4) that the volume of interbank markets in normal times is significantly smaller than the volume in times of distress. This is easily understood in the model setup, as times of distress imply larger liquidity fluctuations and therefore larger amounts of interbank loans issued between agents. However, this implies that interbank markets will be more prone to contagion effects in times of high deposit and asset return volatility. It also implies that interbank markets are more susceptible to systemic risk when the volume of the interbank market is larger.

[7] And similarly for small-world and scale-free networks.

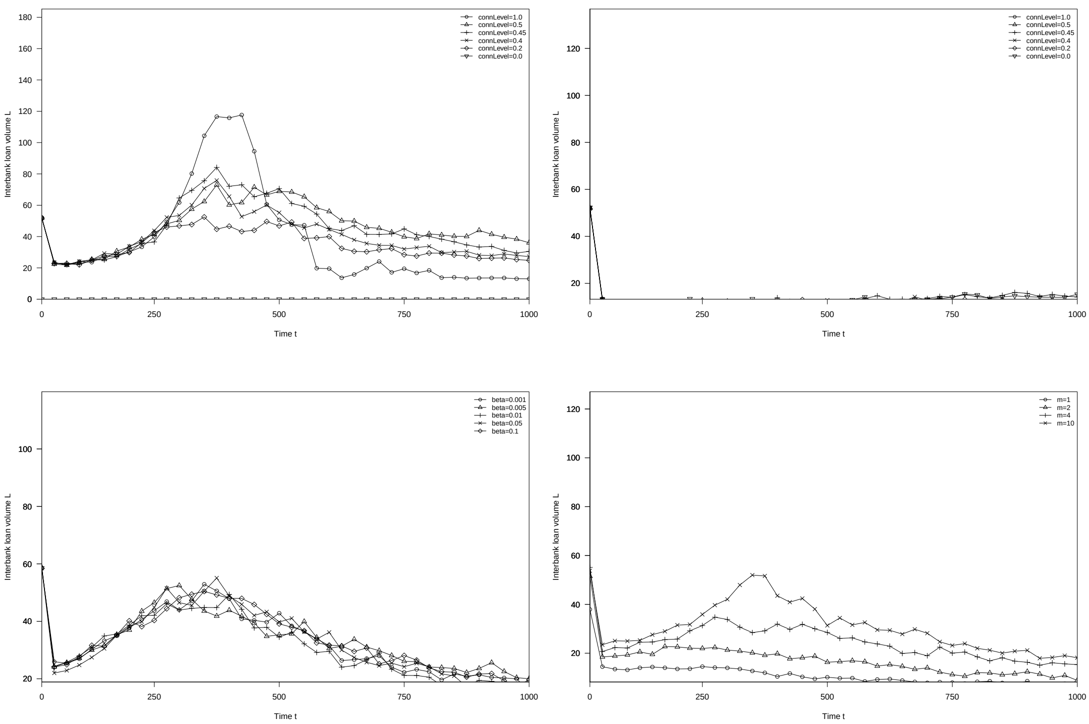

Figure 4.4: The effect of different network topologies on interbank loan volume. Left top: crisis scenario and random topology. Right top: normal scenario and random topology. Connection levels of `connLevel`$= 0.0, 0.2, 0.4, 0.45, 0.5, 1.0$ were used. Bottom left: crisis scenario and small-world network with $\beta = 0.001, 0.005, 0.01, 0.05, 0.1$. Bottom right: crisis scenario and scale-free network with $m = 1, 2, 4, 10$.

To understand the impact of different forms of systemic risk on financial stability, Figure (4.5) compares two different types of shocks. In the case of pure interbank contagion, the largest bank in the system is selected and exogenously sent into default. The impact of this default on the remaining number of active banks in the system is depicted in Figure (4.5) at the top. Again, it can be seen that the impact is larger in times of distress than in normal times. To analyze the impact such a default has on the liquidity provision in interbank markets, Figure (4.5) shows the interbank market volume at the bottom. When a common shock hits the system, banks with insufficient equity will go into insolvency. While this might only be a small number of banks, a larger number of banks become

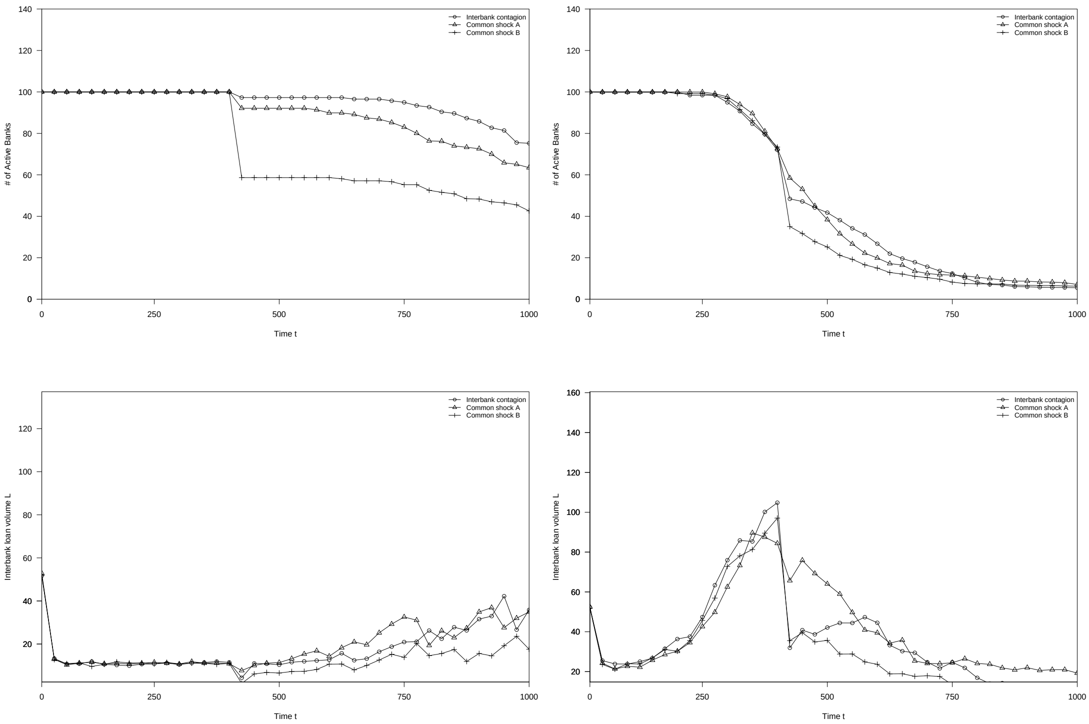

Figure 4.5: The impact of different forms of systemic risk on financial stability and interbank loan volume. Left: normal scenario. Right: crisis scenario. Top: number of active banks over time. Bottom: interbank loan volume voer time. Interbank contagion: the largest bank in the system at time $t = 400$ was sent into insolvency. Common shock A: all banks suffer a common shock of 10% on all their assets. Common shock B: all banks suffer a common shock of 20% on all their assets.

more vulnerable to deposit and asset return fluctuations. As was seen in Figure (4.4), shocks that exceed a certain threshold will lead to an increased number of insolvencies in the system. When banks become more vulnerable, this threshold is reached easier and the whole system remains unstable as long as the volume on the interbank market (and hence the magnitude of possible shocks) will lead to increased insolvencies. When the crisis hits, the volume of interbank transactions drops until it has reached a level where the endogenous deposit and asset return fluctuations will not lead to an increased number of insolvencies. Comparing the case of common shocks to the case of interbank contagion, it can be seen that, while the impact of a common shock on the number of active banks is more severe than in the contagion case, the opposite holds true for interbank market liquidity. The pure contagion case has a substantial impact on interbank market liquidity, which on the other hand implies a smaller size of shocks due to endogenous fluctuations.

4.4 Conclusion and Policy Implications

This chapter develops a dynamic model of a banking system with banks optimizing a portfolio of risky investments and riskless reserves. Banks face stochastic household deposit demand and stochastic asset returns. In order to exchange liquidity, banks engage in interbank lending. In addition to the existing literature, this model incorporates the central bank, whose actions have substantial impact on interbank markets. The model allows for the analysis of the dynamic evolution of systemic risk in interbank markets. Both, the time-varying nature of interbank markets, as well as the impact of different forms of systemic risk have been taken into account. Different network topologies have been studied and their impact on financial stability has been analyzed. Therefore, the model presented in this chapter provides a unique starting point for the analysis of systemic risk on interbank markets.

This chapter provides further evidence that central bank intervention can indeed alleviate financial distress and liquidity shortages on interbank markets in the short run. On the one hand, even small changes in the collateral requirements of central banks can lead to a significant enhancement of liquidity provision on interbank markets. On the other hand, there is a large range of required collateral quality, where even a significant change in the collateral requirements will not lead to a significant enhancement of liquidity provision. The simulation results also show that an abundant provision of central bank liquidity can lead to a crowding-out of interbank liquidity. The desired impact of central bank activity on liquidity provision will thus be smaller in the long run. This is confirmed by the fact that, while the central bank has a stabilizing effect on the financial system in the short-run, the long run equilibrium will always be the equilibrium that would have been reached without central bank activity.

The model developed in this chapter allows for a deeper understanding of the knife-edge property of interbank markets. The results indicate that there is an upper limit of interbank loan volume for different network topologies, where endogenous deposit and asset return fluctuations will lead to an increased number of bank insolvencies. The limit itself depends on the topology of the interbank markets and will be larger for higher interconnected banking systems. This implies that the knife-edge property of interbank markets depends on the precise market structure and level of interconnectedness. For higher connectivity on the interbank market, larger amounts of interbank liquidity can be tolerated by the system without a substantial increase in financial fragility. However, even for complete networks, where every bank is connected to every other bank, such an upper limit exists. In fact, for higher interconnected networks, shocks will spread more rapid, which implies a higher fragility of the system once the tipping point is reached.

Already the correlation of higher interconnectedness and increasing system fragility makes it clear, that the topology of the interbank network is relevant for the assessment of financial stability. This chapter also shows that the topology of the interbank network impacts the assessment of the long-run stability of the banking system. This "topology effect" is more accentuated in times of crisis, while in normal times, the topology has little impact. This result is of particular relevance for the question which interbank network structure is most resilient to financial distress. It turns out that networks with large average path length are more resilient to financial distress and that it is precisely during a crisis where the network topology matters.

Even though contagion effects are far better studied in the literature, it turns out that common shocks pose a greater threat to financial stability. This is also due to the knife-edge property of interbank markets. When a common shock strikes the entire banking system, banks become more vulnerable to endogenous fluctuations and occasional idiosyncractic insolvencies. This leads to a drastic vulnerability of the entire system and a large number of bank insolvencies. However, contagion affects interbank market liquidity more severely than common shocks. Again, the impact of the shocks is larger during times of distress, which holds especially true for the impact of contagious defaults on interbank liquidity provision.

The results presented in this chapter have significant implications for central banks and supervisory authorities. First, from the perspective of monitoring systemic risk, it has become apparent that the topology of the interbank network has to be taken into account. The recently endorsed Basel III framework sets strong incentives to move from intransparent over-the-counter trading of interbank loans to centralized counterparty clearing. One of the advantages of centralized clearing is that policy makers are now able to determine and measure the interbank network structure. The interbank network topology, however, is highly dynamic and varies from day to day. This implies that further analyses of this dynamic behaviour are necessary in order to understand the full impact of the network topology on the propagation of shocks. Second, the results in this chapter have implications for the optimal reaction of central banks to financial crises, as different forms of systemic risk have a different impact on the financial system. In the case where systemic risk is mainly manifesting in the form of contagion, central banks should resort to providing short-term liquidity to the financial system. Because of to the crowding-out of interbank liquidity by abundant central bank liquidity, however, this liquidity provision should be short- or medium-term only. In the case where systemic risk is mainly manifesting in the form of a common shock, the optimal policy reaction is to re-capitalize the financial system. Only a strengthening of the banks' equity will make them more resilient to endogenous fluctuations. This is especially relevant, as the reduction in interbank lending is smaller in the case of a common shock and the simulation results indicate a direct relation between high interbank lending (with respect to the resilience of each individual bank, i.e. the banks' capital buffer) and financial fragility. Thus, a better understanding of all forms of systemic risk is required in order for policy makers to find appropriate crisis reactions. Third, the results in this chapter have implications for the regulation of systemic risk. According to Basel III, banks have to hold capital for all risky assets they hold. This capital is determined by a required capital ratio (that has been raised substantially with respect to Basel II) and the risk-weights for individual asset classes. Historic experience suggested that interbank loans are less risky than loans to the real economy. Therefore, the risk-weights for interbank and financial assets were substantially smaller than the risk-weights for other assets. The simulation results, however, indicate that higher amounts of interbank lending lead to larger financial fragility. In addition to calibrating risk-weights to historic default experience, it is thus necessary to add a "systemic risk weight" on different asset classes in order to counterveil the default risk externality that is at the core of contagious defaults.[8] Even more pressing is the need for regulatory tools to counterveil the correlation externality. One such possible tool would be the asset value correlation factor in Basel III. This factor is currently implemented as a static factor, which is slightly higher for large banks. This ignores the correlation externality that is at the root of common shocks. Supervisory authorities should require more detailed information about banks' trading and bank books and determine the correlation of different asset classes from this data in a macroprudential approach. These "dynamic asset value correlation" factors can then be disseminated to banks who in turn calculate their individual asset value correlation factors in accordance with their portfolio, which will effectively reduce portfolio correlations.

4.5 Appendix

Besides the aforementioned results, a number of other results are worth mentioning, even though they do not directly fit into the main scope of this chapter. This

[8]More on the regulation of systemic risk can be found in chapter (6).

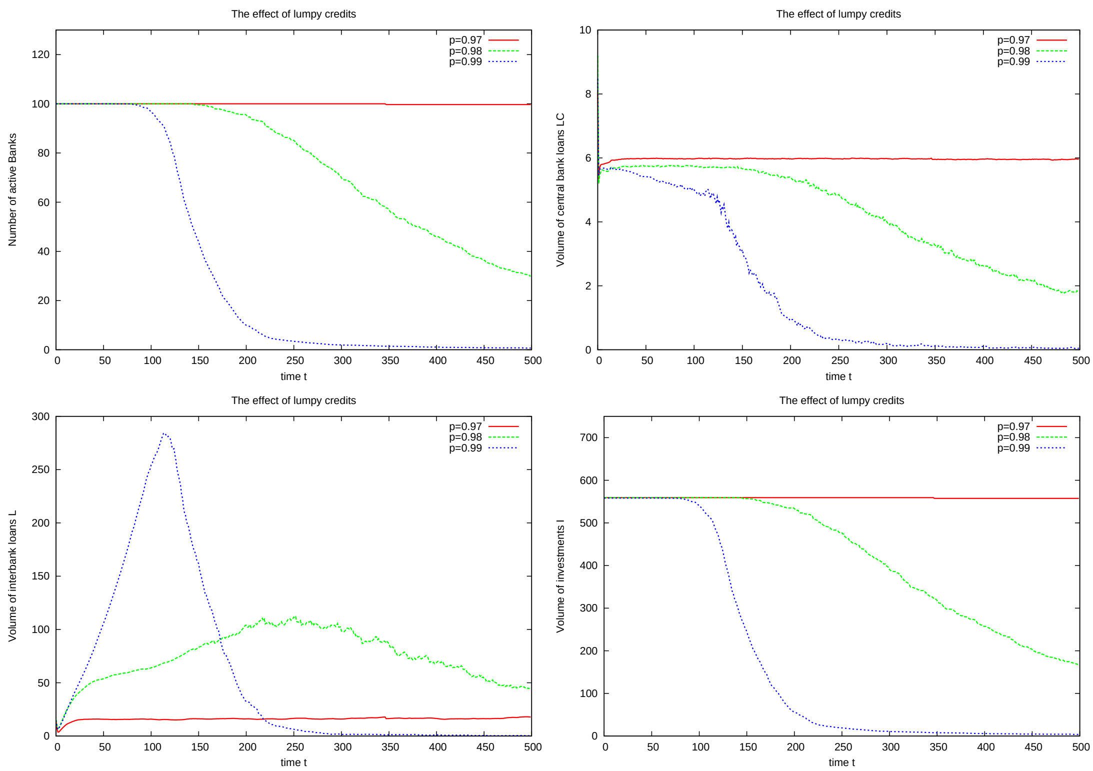

Figure 4.6: The effects of credit lumpiness on financial stability. Top left: number of active banks over simulation time for different expectations. Bottom left: volume of interbank loans L over simulation time for different expectations. Top right: volume of central bank loans LC over simulation time for different expectations. Bottom right: volume of investments to the real economy over simulation time for different expectations. We have used the parameters from section (4.2.3) but with different values for p, ρ^{+} and ρ^{-} as described in the text below.

appendix is therefore a collection of these results with a brief discussion at the end. Throughout this section we have used $\rho_f^{+} = 0.09$, $\rho_f^{-} = -0.05$, $\beta = 0.01$, $m = 1$, `connLevel`$= 1.0$ and $\gamma^k = 0.1$ as parameters.

One factor that determines a bank's default probability is the lumpiness of it's investments. To clarify this, assume two banks A and B with equal investment volume and expected return of the investment. Bank A has loaned a lot of small credits, while B has issued fewer, but larger credits. The success probability of a larger credit will be larger than the success probability of a small credit, as

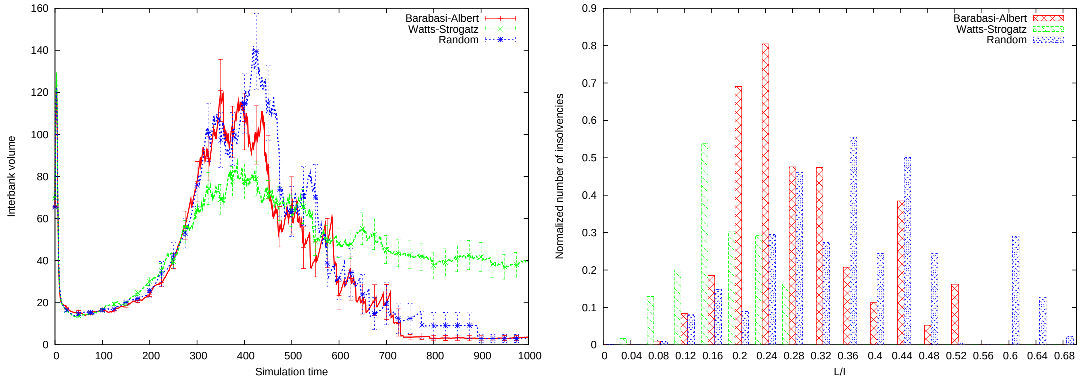

Figure 4.7: Left: Interbank lending over simulation time for different network topologies. Right: normalized number of insolvencies over the fraction L/I of interbank loans over investment level at which the insolvencies occured. We used the parameters defined in section 4.2.3.

banks will audit larger credits with more scrutiny. Since the expected portfolio return μ_R of both banks should be equal and smaller credits have a lower success probability, from the equation:

$$\mu_R = p\rho^+ + (1-p)\rho^- \tag{4.14}$$

one can determine the "return" ρ^- of a defaulting credit, if the return of a successfull credit ρ^+ remains the same. For $\rho_+ = 0.09$, $p = 0.97$ and $\rho_- = 0.05$ one obtains $\mu_R = 0.0858$ for small credits. We now assume a slightly larger success probability for credits of $p = 0.98$. Then one obtains with fixed μ_R a negative return $\rho^- = -0.12$. Now it is not 5% of the invested portfolio volume that defaults if an investment defaults, but 12%. This resembles the greater lumpiness of bank B's portfolio. For $p = 0.99$ one obtains $\rho^- = -0.33$. Those three cases are shown in figure (4.6). It is clear from our simulations, that a larger credit lumpiness leads to larger systemic instability and higher interbank loan volume.

On the left hand side of Figure 4.7 the interbank volume for the three topologies BA, WS and random is shown. Irrespective of the actual network topology, all three simulations exhibit a similar behaviour. Until time $\tau \approx 400$ one can see an increase in interbank lending up to a point, where the volume of interbank lending exceeds a certain fraction of the investment volume. After this point the level of interbank lending decreases, which is due to a drastic decrease in the number of active banks. This result gives rise to the conclusion that there is a negative relationship between the amount of interbank loans and financial stability (measured as the number of active banks over time).[9] On the left hand side of Figure 4.7 the interbank volume for the three topologies is shown. Irrespective of the actual network topology, all three simulations exhibit a similar behaviour. Until time $\tau \approx 400$ one can see an increase in interbank lending up to a point, where the volume of interbank lending exceeds a certain fraction of the investment volume. After this point the level of interbank lending decreases, which is due to a drastic decrease in the number of active banks.

To quantify this effect, the number of insolvencies (normalized by the number of active banks in the system) as well as the fraction L/I at each point in time were measured. The results of this measurement are shown in form of a histogram for the three cases of a BA, WS and random network on the right hand side of figure 4.7. One can see that the distributions of insolvencies peak around a certain amount of L/I. It is possible to fit a normal distribution to the histogram data in order to obtain the value of L/I where the most insolvencies occur. In the Watts-Strogatz case this mean of the distribution is at about $L/I = 0.179$, while in the Barabási-Albert case it is at $L/I = 0.249$ and in the random case at $L/I = 0.355$. The results indicate that there is an "upper limit" to interbank lending in the sense that larger values of interbank lending endogenously lead to financial instability. As long as interbank lending is low, insolvencies cause no problem for systemic stability since their impact is limited. As the amount of interbank lending increases, possible contagion effects increase as well, until finally there are only the most resilient banks (e.g. those with the most banking capital)

[9] In a recent paper Boissay (2010) comes to the same conclusion using a general equilibrium model.The model financial market becomes fragile when the liquidity available exceeds the liquidity absorption capacity of the economy, which is determined by productivity in the real sector.

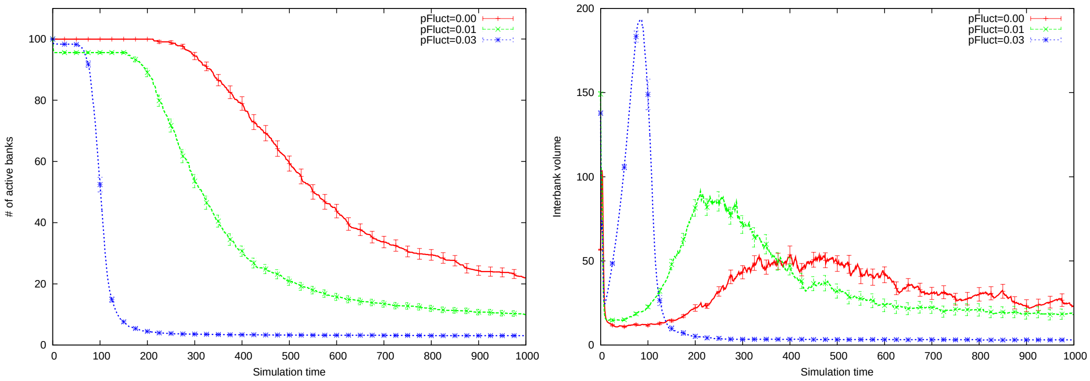

Figure 4.8: The effect of network heterogeneity (i). The effect of banks investment screening. Left: number of active banks over simulation time. Right: The amount of interbank loan volume over simulation time. We have used $ra_{fluct} = 0.01, 0.02, 0.03$ and the parameters from section 4.2.3 otherwise.

left. The results in this chapter indicate that different networks are differently resilient to large amounts of interbank loans. While the WS case is the least resilient to large values of L/I, its short average path length and high clustering makes it easier for banks to obtain funds or lend excess liquidity. In this sense WS networks will on the one hand lead to a more enhanced liquidity allocation than BA and random networks. On the other hand, however, WS networks are more prone to contagion at large interbank loan volumes. Note that this result is not in conflict with the results on the financial stability properties of different network types in section (4.3). While random networks are more resilient to higher L/I values, they also exhibit higher L values such that the overall effect is unclear. However, the analysis in section (4.3) shows that the increase in L dominates and that random networks are thus less stable than BA or WS networks.

In Georg and Poschmann (2010) we analysed the effect of network heterogeneity on financial stability. We assumed that banks could differ only in the risk aversion parameter and that all banks faced the same investment opportunities. In this case systemic stability is driven mainly by the fraction of banks with a large risk aversion.

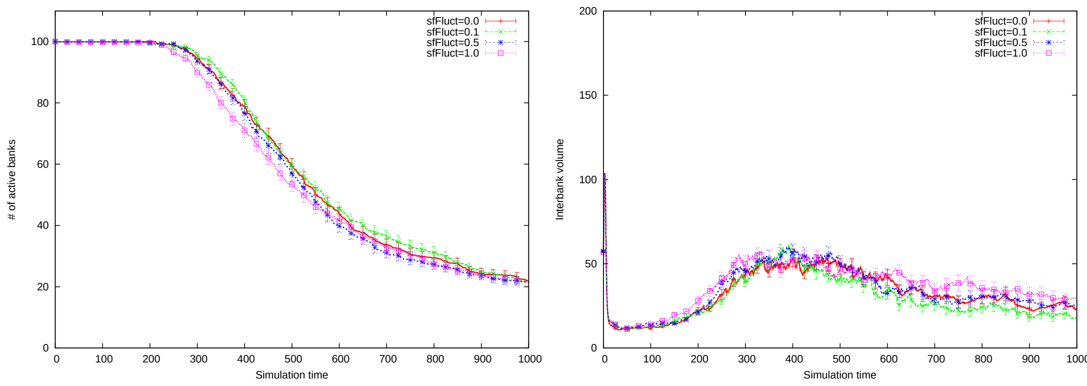

Figure 4.9: The effect of network heterogeneity (ii). The effect of a differing mass of depositors. Left: number of active banks over simulation time. Right: The amount of interbank loan volume over simulation time. We have used $sf_{fluct} = 0.0, 0.1, 0.5, 1.0$ and the parameters from section 4.2.3 otherwise.

This chapter now wants to allow for the possibility that some banks have a better screening mechanism for investments than others. The rationale behind this is, that some banks have better ways to ex-ante assess the default probability of an investment (that ultimately is defined only after it defaulted or not) than others. Therefore, the parameter ra_{fluct} that determines the fluctuations in bank's risk assessment is introduced. The larger this parameter is, the larger is the number of banks that are too optimistic about their investments. The results[10] are shown in Figure 4.8 for a Watts-Strogatz network and are in line with our previous results.

In Figure 4.9 the effect of banks having a different mass of depositors are analysed for a Watts-Strogatz topology. This is done by allowing the possibility of different banks face different scale factors $\gamma'^k = sf_{fluct}\gamma^k$ of household deposits. As it can be seen from Figure 4.9 the effect of this type of heterogeneity is negligible.

The third way heterogeneity can arrive in the presented model is through a larger

[10] See Figure 4 in Georg and Poschmann (2010) and the discussion about the role of expectations in the model.

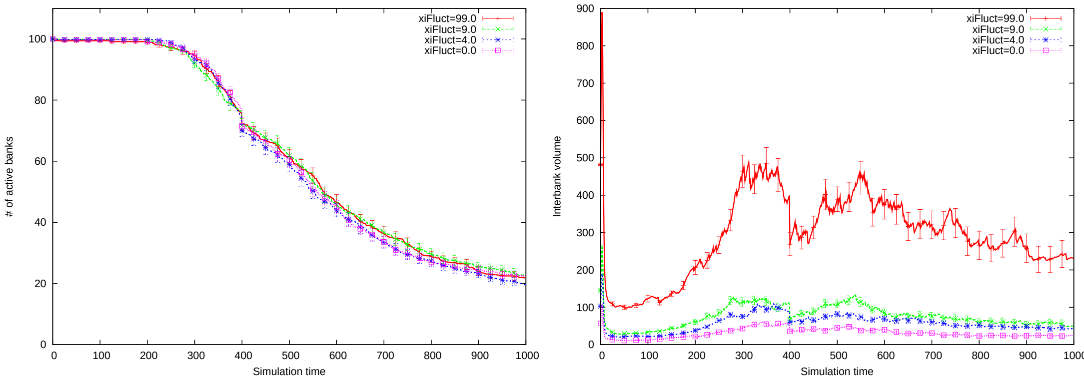

Figure 4.10: The effect of network heterogeneity (iii). The effect of heterogenous size. Left: number of active banks over simulation time. Right: The amount of interbank loan volume over simulation time. We have used $\xi_{fluct} = 0.0, 4.0, 9.0, 99.0$ and the parameters from section 4.2.3 otherwise.

variation in the size of the banks. This is done by allowing the scaling parameter ξ in the utility function to vary over a wider range $\xi := \xi + \xi_{fluct}$. The results of this analysis are shown in Figure 4.10 and indicate that financial stability in very heterogenous systems (in terms of bank size) does not differ considerably from more homogenous systems. To interpret this result in the context of the discussion about institutions that are too-big-to-fail (TBTF), one has to note that this result does not mean there is no problem with TBTF. It is merely shown that banking systems with heterogenous size of banks are not necessarily more prone to contagion. At the core of the TBTF discussion, however, is the observation that banks that are deemed "too-big-to-fail" have an incentive for taking excess risk by implicitely assuming that they will be bailed out should they default. This chapter analyses only systemic risk that arises through contagion and neglects the possibility of informational contagion[11] which will effectively lead to a larger systemic importance for larger banks.

Finally,this chapter analyses the effect of a different clustering coefficient and a different average path length on financial stability. Therefore, various simulations

[11] For a discussion on this see e.g. Acharya and Yorulmazer (2003), Bandt et al. (2009).

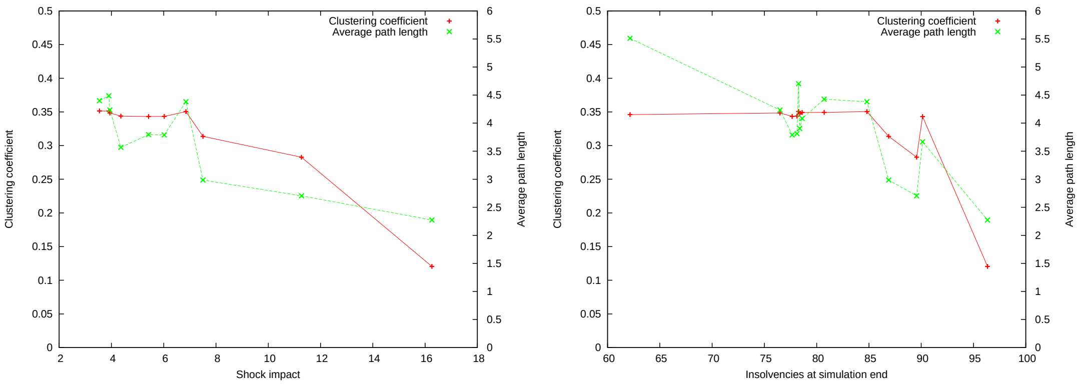

Figure 4.11: The relationship between clustering coefficient and average path length and financial stability. Left: clustering coefficient (left scale) and average path length (right scale) versus the impact of the insolvency of the largest bank in the system. Right: clustering coefficient (left scale) and average path length (right scale) versus the total number of insolvencies at the end of the simulation. We used $\beta_{WS} = 0.005, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7$ and the parameters from section 4.2.3 otherwise.

of WS networks with varying β parameter are performed and the clustering coefficient, average path length and the impact of a shock (where the largest bank goes into insolvency) is measured. The results of these simulations are depicted in Figure 4.11. Note that there is a correlation between the clustering coefficient and the average path length which makes it impossible to isolate the influence of a variation in clustering or average path length on financial stability. As shown by Watts and Strogatz (1998) in the region where $\beta_{WS} = 0.005, \ldots, 0.1$ the clustering coefficient stays approximately constant, while average path length drops drastically. In the region where $\beta_{WS} = 0.2, \ldots, 0.7$ the average path length does not change much, while the clustering coefficient drops drastically.

As can be seen in Figure 4.11 there is a tendency for shocks to be more severe in situations where clustering and average path length are low. The same tendency is observable when analyzing the total number of insolvencies instead of the impact of a shock to the system. It is intuitively clear that the average path length is negatively correlated with financial instability, since shocks can spread easier in networks with short average path lengths. The role of the clustering coefficient is less clear, however. By definition the clustering coefficient gives the probability that two banks A and B are connected with each other if they are both connected to a third bank, bank C. In the presented model each bank is at every point in time either a provider or a receipient of liquidity. This is a simplification of reality where banks can and will be provider and receipient of interbank liquidity at the same time. One consequence of this behaviour is that in the case of high clustering, a bank with a liquidity deficit will have more sources of funding than in the case of low clustering. This in turn will lead to an effective reduction of the average size of interbank exposures as the total liquidity demand is driven by either deposit outflows or losses on investment. This behaviour is depicted in Figure 4.12 where two simple networks consisting of four banks with different clustering coefficient are shown. During the initialization of the network, contractual agreements between the banks about their relationships and the possible direction of interbank flows are generated. These agreements define the structure of the interbank network.

At a given point in the simulation, each bank in the network has either a liquidity surplus or a deficit (or none, but that situation is very rare). The banks will then check their contracts with other banks to find possible partners for interbank transactions. This situation is depicted in the second column in Figure 4.12 where banks 1 and 4 have a liquidity surplus, while banks 2 and 3 are in need of liquidity. The solid lines denote actual interbank loans amongst the banks. Now assume that bank 2 goes into insolvency. In the case of high clustering it had two contractual partners, bank 1 and bank 3 (in the simulation these contractual partners are chosen upon initialization), each suffering losses on their loan books. In the case of low clustering, it is bank 1 that suffers the entire loss, which most likely is larger than in the case of high clustering. This will force bank 1 into a position where it is in need of liquidity itself. In the case of high clustering it can ask bank 4 for additional liquidity and maybe aquire the necessary funds. In the case of low clustering this possibility does not exist and bank 1 has to go into

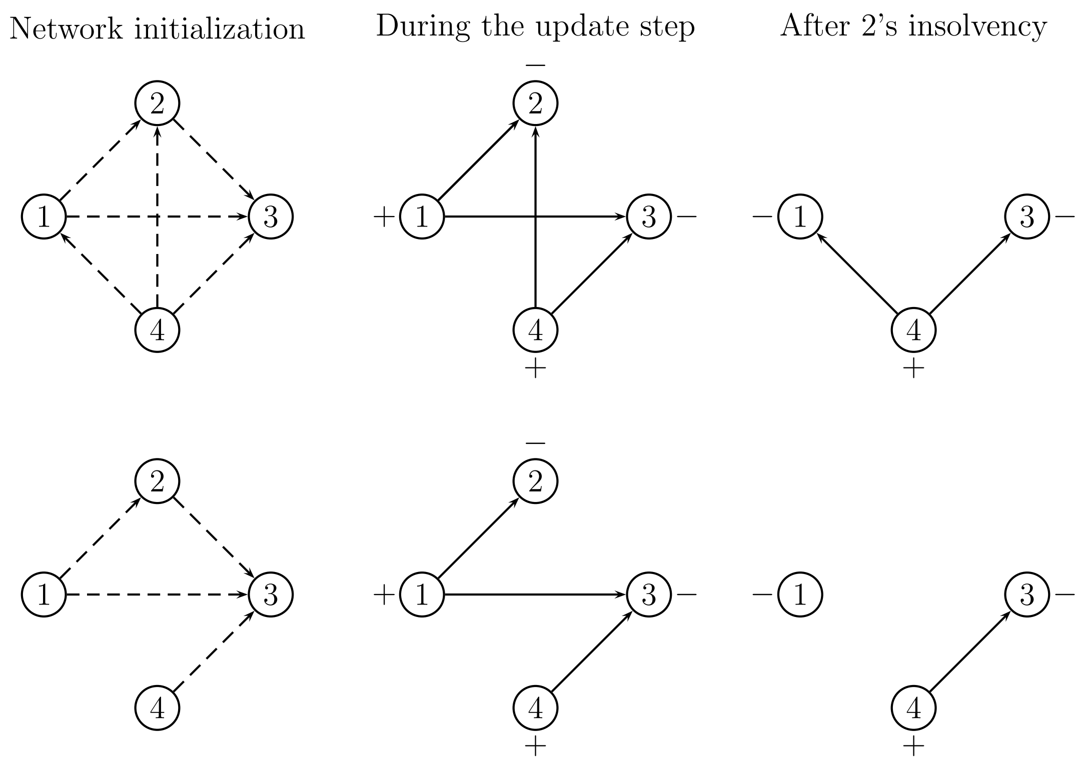

Figure 4.12: Comparison of high versus low clustering in interbank networks. Top: network with high clustering. Bottom: network with lower clustering. Left: the network at initialization stage where a dashed line indicates that the one bank is able to lend to the other. Middle: a realized network configuration where $\pm$ denotes liquidity surplus/shortage and solid lines denote interbank loans. Right: realized network configuration after bank 2 has gone into insolvency.

insolvency as well. The results hold true even in the presence of a central bank, as the central bank does not provide infinite liquidity, but only the amount that a bank can provide collateral for.

Note that this logic will change if banks have interbank assets and liabilities at the same time. The structure of the contractual relationships between banks can still remain the same, but for example bank 1 can be provider and receipient of liquidity at the same time.

Chapter 5

Systemic Interaction Risk

The financial crisis emphasized the importance of systemic risks for financial stability. While the existing literature studies different forms of systemic risk in isolation only, we develop a banking model that features all relevant forms in a unified framework.

5.1 Introduction

Systemic risk and systemic crises, in which a large part of the financial system fails, have gained much attention in recent years. The literature typically considers three different forms of systemic risk that contribute to the probability of a systemic crisis. First, interbank contagion refers to a situation in which banks lend funds among themselves to insure against liquidity shocks. This makes the banking system susceptible to the default of one bank, triggering default of other banks due to existing interbank loan default. Second, a correlated or common shocks materializes when the banks' asset returns are positively correlated and a negative realization hits several banks. Third, informational spillovers take place when news about one bank are useful for the prediction of another bank's health. Then, a bad news about one bank affects all related banks.

While there exists a large body of theoretical work on the individual forms of systemic risk, a unified framework is still missing. The present paper closes this gap. We develop a model of a banking system that features interbank contagion, common shocks, and informational spillovers and analyse their individual contribution to financial (in-)stability. We also analyze the interplay of these forms of systemic risk and call the interaction effect the *systemic interaction risk*.

While there is an independent role for each form of systemic risk, the systemic interaction risk is large. Notably, the systemic interaction risk increases with measures of a financial crisis, such as volatility of asset returns. In the baseline calibration systemic interaction risk constitutes about 30% of the total systemic risk. Our results therefore demonstrate the importance of the unified systemic risk framework in the analysis of financial stability.

The proposed framework has strong implications for capital adequacy requirements. Given the large interaction effect between forms of systemic risk, capital adequacy requirements may need to be adjusted substantially. Especially, since the interaction effect becomes more prominent in times of crises, capital requirements based on an assessment in tranquil times may be misleading. This questions the role of capital adequacy requirements as a countercyclial tool.

5.1.1 Model Features and Results

We consider an economy that extends over three time periods and has two regions. In each region there exists one bank and a large number of ex-ante identical households endowed with one unit of an all-purpose consumption and investment good. While both households and banks have access to a risk-free storage technology that matures after one period, only banks may access a risky asset. This asset matures after two periods and pays a risky return in period two superior in expectation to the risk-free return, but only an inferior return if prematurely liquidated in period one. We allow the regions' asset returns to be (positively) correlated, thereby introducing common shocks.

Households differ in their liquidity preferences. They either value consumption in period one only (early consumers), or value consumption in period two only (late consumers). Households privately learn their type at the beginning of period one. By assuming regional differences in the fraction of early consumers, from which idiosyncratic household liquidity preferences are drawn, regional liquidity demand shocks are introduced. This gives rise to interbank loans as an insurance mechanism and therefore potential interbank contagion.

The timing of the model is summarized in figure (5.10). Banks offer deposit contracts to households that specify withdrawals in periods one and two. Motivated by free entry, banks make zero profits on contract offered. Provided the expected return from the risky asset is sufficiently high relative to the consumers risk preference (and the model's parameters), households will deposit in full. Banks then make an investment decision about the risky asset and agree on an amount of interbank loans, which is to be transferred after the observation of the regional liquidity shock in period one.

How do households determine their optimal point of withdrawal? Early consumers simply always withdraw in period one, while late consumers might have an incentive to misrepresent their type and withdraw prematurely. Before making their strategical withdrawal decision, households receive a signal about the risky asset return. Each bank observes its liquidity demand and pays out demand deposits in period one if sufficient liquidity is available. If not, it declares bankruptcy, prematurely liquidates its assets (risky asset holdings and potentially interbank claims), and pays an equal share to all depositors.

We consider a sequential timing of the withdrawal decisions. Households in the region with a high fraction of early consumers receive their signal first. After they have made their withdrawal decision, households in the other region receive their signal and decide about withdrawal. Although the sequentiality of withdrawal decisions enhances the model's tractability, its attractiveness is to allow the study of informational spillovers. In particular, signals about the first region's risky asset return help households in the second region predict their own risky asset return.

Our focus is on systemic crises, defined as the joint default of both banks. We therefore use the ex-ante probability of joint bank default as our measure of systemic risk, which enables us to compare different scenarios in terms of their "systemic crisis content". The primary goal of this paper is to understand the contributions from each form of systemic risk as well as from the interaction between them (interaction effect). Hence, our exposition consists of four cases: (i) A baseline case without interbank lending, correlated portfolios or informational spillovers. In this case, no systemic risk is present. (ii) The case of pure interbank contagion. Banks insure themselves against regional liquidity shocks by exchanging interbank deposits. However, as banks are unaware of a counterparty externality, i.e. they do not take a possible default of their counterparty into consideration, there is overinsurance and contagion through the interbank channel. (iii) The case of informational spillovers and common shocks. The portfolio of banks are correlated, even though banks are not aware of it. This gives rise to a correlation externality where households in one region extract information about their own banks' returns by receiving a signal about the returns of the bank in the other region. (iv) The principal case of simultanous presence of all three forms of systemic risk: interbank contagion, common shocks, and informational spillovers. Such a situation occurs whenever bank defaults occur during times of high uncertainty as i.e. during the peak of the last financial crisis. It is precisely these situations where systemic risks have the most devastating impact on financial stability.

Technically, we solve for symmetric Bayesian Nash equilibria in threshold strategies. The baseline case features no interbank linkages. Therefore, the individual bank default probabilities are identical. Moving on to pure interbank contagion leaves the joint probability density and the conditional expectation unchanged, while the signal thresholds are affected by the change in payoffs. As there are more resources to keep by defaulting in period one, bank runs in the high liquidity demand region are more likely compared to the baseline case. Likewise, bank runs are less likely in the low liquidity demand region. However, the interbank linkages in the form of interbank loans drive a wedge between default probabilities in the low liquidity demand region in the two scenarios. Default is more likely if the bank in the high-liquidity bank has defaulted already, illustrating the well-known effect of interbank contagion. This is sometimes referred to as the knife-edge property of interbank contagion. Regarding systemic risk, the effect on the probability of a systemic crisis is ambiguous in general. Under a mild sufficient condition, however, a systemic crisis becomes more likely.

Turning to the case of informational contagion and common shocks, we obtain strong results. First, the chance of default is much reduced when the first bank did not default. Second, default in the low liquidity demand region has a higher probability if the first bank defaulted. While the severity of these results partially hinges on the strong common shock component, it nonetheless illustrates the power of information contagion. In addtion, information contagion also possesses a knife-edge property similar to interbank contagion, with a stabilizing effect after non-default and a destabilizing one after default.

Finally, we consider the presence of all forms of systemic risk. We define the systemic interaction effect as the contribution to systemic risk stemming from the unified model less the sums of the individual contributions from information contagion and interbank contagion. (As before, we economize on notation and use "systemic risk" as a short-hand for the probability of a systemic crisis.) We establish the importance of the interaction effect that accounts for a substantial part of the total systemic risk in the baseline calibration. Notably, the size of the interaction effect increases with measures of crisis, such as volatility of asset returns.

Therefore, we demonstrate the importance of the unified systemic risk framework in the analysis of financial stability. The size of the interaction effect also suggests strong implications for capital adequacy requirements and the regulation of systemic risk. In particular, the counterparty and correlation externalities call for regulation that will counterveil both effects. We briefly discuss the current Basel III framework in the light of our results and argue that, while it makes some progress on regulating counterparty externalities, it is insufficient to regulate the correlation externalities. Finally, we suggest measures that would enhance the current framework and give rise to a more thorough regulation of systemic risk.

5.1.2 Related Literature

Our paper is related to a growing literature on systemic risk and financial contagion. The interbank contagion literature builds on the seminal contribution of Diamond and Dybvig (1983), who study a demand deposits contract in a world of non-verifiable idiosyncratic liquidity demand. This setup gives rise to strategic complementarity between depositors and therefore multiplicity of equilibria. One equilibrium improves upon the competitive equilibrium allocation because of improved risk-sharing, whereas the second equilibrium features an inefficient bank-run, thus highlighting the importance of confidence. The authors also demonstrate that deposit insurance and a suspension of convertibility exclude the bank-run equilibrium. Morris and Shin (1998) revisit the multiplicity of equilibria in setups like Diamond and Dybvig (1983). They show that multiple equilibria rest on the assumption of perfect common knowledge about the economy's fundamentals, such as the second period's asset return in the Diamond-Dybvig model. Unique equilibria, by contrast, result from a small adjustment to the information structure. The authors demonstrate that any sufficiently small idiosyncratic uncertainty, which the agent will then primarily use, eliminates multiplicity of equilibria. They further demonstrate the desirability of unique equilibria since they put comparative statics and policy analysis on a stronger footing. Reexamining coordination games with imperfect and asymmetric information, Angeletos and Werning (2006) demonstrate that the uniqueness result stems from making the private or idiosyncratic signal arbitrarily precise relative to the public signal. While this is possible in the setup of exogenous information studied by Morris and Shin (1998), the authors introduce an asset market prioir to the coordination game. The asset price will then aggregate private information into a endogenous public signal. This ensures that greater precision of the private signal entails greater precision of the public signal as well, reestablishing multiple equilibria.

The model of Diamond and Dybvig (1983) is extended by Allen and Gale (2000) who study the role of interbank connections and obtain financial contagion as an equilibrium outcome. Faced with idiosyncratic liquidity shocks, banks insure themselves fully by holding loans on each other, thus reaching the first-best allocation. While achieving efficiency, this arrangement is financially fragile as a positive liquidity demand shock may travel through the entire financial system. The authors demonstrate that the size and the interconnectedness of the banking system matter, with complete loan structures being more robust than incomplete ones. Hence, systemic risk is modelled via the valuation of inter-bank loans on the asset side and contagion arises when one bank's bankruptcy affects other banks negatively. A similar approach is taken by Freixas et al. (2000) who analyze interbank networks and possible contagion effects. They consider a banking system with three periods and one investment and consumption good. This good that can be stored from one period to the next or invested into a risky asset which matures after two periods. There are N regions with one bank each and a continuum of risk-neutral investors that will consume in period two only. To motivate interbank transactions, some of the depositors consume in period two at locations different from those where they deposited in period zero. The authors find that interbank loans can reduce the cost of holding a liquid asset. This is similar to Allen and Gale (2000) who argue that interbank loans serve as insurance against liquidity shocks. Freixas et al. (2000) also show that the interbank market enhances the resilience of the banking system to the insolvency of a single bank. Our paper deviates from this literature insofar as we consider interbank contagion only as one possible form of systemic risk.

Extending the model of Allen and Gale, Dasgupta (2004) introduces imperfect information about the fundamentals in each region. Depositors now face a coordination problem and wish to strategically withdraw, if they believe that other depositors will do the same. This setup removes the typical multiplicity of equilibria in the Diamond/Dybvig type models and follows the coordination games outlined in Morris and Shin (1998). Dasgupta calculates the optimal level of interconnectedness in the banking system and shows that contagion can arise in equilibrium. It is precisely in stable banking systems with rare defaults that the impact of such a default is most severe. This result is confirmed by Gai and Kapadia (2009) who use a network model of a banking system and show that with increasing connectivity the risk of systemic crisis is reduced, while the crisis' impact increases. While our paper follows the aforementioned literature to some extend, it is closest in spirit with the model of Dasgupta (2004). The main difference, however, is that we explicitely consider correlations of regional fundamentals and thus the possibility of informational spillovers and common shocks as another form of systemic risk.

The distinction of different equally important forms of systemic risk has emerged in recent years. Bandt et al. (2009) distinguish between a broad and a narrow sense of systemic risk. While interbank contagion, as described i.e. by Allen and Gale (2000), Freixas et al. (2000) and Dasgupta (2004), poses a systemic risk in the narrow sense, the broad sense of systemic risk is characterized by a common shock to multiple banks and informational spillovers. Such a common shock can be caused by a fire-sale, where all banks that have invested into a given asset are affected simultaneously. In Acharya (2009), systemic risk is modelled as the endogenously chosen correlation of returns on assets held by banks. Because of limited liability and the negative externality of one bank's failure on the health of other banks, all banks undertake correlated investments, thereby increasing economy-wide aggregate risk (a so-called a "systemic risk-shifting incentive"). The author demonstrates the inefficiency of standard regulation policies, such as bank closure policy and capital adequacy requirements, as these policies are based on a banks own risk only. Even worse, such policies may accentuate systemic risk. Optimal regulation, by contrast, is shown to take into account a bank's joint (correlated) risk with other banks as well as its individual (bank-specific) risk. Acharya (2009) argues that common shocks are not subordinate to contagion effects. This result is confirmed by Georg and Poschmann (2010) who develop a dynamic multi-agent simulation to compare systemic risk that arises through contagion effects with the systemic risk that is posed by common shocks. Cifuentes et al. (2005) present a model of systemic risk where financial institutions are connected via portfolio holdings. Adrian and Shin (2010) address the issue of financial contagion through fire-sales and mark-to-market accounting. They argue that this can amplify the potential impact of a shock and therefore pose a systemic risk. Wagner (2010) states that one key reason behind the severity of the financial crisis of 2007/2008 was that many financial institutions had invested in the same assets (e.g. subprime mortgages), therefore exposing them to a common shock. Our model combines the results from these distinct strands of literature into a unified model of systemic risk that takes interbank contagion, common shocks and informational spillovers into account. We are thus able to calculate the interaction effect that is associated with the simultaneous occurance of different forms of systemic risk. One situation where our model is particularly relevant is the insolvency of the US investment bank Lehman Brothers in September 2008. The insolvency itself was modest in terms of contagion effects, the only reported insolvency due to the Lehman default was Reserve Primary Fund breaking the buck. This however was considered to be a signal that triggered a run of institutional investors on money market funds that were originally unaffected by the Lehman insolvency. Thus, it is precisely a situation where different forms of systemic risk act simultaenously and that cannot be explained in full by the existing literature.

5.2 The Model

This section outlines the model structure and derives the bank's default probabilities in the baseline case of no interbank linkages (no interbank lending and no informational spillovers).

5.2.1 The Model Setup

The economy consists of two regions $k \in \{A, B\}$ and extends over three periods $t = 0, 1, 2$. There exists an all-purpose consumption and investment good. In each region, there is one bank and a large number of ex-ante identical households, $i \in [0, 1]$. Households are endowed with one unit in $t = 0$ only. There are two types of households, early and late consumers, denoted by $\theta \in \{1, 2\}$, respectively. Early consumers value consumption in $t = 1$ only, while late consumers value consumption in $t = 2$ only. Early consumers will always consume in $t = 1$, while late consumers may have an incentive to misrepresent their type by withdrawing prematurely as the household's type is observed privately. The region-wide probability of being an early consumer is identical across consumers: $\lambda_k = \Pr\{\theta_{i,k} = 1\}\ \forall i$. Therefore, by the law of large numbers, the fraction of households in region k that wishes to consume early is given by λ_k.

There are perfectly negatively correlated regional liquidity shocks that motivate interbank insurance. In particular, excess regional liquidity in region A is associated with regional liquidity shortage of identical size in region B and vice versa, with equal probability for simplicity. Since we do not consider situations in which

(i) bank runs that are merely driven by aggregate liquidity shortage or (ii) the possibility of bank runs is excluded due to excess aggregate liquidity, we focus on perfectly negatively correlated regional shocks of equal size. In short:

Probability	Region	
	A	B
p	$\lambda_A = \lambda + \eta \equiv \lambda_H$	$\lambda_B = \lambda - \eta$
$1 - p$	$\lambda_A = \lambda - \eta \equiv \lambda_L$	$\lambda_B = \lambda + \eta$

Table 5.1: Liquidity shocks in different regions.

There are two assets. First, a risk-free short asset matures after one period and yields a return of one, interpreted as a storage technology. Second, a risky long asset matures after two periods. It yields a uniformly distributed gross return $\mathfrak{R} \sim U[\mu - \sigma, \mu + \sigma]$ if held to maturity, where $\mu > 1$ is the expected return and $\sigma > 0$ a volatility measure. Premature liquidation after one period yields an inferior return $\beta \in [0, 1)$ only. Note that $\mathfrak{R}$ denotes a random variable as opposed to its realization R.[1] The payoffs are summarized as follows:

Asset	$t = 0$	$t = 1$	$t = 2$
Short $(0 \rightarrow 1)$	-1	1	0
Short $(1 \rightarrow 2)$	0	-1	1
Long $(0 \rightarrow 2)$	-1	$\beta \in [0, 1)$	$\mathfrak{R} \sim U[\mu + \sigma, \mu - \sigma]$

Table 5.2: Summary of payoffs.

Banks have a comparative advantage in managing funds because of greater access to assets. That is, households have only access to the short asset, such as saving in a piggy-bank, whereas banks may invest in either the short or the long asset.

[1]Note that we use Fraktur for random variables, their corresponding capital latin letters for their realizations, Latin for variables, and Greek for parameters throughout.

5.2.2 The Model Timeline

Period Zero: The complete timeline of the model is depicted in Figure (5.10) and the payoff structure in Figure (5.11). First, all households in both regions receive their endowment. Next, regional banks offer a deposit contract to the households in their region that specifies withdrawals c_1, c_2 in $t = 1, 2$.[2] More precisely, banks pay out deposits c_1 in $t = 1$ if there is sufficient liquidity available. If not, it declares insolvency. A bankrupt bank neither pays interbank claims nor deposits in $t = 2$. Note that insolvent banks may receive repayment from interbank loans. In the case of insufficient liquidity, the long asset and interbank claims are liquidated. All depositors receive an equal share of total resources. We therefore abstract from a sunspot induced bank run implied by a first-come first-serve allotment rule.

If the bank survives, it settles its liabilities in the interbank market and pays out its remaining resources to depositors in $t = 2$. Following Dasgupta (2004), $c_1 \equiv 1$ for simplicity.[3] Note that c_2 is contingent on the realization of the investment return R_k, the regional liquidity shock λ_k, and both bank's default probabilities, defined as a_k. We assume that banks make zero profits motivated by free entry.[4]

Third, the households decide whether to deposit or to store their endowment, giving rise to a participation constraint:

$$\mathrm{E}[U] = \mathrm{E}\left[\lambda u(c_1) + (1-\lambda)u(c_2)\right] \geq u(1) \ , \tag{5.1}$$

where E is the expectation operator that takes into account regional liquidity

[2]The non-observability of the idiosyncratic liquidity shock prevents the deposit contract between the bank and the household to be contingent on the household's liquidity shock.

[3]This corresponds to the first-best allocation for log-utility.

[4]This implies that the number of banks operating in a region is indeterminate. Without loss of generality it is taken to be one for expositional clarity. To inactivity of a given bank in another region is motivated as an equilibrium outcome in a game in which banks face a positive but arbitrary small fixed cost of operating (i.e. the cost of setting up a branch in the other region, obtaining regional knowledge) in the other region.

shocks, investment risk, and the joint probability distribution of banks' default. The participation constraint specifies a joint constraint on the model parameters that can be interpreted as a constraint on the lower bound of the average return μ. The maintained assumption is that the households' participation constraints are satisfied. Each household will therefore deposit in full.

Finally, each risk-neutral bank maximizes its expected valuation by (i) choosing the investments in the short and long asset $(y, 1 - y)$, where defaults from insufficient liquidity are taken into account; and (ii) agreeing upon the amount of interbank insurance b at price $\phi > 1$. The interbank interest rate ϕ can be thought of being set by a central bank and banks take it as given.[5] The interbank loan b will be transferred from the liquidity surplus region to the liquidity shortage region at the beginning of $t = 1$ and repaid at the beginning of $t = 2$. Banks are identical in $t = 0$ and will therefore choose the same level of investment and interbank insurance y, b.

Period One: First, the short asset matures and pays off. Next, the regional liquidity shocks λ_k are drawn and publicly observed. As a consequence, the exchange of interbank deposits is initiated. Households in both regions draw their individual liquidity demands and observe them privately.[6]

Third, households sequentially receive a signal of the the long asset's return. There are two cases: (a) households in the low liquidity demand region (L) receive the signal first and (b) households in the high liquidity demand region (H) receive the signal first. In case (a), households in region H observe whether or not the other region's bank defaults. However, payoffs in region H are unaffected

[5] We abstract from variation of the interbank rate around the main refinancing rate for simplicity.

[6] In practice, the timing of individual and regional liquidity shocks is likely to be reversed: many individual shocks add up to a regional shock. Exclusively to ease exposition, we derive the individual shocks after the realization of regional shocks.

by this (see Figure 5.11). In case (b), the default in region H implies a repayment failure of its interbank liabilities, resulting in contagious effects in region L.[7] Without loss of generality, we focus on case (b). Then, the high liquidity demand region's households strategically decide whether or not to withdraw. Subsequently, all households in the low liquidity region receive a signal and decide on whether to withdraw.

Signals have the following form:

$$\mathfrak{S}_k = \mathfrak{R}_k + \mathfrak{E}_k \tag{5.2}$$

$$\mathrm{E}[\mathfrak{E}_k] = 0 \quad , \quad \mathrm{E}[\mathfrak{E}_A\,\mathfrak{E}_B] = 0 \quad , \quad \mathrm{E}[\mathfrak{E}_k\,\mathfrak{R}_{k'}] = 0\ \forall (k,k') \tag{5.3}$$

where $\mathfrak{E}_k \sim U[-\chi, \chi]$ is a uniformly distributed noise with realization E that is identically and independently distributed across regions and uncorrelated with any region's fundamental, $\mathfrak{R}_k$. For tractability we assume that signals are public: households in region L not only observe whether there was a bank run in region H, but also the underlying signal S_H. To ensure symmetric equilibrium actions, all households in region $k \in \{A, B\}$ receive the same signal S_k from the random variable $\mathfrak{S}$.

Finally, banks use their liquidity to pay out the depositors. If withdrawals exceed the bank's liquidity, the bank declares bankruptcy, liquidates its long assets and interbank claims to pay an equal share to all depositors. There will be no activity of bankrupt banks in $t = 2$.

Period Two: First, the long asset matures and pays the return as realized in $t = 1$. Then, a surviving bank settles its interbank position, including repayment to an insolvent counterpart. Finally, all surviving banks pay out deposits.

[7] In general, a fraction $\xi \in [0, 1)$ is repaid. Effectively, we focus on $\xi = 0$ to highlight the impact of the contagion channel. While $\xi \in (0, 1)$ yields qualitatively identical results, a low value of ξ appears to be corroborated by the observation that debtors receive a tiny share of the insolvency assets.

5.2.3 Strict Pro-Rata and Uniqueness of Equilibria

The seminal contribution of Diamond and Dybvig (1983)considers a demand deposits contract in a world of non-verifiable idiosyncratic liquidity demand. This setup gives rise to strategic complementarity between depositors implying multiplicity of equilibria. One equilibrium improves upon the competitive equilibrium allocation because of improved risk-sharing, whereas the second equilibrium features an inefficient bank-run. Multiplicity arises from *weak pro-rata*, that is the resources of a bank run are distributed among those depositors who run only. Hence, any depositor's incentive to run increases with the number of depositors running. Maintaining weak pro-rata, Morris and Shin (2000) demonstrate the uniqueness of equilibrium can be restored when some sufficiently precise idiosyncratic information about the economy's fundamentals, such as the second period's asset return, is introduced (global games). See also Angeletos and Werning (2006) for a recent critique.

By contrast we consider a *strict pro-rata* allotment. That is, all depositors, not only those who ran the bank, receive an equal share upon default of a bank. This appears to be an appropriate description of the legal arrangement in many countries, including the US[8] and Germany.[9] Strict pro-rata excludes strategic complementarities between late consumers. Inspecting the payoff structure in figure (5.11), we observe that late consumers now have a weakly dominant strategy in the Bayesian Nash threshold equilibrium - irrespective of the other late consumers. Then, the uniquesness of equilibria is guaranteed even with region-specific non-idiosyncratic signals. Hence, we do not need to resort to global games techniques.

[8]See US Federal Deposit Insurance Corporation Act and article 11(d)(11) in particular. Also: http://www.law.cornell.edu/uscode/html/uscode11/usc_sup_01_11.html.

[9]See for the legal arrangement: http://www.gesetze-im-internet.de/inso/.

5.3 The Baseline Case

The baseline case abstracts from interbank links. There are no liquidity demand shocks, $\eta = 0$, and the long asset's returns are uncorrelated across regions, $\rho = 0$. This case is useful to illustrate the techniques used to solve for the equilibrium and to determine default probabilities as well as probabilities of systemic crisis.

Equilibrium is solved by backward induction. First, households in the high liquidity demand region H receive their signal S_H, update their expectations $E[\mathfrak{R}_H|S_H]$ about the long asset's return, and decide strategically whether or not to withdraw at the end of $t = 1$. All early consumers will withdraw and consume, whereas late consumers will withdraw and store for $t = 2$ if and only if the expected asset return conditional on the signal falls short of a threshold level $\hat{R}_H$, implying a signal threshold $\hat{S}_H$. These thresholds are determined by the (late) households' indifference between withdrawing in $t = 1$ and waiting for repayment in $t = 2$. If the signal falls short of the threshold $S_H < \hat{S}_H$, all households in region H withdraw and the bank defaults. Then, households in L receive their signal S_L, update their expectations $E[\mathfrak{R}|S_L]$ and decide whether or not to withdraw at the end of $t = 1$. The threshold level is denoted by $\hat{R}_L$, implying a threshold $\hat{S}_L$ for the signal.

5.3.1 Probability Distribution of the Signal

We start by deriving the signal's distribution. Let $E_{\min} = -\chi$, $E_{\max} = +\chi$, $R_{\min} = \mu - \sigma$, and $R_{\max} = \mu + \sigma$ be the lower and upper bounds of the noise and the asset return, respectively. Assuming that a signal-to-noise ratio of above one,

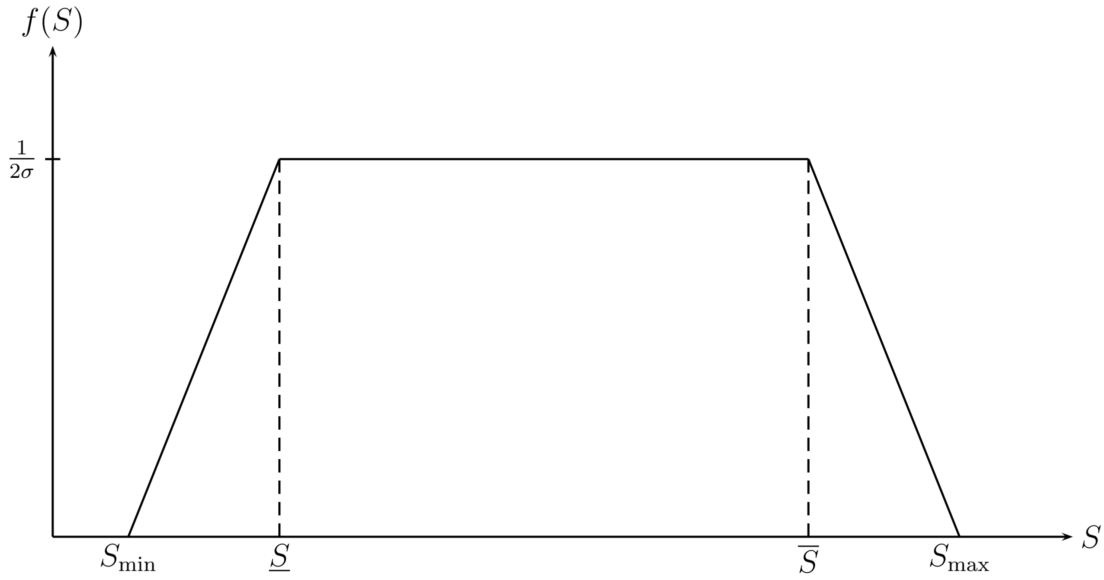

Figure 5.1: The signal's probability density ($\sigma > \chi$).

$\sigma > \chi$, we partition the support of $\mathfrak{S}$:

$$S_{\min} \equiv R_{\min} + E_{\min} = \mu - \sigma - \chi \tag{5.4}$$

$$\underline{S} \equiv R_{\min} + E_{\max} = \mu - \sigma + \chi \tag{5.5}$$

$$\overline{S} \equiv R_{\max} + E_{\min} = \mu + \sigma - \chi \tag{5.6}$$

$$S_{\max} \equiv R_{\max} + E_{\max} = \mu + \sigma + \chi \tag{5.7}$$

By convolution, the signal's probability density $f(S)$ is (see appendix 5.8.2 for a proof):

$$f(S) = \begin{cases} \frac{S - S_{\min}}{4\chi\sigma} & \text{for} \quad S \in [S_{\min}, \underline{S}] \\ \\ \frac{1}{2\sigma} & \text{for} \quad S \in [\underline{S}, \overline{S}] \\ \\ \frac{S_{\max} - S}{4\chi\sigma} & \text{for} \quad S \in [\overline{S}, S_{\max}] \end{cases} \tag{5.8}$$

which is depicted in Figure (5.1).

5.3.2 Conditional Expectation

The update of the expectations about asset return is identical across regions because of the returns' statistical independence. The conditional expectation

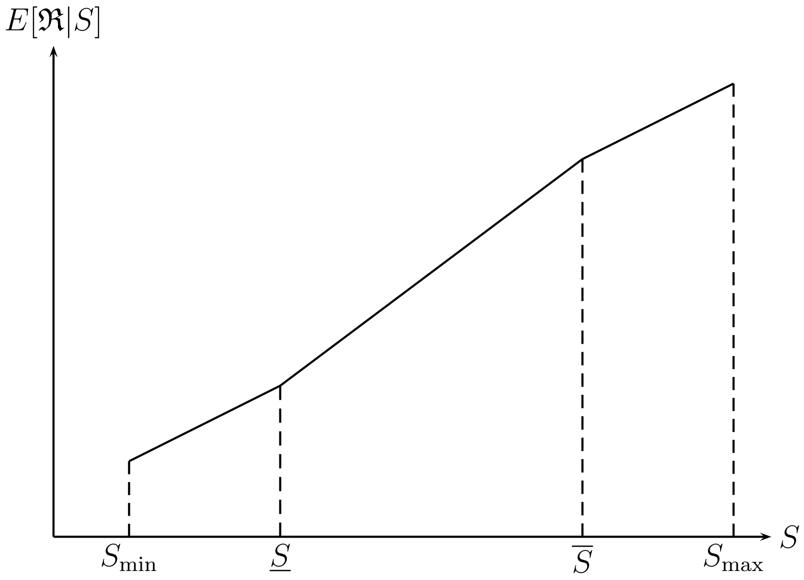

Figure 5.2: Conditional expectation $E[\mathfrak{R}|S]$ as a function of S.

$E[\mathfrak{R}|S]$ is shown in Figure 5.2 (see Appendix 5.8.2 for a proof) and given as:

$$E[\mathfrak{R}|S] = \begin{cases} \frac{1}{2}(S+\underline{S}) & \text{for} \quad S \in [S_{\min}, \underline{S}] \\ \\ S & \text{for} \quad S \in [\underline{S}, \overline{S}] \\ \\ \frac{1}{2}(S+\overline{S}) & \text{for} \quad S \in [\overline{S}, S_{\max}] \end{cases} \tag{5.9}$$

The joint probability density $g(S_H, S_L)$ is given as $g(S_H, S_L) = f(S_H)\, f(S_L)$ and partitioned as shown in Figure (5.3). Statistical independence of long asset returns implies a symmetry in terms of withdrawal decisions, denoted as $d \in \{0, 1\}$, and therefore identical thresholds in regions H and L, $\hat{R}_H = \hat{R}_L \equiv \hat{R}$. Thus, default $d = 1$ takes place if and only if $S \leq \hat{S}$. Withdrawing yields $y + \beta(1-y)$ for the late consumer, whereas not withdrawing yields $\frac{1}{1-\lambda}\left[E[\mathfrak{R}|S](1-y) + (y-\lambda)\right]$. Hence, the threshold of the long asset's conditional expectation is given by:

$$\hat{R} = \lambda + \beta(1-\lambda) \tag{5.10}$$

We assume that households will always default if they receive the lowest possible signal $S_{\min}$ and will never default if they receive the highest possible signal $S_{\max}$,

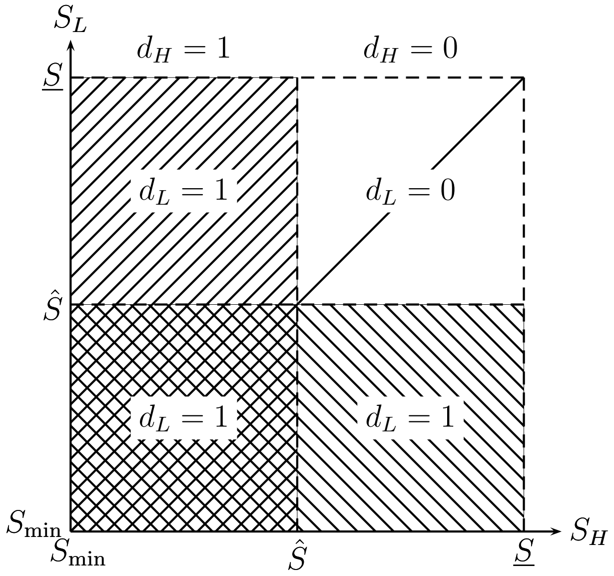

Figure 5.3: The support of the signals' joint density $g(S_H, S_L)$ in the absence of any form of contagion.

implying a parameter constraint $R_{\min} \leq \hat{R} \leq R_{\max}$. In order to capture the low relative frequency of bank defaults in reality, we focus on default for low signal levels, that is $S \in [S_{\min}, \underline{S}]$. The signal's threshold is:

$$\hat{S} = 2\hat{R} - \underline{S} \tag{5.11}$$

5.3.3 Default Probabilities and Systemic Crises

This signal leads to the probability of a bank default in any region:

$$\begin{aligned}
a^{(1)} &\equiv \Pr\{S \leq \hat{S}\} = \int_{S_{\min}}^{\hat{S}} f_S(S)dS && (5.12)\\
&= \frac{1}{8\chi\sigma}\int_{S_{\min}}^{\hat{S}} (S - S_{\min})dS && (5.13)\\
&= \frac{1}{8\chi\sigma}\left(\frac{1}{2}\hat{S}^2 - \hat{S}S_{\min} + \frac{1}{2}S_{\min}^2\right) && (5.14)\\
&= \frac{1}{8\chi\sigma}\left(\hat{S} - S_{\min}\right)^2 && (5.15)\\
&= \frac{1}{2\chi\sigma}\left(\hat{R} - R_{\min}\right)^2 && (5.16)\\
&= a_H^{(1)} = a_L^{(1)} && (5.17)
\end{aligned}$$

We define a *systemic crisis* as the default of both banks.[10] The probability of a systemic crisis is then the ex-ante probability of joint default, denoted as $\overline{a}_D$. In the baseline case, indexed as scenario (1), the probability of a systemic crisis is:

$$\overline{a}_D^{(1)} \equiv \Pr\{d_H = 1, d_L = 1\} = a^{(1)}\, a^{(1)} \ . \tag{5.18}$$

Also, the joint probability of default in region L and survival in region H, useful to evaluate beneficial contagion effect upon non-default in subsequent sections, is given by:

$$\overline{a}_N^{(1)} \equiv \Pr\{d_H = 0, d_L = 1\} = (1 - a^{(1)})\, a^{(1)} \ . \tag{5.19}$$

5.4 Interbank Contagion

We now consider interbank linkages in the form of interbank loans, caused by liquidity fluctuations $\eta > 0$. We proceed with backward induction as before. First, households in the high liquidity demand region H receive their signal S_H, update their expectations $E[\mathfrak{R}_H|S_H]$ about the long asset's return, and decide strategically whether or not to withdraw at the end of $t = 1$. All early consumers will withdraw and consume, whereas late consumers will withdraw and store for $t = 2$ if and only if the expected asset return conditional on the signal falls short of a threshold level $\hat{R}_H$, determined by the indifference between withdrawing in $t = 1$ and waiting for repayment in $t = 2$. Note that the threshold differs from the baseline case because of the presence of interbank loans. Withdrawal of households and bank default are synonymous and will take place if and only if $S_H < \hat{S}_H$.

Second, households in region L observe whether or not the bank in H has defaulted and receive their signal S_L. Signal thresholds are determined as before, but now depend on whether default in region H occurred (state N for no default and D for default). Hence, thresholds are denoted as $\hat{S}_{L,N}$, $\hat{S}_{L,D}$ for signals and

[10] Note that a systemic crisis is not necessarily caused by systemic risk, as a sufficiently bad signal in both regions will also lead to the default of both banks. This can be interpreted as a macroeconomic shock as the cause of a systemic crisis.

$\hat{R}_{L,N}$, $\hat{R}_{L,D}$ for the conditional expectation about the long asset's return. As before, households in region L then strategically decide whether or not to withdraw.

Consider households in region H who move first. Note that their payoffs are independent of the withdrawal decision of households in region L. They receive $y+\beta(1-y)+b$ if they withdraw and $\frac{1}{1-\lambda_H}\left[E[\mathfrak{R}_H|S_H](1-y)+(y-\lambda_H+b)-\phi b\right]$ otherwise. The cutoff values of the expected asset return is:

$$\hat{R}_H = \lambda_H + \beta(1-\lambda_H) + \frac{\phi - \lambda_H}{1-y} b \tag{5.20}$$

Now consider a household in region L who has observed a default of region H's bank. Then, not withdrawing yields $\frac{1}{1-\lambda_L}\left[E[\mathfrak{R}_L|S_L](1-y)+(y-b-\lambda_L)\right]$, while withdrawing yields $y+\beta(1-y)-b$. This leads to a threshold:

$$\hat{R}_{L,D} = \lambda_L + \beta(1-\lambda_L) + \frac{\lambda_L}{1-y} b \tag{5.21}$$

Likewise, in the case of no default in H, withdrawing yields $y+\beta(1-y)-b+\beta\phi b$, whereas not withdrawing yields $\frac{1}{1-\lambda_L}\left[E[\mathfrak{R}_L|S_L](1-y)+(y-\lambda_L-b)+\phi b\right]$. Hence, the threshold of the long asset's conditional expectation is given by:

$$\hat{R}_{L,N} = \lambda_L + \beta(1-\lambda_L) + \frac{\lambda_L - \phi\left[1-\beta(1-\lambda_L)\right]}{1-y} b \quad < \quad \hat{R}_{L,D} \tag{5.22}$$

The larger cutoff value in region L after a default in region H is intuitive: the default reduces the available assets in region L in period $t=2$ and induces late consumers to withdraw prematurely for a larger range of expected asset returns. This is the classical contagion case.

Any threshold of the conditional expectation translates uniquely into a threshold of the signal S:

$$\hat{S}_j = 2\hat{R}_j - \underline{S} \quad \text{for } j \in \{H, LD, LN\} \tag{5.23}$$

There are parameter constraints as in the baseline case: $\hat{R}_{L,N} \geq R_{\min}$ and $\hat{R}_H \leq R_{\max}$. The default decisions are depicted in Figure (5.4).

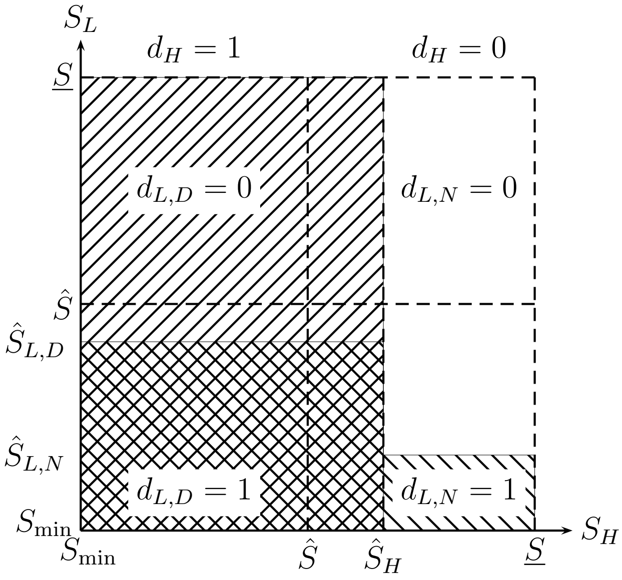

Figure 5.4: The support of the joint density $g(S_H, S_L)$ if there is interbank contagion, but no informational contagion.

To compare the default probabilities ot the baseline case, we first define the individual default probabilities:

$$a_j^{(2)} \equiv \Pr\{S \leq \hat{S}_j\} = \frac{1}{2\chi\sigma}\left[\hat{R}_j - R_{\min}\right]^2 \quad , \quad j \in \{H, (L,D), (L,N)\} \tag{5.24}$$

Comparing this to the baseline case without interbank loans, it can be seen that the area where a joint default occurs increases, since $\hat{S}_H > \hat{S}$ while $\hat{S}_{L,D}$ can be larger or smaller than $\hat{S}$ and $\hat{S}_H > \hat{S}_{L,D}$). At the same time, the probability of a default of the bank in L decreases if there is no default in H.

The probability of a systemic crisis reads as:

$$\overline{a}_D^{(2)} \equiv \Pr\{d_H = 1, d_{L,D} = 1\} = a_H^{(2)} a_{L,D}^{(2)} \tag{5.25}$$

While the impact on the probability of a systemic crisis is in general ambiguous, imposing equilibrium conditions, a sufficient condition for the increase in systemic risk is:

$$\frac{\lambda_L b}{1 - y} \geq (1 - \beta)\eta \tag{5.26}$$

which is satisfied, unless liquidation values are tiny and liquidity shocks are huge.

Likewise, the probability of default in region L after no default in region H is given as:

$$\overline{a}_N^{(2)} \equiv \Pr\{d_H = 0, d_{L,N} = 1\} = (1 - a_H^{(2)})a_{L,N}^{(2)} \ll a^{(1)}\,(1 - a^{(1)}) = \overline{a}_N^{(1)} \tag{5.27}$$

In the case of interbank loans the probability of default upon survival in region H falls due to lower survival probability in region H $(1 - a_H^{(2)} < 1 - a_H^{(1)})$ and lower default probability when region H's bank did not default $(a_{L,N}^{(2)} < a_L^{(1)})$. This is the mutual insurance character of interbank loans, a positive effect of interbank linkages.

5.5 Informational Contagion

Informational contagion poses another form of systemic risk. If asset fundamentals are correlated, the observation of region H's signal helps households in region L to infer their own asset fundamentals. In particular, region H's signal may not only trigger a bank run in this region but may suffice to induce a run in region L as well, even in the absence of interbank markets. Let $\rho \equiv corr(\mathfrak{R}_H, \mathfrak{R}_L) \in [0, 1]$ denote the correlation of long assets, where $\rho = 0$ excludes informational contagion altogether. For tractability we focus on the case $\rho = 1$, a perfect common shock, that implies $\mathfrak{R}_L = \mathfrak{R}_H$. [11]

We start by calculating the two-dimensional density $g(S_H, S_L)$. The pdf, depicted in Appendices (5.14), is fully symmetric but differs from the baseline and interbank contagion case's pdf. We maintain our focus on low signal levels, that is $S_k \in [S_{\min}, \underline{S}]$ to match the emprirical relative frequency of bank defaults. The support in this area is depicted in figure (5.5). The joint density in this area is

[11] Up to a scaling factor that is set to unity for simplicity.

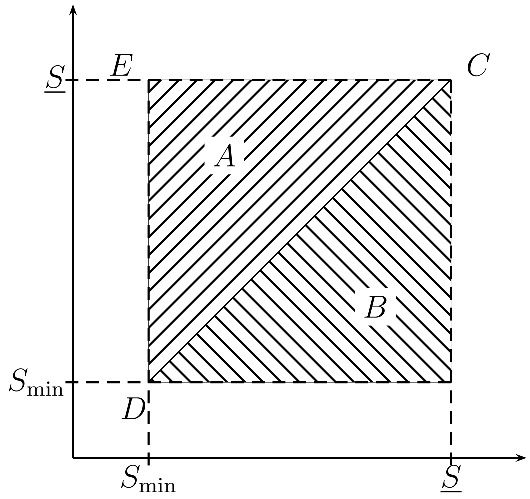

Figure 5.5: Support of $g(S_H, S_L)$ with the partition into two regions A, B.

given as (see Appendix (5.8.2) for a proof):

$$g(S_H, S_L) = \begin{cases} \frac{1}{8\chi^2\sigma}(S_H - S_{\min}) & \text{in Region A} \\ \\ \frac{1}{8\chi^2\sigma}(S_L - S_{\min}) & \text{in Region B} \end{cases} \tag{5.28}$$

Households in region L use both signals to update their expectation about the long asset's return. The conditional expectation $E[\mathfrak{R}|S_H, S_L]$ is then given as (see Appendix (5.8.2) for a proof):

$$E[\mathfrak{R}|S_H, S_L] = \begin{cases} S_H + \chi & \text{in Region A} \\ \\ S_L + \chi & \text{in Region B} \end{cases} \tag{5.29}$$

As the payoffs for early households are unchanged from the baseline case, the thresholds for the conditional expectations are unchanged, $\hat{R}_H = \hat{R}$. The signal's threshold is $\hat{S}_H = \hat{S}$. Hence, $d_H = 1$ if and only if $S_H \leq \hat{S}$. Households in region L take both signals into account and thus use the conditional expectation $E[\mathfrak{R}|S_H, S_L]$, which leads to a signal threshold $\tilde{S} = \hat{R} - \chi$. Therefore, households in region L *always* withdraw given that the signal in region H is smaller than $\tilde{S}$, illustrating the power of informational contagion. Figure (5.6) displays the

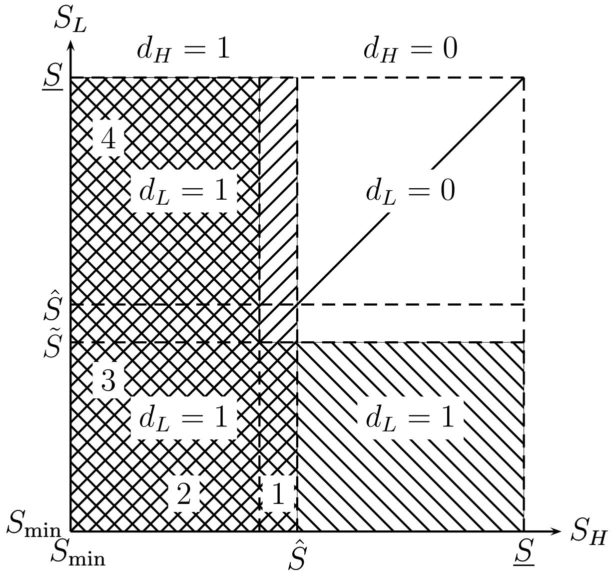

Figure 5.6: Support of the joint density $g(S_H, S_L)$ in the case of pure informational contagion.

default pattern in the presence of informational contagion.

To determine default probabilities, it is useful to find the individual probabilities of the areas 1,2,3, and 4 as marked in Figure (5.6):

$$
\begin{aligned}
a_2^{(3)} &= \frac{1}{8\chi^2\sigma}\int_{S_{\min}}^{\tilde{S}}\int_{S_{\min}}^{S_H}(S_L - S_{\min})dS_L dS_H && (5.30)\\
&= a^{(1)}\frac{1}{24\chi}(\hat{R} - R_{\min}) && (5.31)\\
&= a_3^{(3)} && (5.32)
\end{aligned}
$$

$$
\begin{aligned}
a_1^{(3)} &= \int_{\tilde{S}}^{\hat{S}}\int_{S_{\min}}^{\tilde{S}}(S_L - S_{\min})dS_L dS_H && (5.33)\\
&= a^{(1)}\frac{1}{8\chi}(\hat{R} - R_{\min}) && (5.34)
\end{aligned}
$$

$$
\begin{aligned}
a_4^{(3)} &= \int_{S_{\min}}^{\tilde{S}}\int_{\tilde{S}}^{\underline{S}}(S_H - S_{\min})dS_L dS_H && (5.35)\\
&= a^{(1)}\left[\frac{1}{4} - \frac{1}{8\chi}(\hat{R} - R_{\min})\right] && (5.36)
\end{aligned}
$$

where the first equality holds because of symmetry. The relevant default probabilities are then:

$$\bar{a}_N^{(3)} \equiv \Pr\{d_L = 1, d_H = 0\} = a_1^{(1)} \left[\frac{1}{4} - \frac{1}{8\chi}(\hat{R} - R_{\min})\right] \tag{5.37}$$

$$\bar{a}_D^{(3)} \equiv \Pr\{d_L = 1, d_H = 1\} = a^{(1)} \left[\frac{1}{4} + \frac{1}{12\chi}(\hat{R} - R_{\min})\right] \tag{5.38}$$

Comparing these default probabilities to the ones of the baseline case, we find for the joint probability of no default in region H and default in region L:

$$\bar{a}_N^{(3)} \leq \bar{a}_N^{(1)} \Leftarrow \mu > \lambda + \beta(1 - \lambda) \tag{5.39}$$

which is always satisfied. Finally, we compare the setup of information contagion with the baseline case regarding the probability of systemic crisis:

$$\bar{a}_D^{(3)} \geq \bar{a}_D^{(1)} \Leftarrow \mu - \sigma > 1 - \sqrt{\frac{\chi\sigma}{2}} \tag{5.40}$$

which is a mild condition and likely to be satisfied. This shows that informational contagion acts stabilizing if no default occurs, destabilizing otherwise, and is thus pro-cyclical.

5.6 Systemic Interaction Risk

5.6.1 Default Probabilities

Banks are now linked via interbank lending and the correlation of asset returns. While the joint density of signals $g(S_H, S_L)$ and the conditional expectation $E[\mathfrak{R}|S_H, S_L]$ are unchanged from the pure information contagion case, the payoff structure and hence the signal thresholds are as in the pure interbank contagion case.

The households' withdrawal decisions are depicted in (5.7). Households in region H default if and only if $S_H \leq \hat{S}_H$ as before. Given no default in region H, households in region L default if and only if $S_L \leq \tilde{S}_{L,N}$. Given default in region H, households in region L default if and only if $S_L \leq \tilde{S}_{L,D}$ in area B and if and only

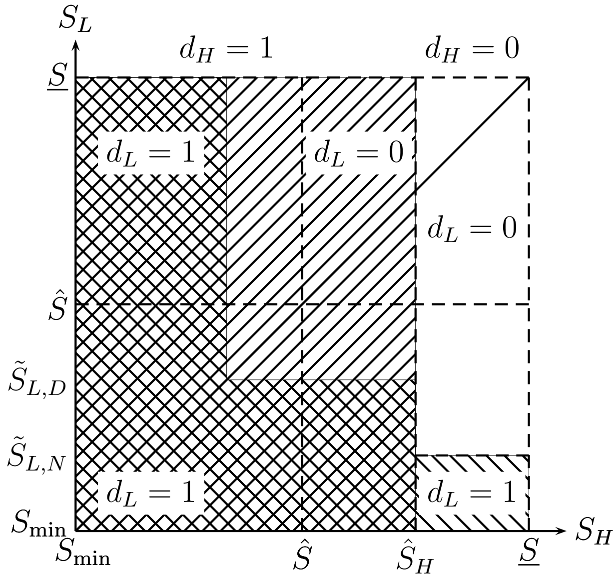

Figure 5.7: Partitioning of the joint density $g(S_H, S_L)$ in the presence of both forms of contagion. Gains and losses are relative to the case of pure informational contagion.

if $S_H \leq \tilde{S}_{L,D}$ in area A.

The relevant default probabilities are again found by appropriately dividing the support and are given as:

$$\bar{a}_N^{(4)} = a_{L,N}^{(2)} \left[\frac{1}{4} - \frac{1}{4\chi}(\hat{R}_H - R_{\min}) \right] \leq \bar{a}_N^{(2)} \tag{5.41}$$

$$\bar{a}_D^{(4)} = a_{L,D}^{(2)} \left[\frac{1}{4} + \frac{1}{4\chi}\hat{R}_H + \frac{1}{12\chi}(\hat{R}_{L,D} - R_{\min}) \right] \tag{5.42}$$

The probability of default in region L and survival in region H is smaller than in the case of pure interbank contagion. This illustrates the stabilizing or positive effect of informational contagion, as $\tilde{S} \leq \hat{S}$. Survival in region H is good news for households in region L as their expected asset return is higher than without the news, making default in region L less likely.

5.6.2 The Interaction Effect

Having studied the models with one form of systemic risk as well as the complete model, we are now ready to proceed to the principal contribution of this chapter.

First, let Δ_{SR} denote the interaction effect of the different forms of systemic risk. It is defined as the contribution to the probability of a systemic crisis in excess of the sum of the individual contributions from information contagion and interbank contagion:

$$\Delta_{\text{SR}} \equiv \underbrace{(\bar{a}_D^{(4)} - \bar{a}_D^{(1)})}_{\text{total effect}} - \underbrace{(\bar{a}_D^{(3)} - \bar{a}_D^{(1)})}_{\text{inform. contagion}} - \underbrace{(\bar{a}_D^{(2)} - \bar{a}_D^{(1)})}_{\text{interb. contagion}} \tag{5.43}$$

$$\Delta_{\text{SR}} = (\bar{a}_D^{(4)} - \bar{a}_D^{(3)}) - (\bar{a}_D^{(2)} - \bar{a}_D^{(1)}) \;, \tag{5.44}$$

where the second line decomposes the systemic interaction into the difference of two components. The first one is the increase in the probability of a systemic crisis when interbank lending is added to a model of informational contagion. The second component refers to the increase in the probability of a systemic crisis arising from the pure interbanking contagion case. As each component used the same density, it makes the change more comparable.

5.6.3 Numerical Results

Figure (5.8) shows the probability of a systemic crisis in each of the four cases. As a baseline calibration we chose the following set of parameters: $\mu = 1.1$, $\chi = 1/3$, $\gamma = 0.5$, $p_H = 0.5$, $\beta = 0.15$, and $\phi = 1.1$. Systemic risk is plotted against the volatility of the risky asset, $\sigma \in [0.5, 0.9]$, and a measure of the volatility of liquidity demand, $\eta \in [0.0, 0.08]$. Larger volatility of the long asset return is interpreted as measure of crisis. Under sufficient conditions, larger regional liquidity shocks map into larger interconnectedness on the interbank market.

As there is no interbank lending in the baseline case and in the case of informational spillover, the probability of a systemic crisis is independent of η but rises with our measure of the financial crisis. While the probability of systemic crisis rises after the introduction of each form of systemic risk, the effect is larger for the case of informational contagion and common shocks. This is driven by the large common shock and we expect a different effect once a generalized common

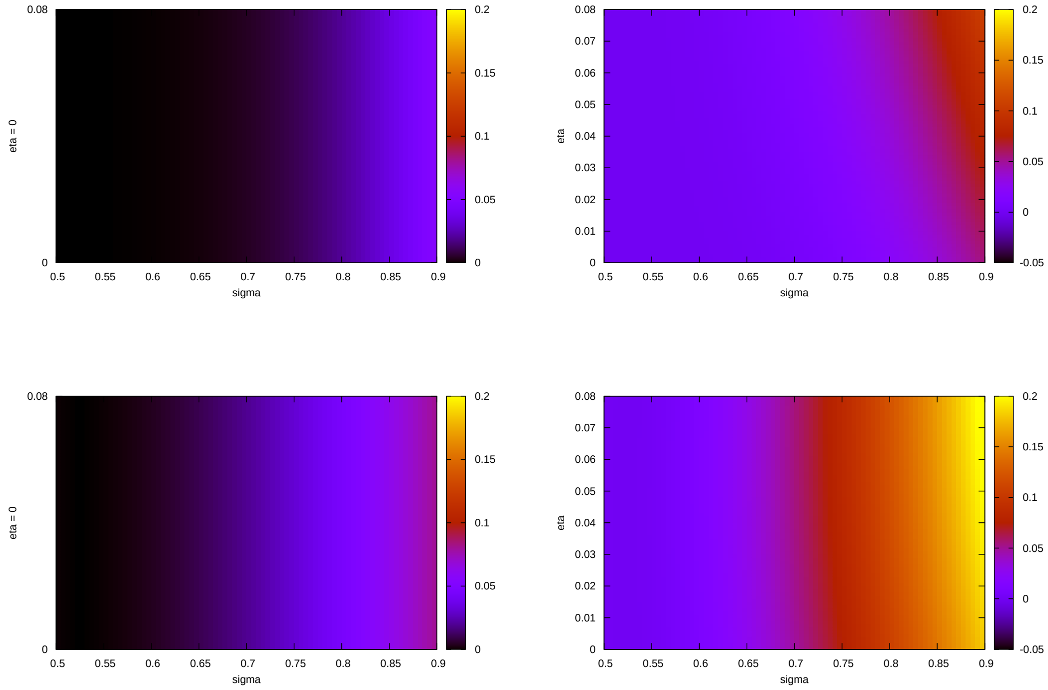

Figure 5.8: Systemic risk in each of the four cases: $\bar{a}_D^{(1)}$ (top left), $\bar{a}_D^{(2)}$ (top right), $\bar{a}_D^{(3)}$ (bottom left), $\bar{a}_D^{(4)}$ (bottom right) for $\sigma \in [0.5, 0.9]$ and $\eta \in [0.0, 0.08]$.

shock with positive but less than full correlation $\rho < 1$ is considered. Our calculation, however, shows that there is non-negligible systemic risk associated with common exposures, as they yield large informational spillovers. Also note that the probability of systemic crisis is especially high when both the risky asset's volatility is high (financial crisis) and there are large regional liquidity shocks (high extent of interconnectedness).

Figure (5.9) depicts the absolute systemic interaction risk Δ_{SR} . It can be seen, that the systemic interaction risk, the interaction effect of several forms of systemic risk, is much larger in times of financial crises (high asset return volatility) and in times of small bank interconnectedness. In tranquil times (low long-asset return volatility), the systemic interaction risk is relatively small and can even be negative for financially stable economies with a high degree of interconnectedness. This highlights the pro-cyclical behaviour of the systemic interaction risk term.

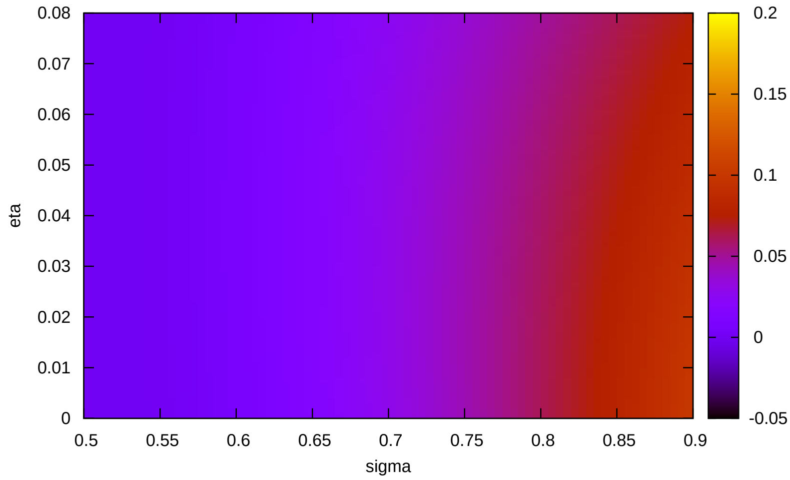

Figure 5.9: Absolute systemic interaction risk Δ_{SR} for $\sigma \in [0.5, 0.9]$ and $\eta \in [0.0, 0.08]$.

5.7 Conclusion

The financial crisis has highlighted the necessity for a better understanding of the different forms of systemic risk. The existing literature focusses largely on contagion effects via interbank connections and only recently analyses common shocks and informational spillovers. However,the different forms of systemic risk have been studied in isolation only and a unified framework of systemic risk was still missing. This papers closes this gap by developing a model of a banking system that allows for the simultaneous analysis of interbank contagion, common shocks, and informational spillovers. This theoretical framework allows us to study the contribution of the various forms of systemic risk to financial (in-)stability. We furthermore show that the size of the interaction effect of the different forms of systemic risk, the systemic interaction risk, depends on the volatility of the long asset and the regional liquidity shock. While low asset return volatility implies small systemic interaction risk, high asset return volatility, as in times of financial crises, leads to high systemic interaction risk.

This highlights the importance of a unified systemic risk framework in the analysis of regulation proposals that aim at strengthening financial stability. A number of policy conclusions can be drawn from our analysis. First, prudential regulation has to take all forms of systemic risk into account in order to be effective. The different forms of systemic risk act pro-cyclical as the interaction term reduces the overall systemic risk in normal times (emphasizing the insurance character of interbank networks), while it significantly contributes to overall systemic risk in times of distress. Regulation proposals that take only individual forms of systemic risk into account will necessarily underestimate the overall systemic risk and hence be less effective. Second, given the large overall effect if all forms of systemic risk are considered ($a_D^{(4)}$ in the notation above), the overall capital adequacy requirements may need to be adjusted substantially. While the new Basel III capital requirements strengthen the quality and quantity of regulatory capital, the risk weights used to calculate the amount of required capital are almost unchanged. This incentivizes banks to hold financial assets and effectively increases the interconnectedness in the financial system. Our results show that it is precisely this situation where the systemic interaction effect is most severe. And third, systemic risks emerging from common shocks and informational spillovers have to be adequately regulated. There are currently no incentives for banks to diversify their portfolio, which can lead to high correlations amonst banks' portfolios. Common shocks, however are not subordinate to contagion effects and thus have to be taken into account. One way of incentivizing banks to diversify their portfolios would be to employ dynamic asset value correlations in Basel III. A macroprudential supervisory authority could calculate the asset value correlations for certain classes of assets and disseminate them to banks who would have to hold more regulatory capital for higher correlated assets. This proposal is outlined in chapter (6) in more detail.

There are several promising avenues for future research. First, a natural next step would be the analysis of design of optimal regulatory policy. In particular, Basel III suggests the use of capital requirements, leverage ratio, and liquidity ratios. It would be interesting to study the role of these tools in the context of the unified model of systemic risk. Second, we are interested in further exploring the role of shadow banks within the proposed banking model. This should include the non-trivial trade-off of enhanced liquidity provision and risk-sharing in tranquil times and amplification of systemic risks during a crisis.

5.8 Appendix

5.8.1 Figures

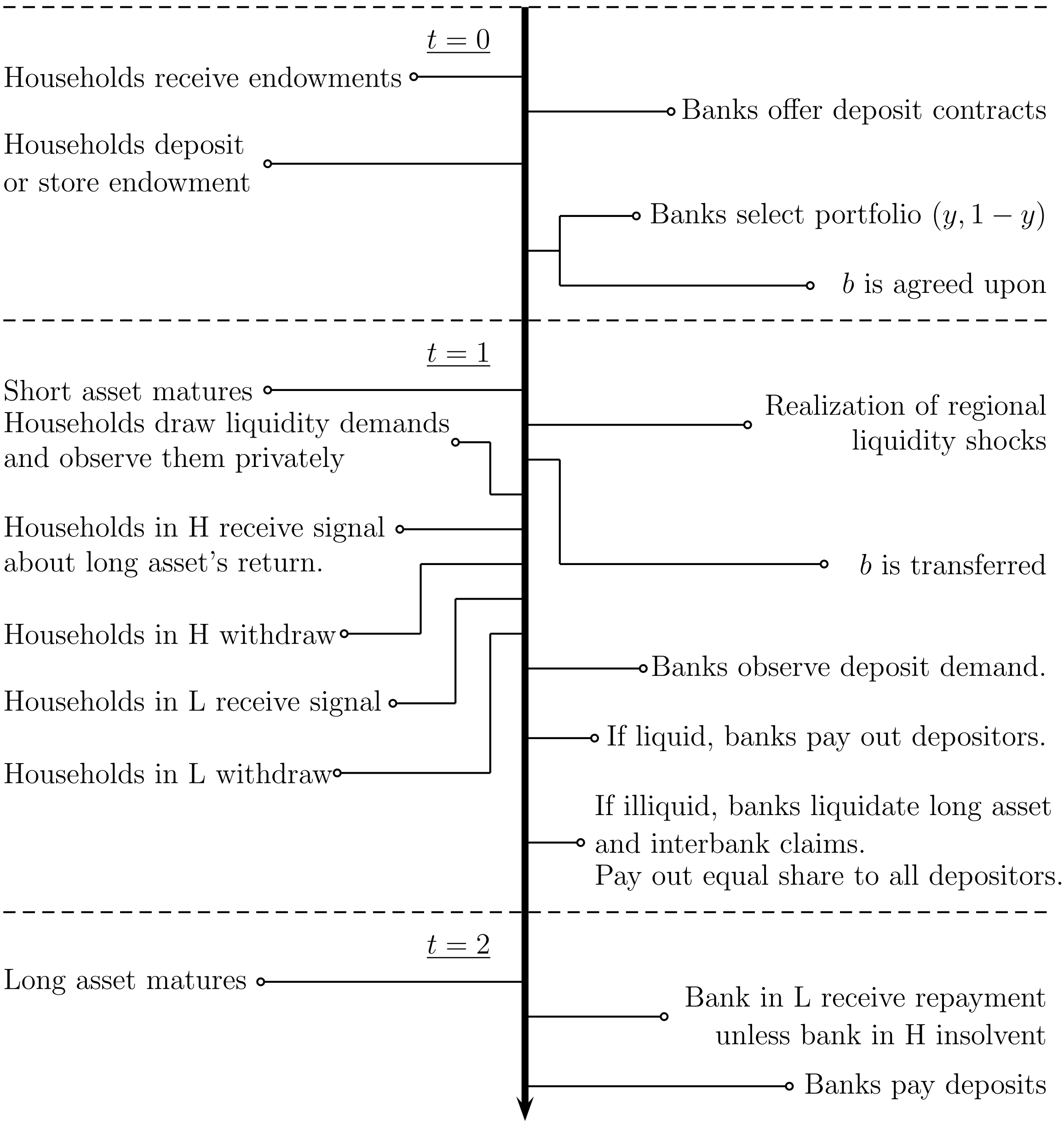

Figure 5.10: Timeline of the model

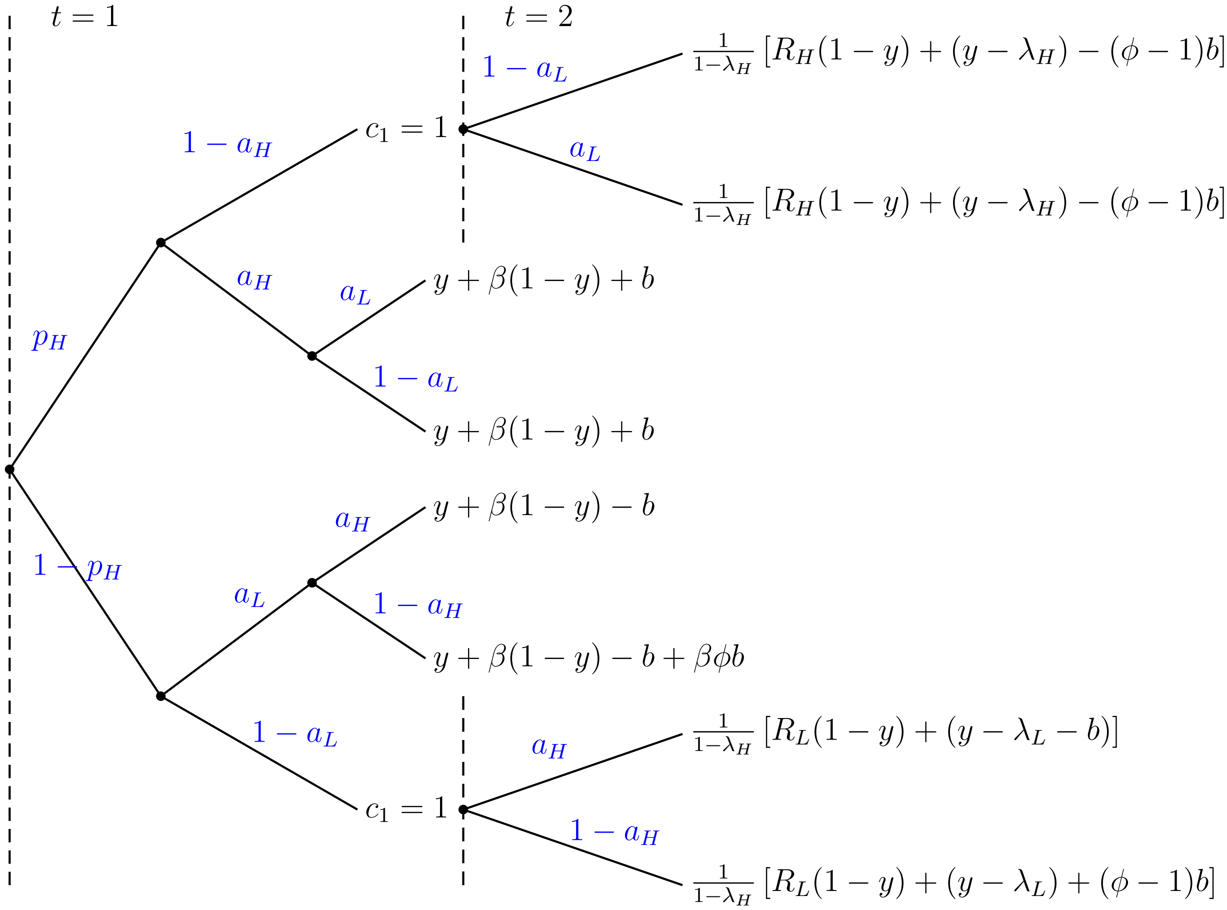

Figure 5.11: Payoff structure of the model.

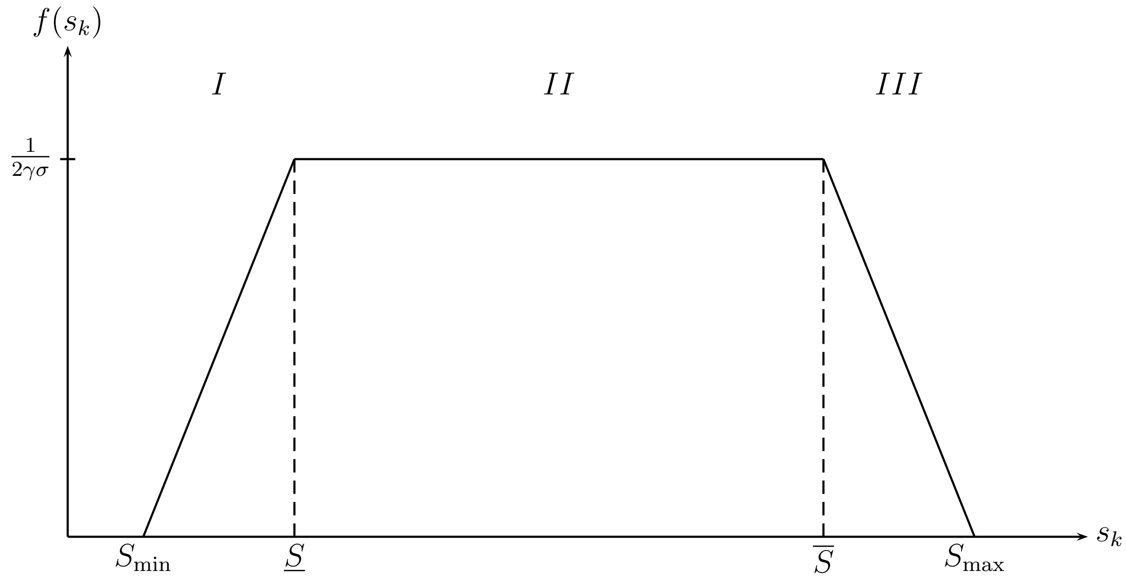

Figure 5.12: Density of the signal in the case $\sigma \neq \chi(1-\gamma)/\gamma$.

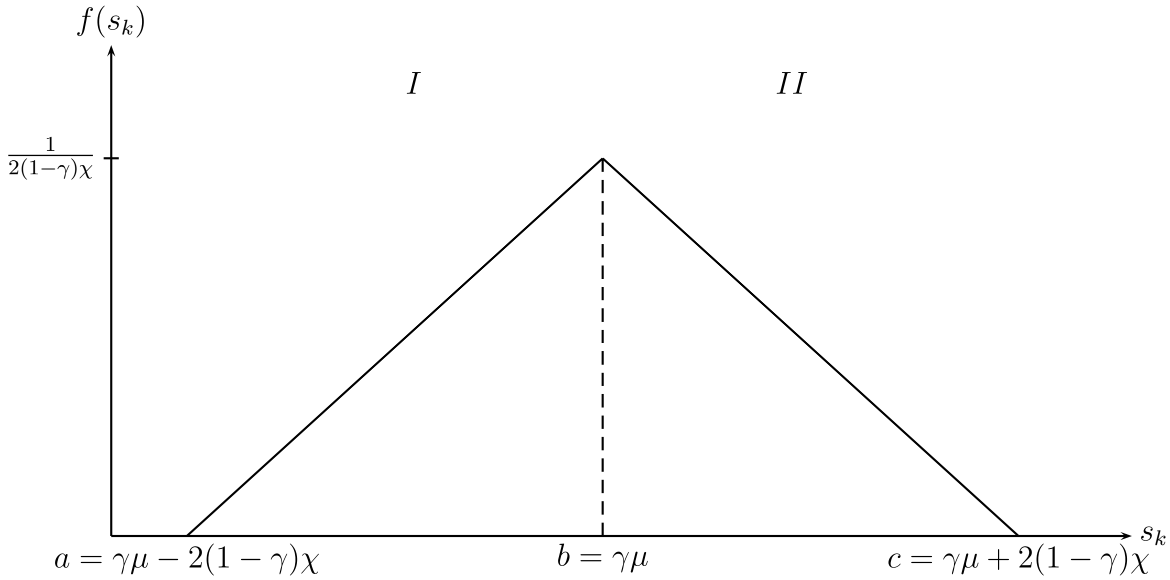

Figure 5.13: Density of the signal S in the limiting case $\sigma \to \chi(1-\gamma)/\gamma$.

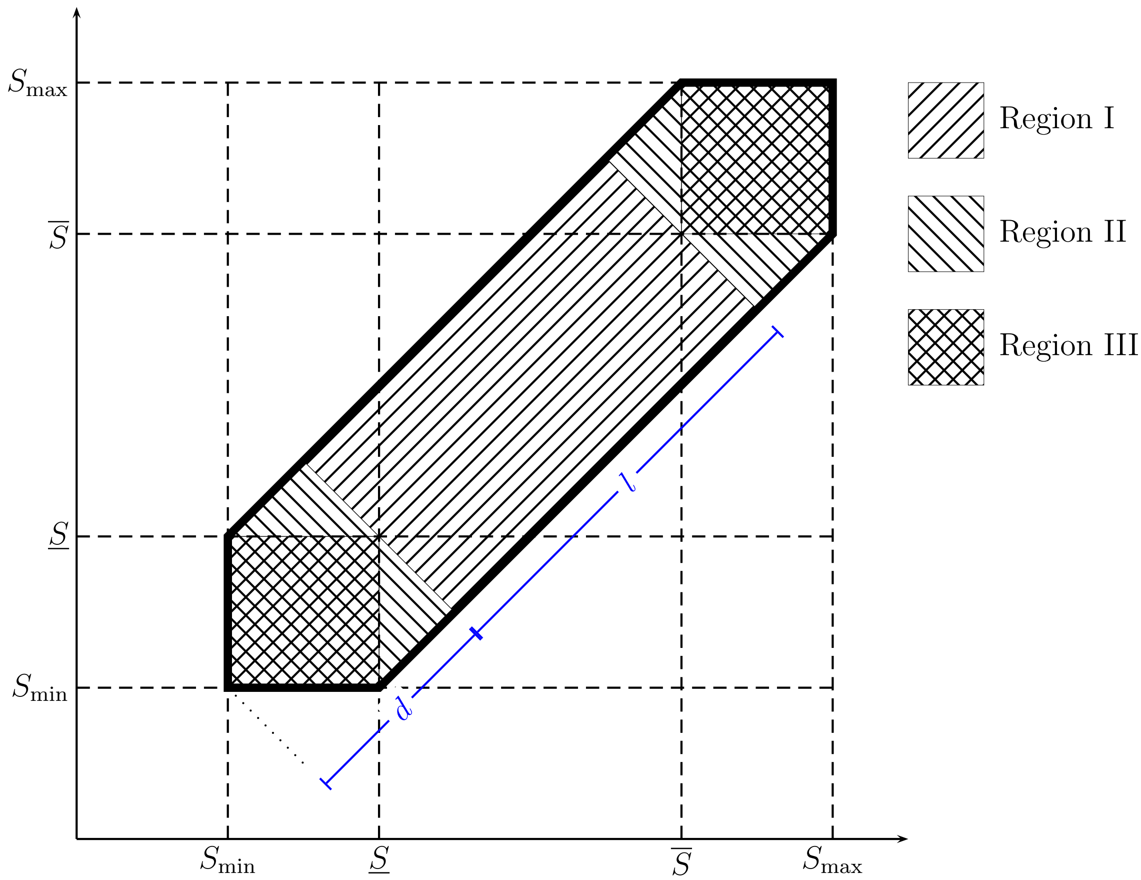

Figure 5.14: Support of $g(S_H, S_L)$ with partitioning into three regions.

5.8.2 Proofs

Distribution of the signal S

A convolution for random variable $Z \equiv X + Y$ is defined as:

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(z-y) f_Y(y) dy \tag{5.45}$$

To rewrite our signal extraction problem accordingly, let $\mathfrak{R}' \equiv \gamma\,\mathfrak{R}$ and $\mathfrak{E}' \equiv (1-\gamma)\,\mathfrak{E}$ where γ and $(1-\gamma)$ are weights.[12] Then,

$$\begin{aligned}
\mathfrak{R}' &\sim U[\gamma(\mu-\sigma), \gamma(\mu+\sigma)] && (5.46)\\
\mathfrak{E}' &\sim U[-(1-\gamma)\chi, (1-\gamma)\chi] && (5.47)\\
\mathfrak{S} &= \mathfrak{R}' + \mathfrak{E}' && (5.48)
\end{aligned}$$

Applying the convolution theorem, the density of the signal reads as:

$$\begin{aligned}
f_S(S) &= \int_{-\infty}^{\infty} f_{R'}(S-E') \cdot f_{E'}(E') dE' \\
&= \int_{-(1-\gamma)\chi}^{(1-\gamma)\chi} f_{R'}(S-E') \cdot \frac{1}{2(1-\gamma)\chi} dE' \\
&= \frac{1}{2\chi(1-\gamma)} \int_{-(1-\gamma)\chi}^{(1-\gamma)\chi} f_{R'}(S-E') dE'
\end{aligned}$$

It is useful to distinguish three cases throughout. The idea is that in the case II, the intermediate case, the noise has full support. In other words, the signal is not sufficiently bad or good to constraint the noise's support.

Case I: $S \in [S_{\min}, \underline{S}] = [\underline{R}' + \underline{E}', \underline{R}' + \overline{E}']$.

$$f_S(S) = \frac{1}{2(1-\gamma)\chi} \int_{-(1-\gamma)\chi}^{UB} f_{R'}(S-E') dE' \tag{5.49}$$

where the upper bound UB is a function of S. If $S = S_{\min}$ then $UB = \underline{E}' = -(1-\gamma)\chi$, and if $S = \underline{S}$ then $UB = \overline{E}' = +(1-\gamma)\chi$. Given the linearity of the setup, we conjecture that $UB(S) = \kappa_0 + \kappa_1 S$. From the conditions

$$\begin{aligned}
UB(S_{\min} = \gamma(\mu-\sigma) + (1-\gamma)(-\chi)) &= -(1-\gamma)\chi && (5.50)\\
UB(\underline{S} = \gamma(\mu-\sigma) + (1-\gamma)(\chi)) &= +(1-\gamma)\chi && (5.51)
\end{aligned}$$

[12] This explicitely allows for the special case of $\gamma = 1$ and $(1-\gamma) = 1$, as the two weights are independent.

we obtain $\kappa_0 = -\gamma(\mu - \sigma)$ and $\kappa_1 = 1$. Thus, the upper bound is given by $UB(S) = -\gamma(\mu - \sigma) + S$. This gives:

$$\begin{aligned} f_S(S) &= \frac{1}{2(1-\gamma)\chi} \int_{-(1-\gamma)\chi}^{S-\gamma(\mu-\sigma)} f_{R'}(S - E')dE' && (5.52) \\ &= \frac{S - \gamma(\mu - \sigma) + (1-\gamma)\chi}{4(1-\gamma)\chi\gamma\sigma} && (5.53) \\ &= \frac{S - S_{\min}}{4(1-\gamma)\chi\gamma\sigma} \text{ for } S \in [S_{\min}, \underline{S}] && (5.54) \end{aligned}$$

Case II: $S \in [\underline{S}, \overline{S}] = [\underline{R}' + \overline{E}', \overline{R}' + \underline{E}']$. Then, $\mathfrak{E}$ has full support.

$$\begin{aligned} f_S(S) &= \frac{1}{2\chi(1-\gamma)} \int_{-(1-\gamma)\chi}^{(1-\gamma)\chi} f_{R'}(S - E')dE' && (5.55) \\ &= \frac{1}{2\gamma\sigma} \text{ for } S \in [\underline{S}, \overline{S}] && (5.56) \end{aligned}$$

Case III: $S \in [\overline{S}, S_{\max}] = [\overline{R}' + \underline{E}', \overline{R}' + \overline{E}']$. This case is treated analogous to case I. Then:

$$f_S(S) = \frac{1}{2(1-\gamma)\chi} \int_{LB}^{(1-\gamma)\chi} f_{R'}(S - E')dE' \quad (5.57)$$

where the lower bound again is a function of S. Again we conjecture that $LB = \kappa_0' + \kappa_1' S$ and obtain $\kappa_1' = 1$, $\kappa_0' = -\gamma(\mu - \sigma)$ and hence $LB = -\gamma(\mu - \sigma) + S$. This gives:

$$\begin{aligned} f_S(S) &= \frac{(1-\gamma)\chi + \gamma(\mu - \sigma) - S}{4(1-\gamma)\chi\gamma\sigma} && (5.58) \\ &= \frac{S_{\max} - S}{4(1-\gamma)\chi\gamma\sigma} \text{ for } S \in [\overline{S}, S_{\max}] && (5.59) \end{aligned}$$

Conditional Expectation

The calculation of the conditional expectation also uses the partitioning support of the signal S support, giving rise to three three cases.

Case I: $S \in [S_{\min}, \underline{S}]$ Even if the lowest possible value for R is attained, receiving such a bad signal implies that not all realizations E are consistent with it. Hence, we have $E_{LB} = -\chi$, and $E_{UB} = (S - (\mu - \sigma)/(1 - \gamma)$. Note that

$E_{UB} \to -\chi$ if $S \to S_{\min}$ and $E_{UB} \to +\chi$ if $S \to \underline{S}$. This leads to:

$$\begin{aligned}
E[\mathfrak{R}|S] &= E[\mathfrak{R}|\mathfrak{R} = \frac{S}{\gamma} - \frac{1-\gamma}{\gamma}\mathfrak{E}] && (5.60)\\
&= E[\mathfrak{R}|\frac{S}{\gamma} - \frac{1-\gamma}{\gamma}E_{UB} \leq \mathfrak{R} \leq \frac{S}{\gamma} - \frac{1-\gamma}{\gamma}E_{LB}] && (5.61)\\
&= E[\mathfrak{R}|R_{\min} \leq \mathfrak{R} \leq \frac{S}{\gamma} + \frac{1-\gamma}{\gamma}\chi] && (5.62)\\
&= \frac{1}{2}\left[R_{\min} + \frac{S}{\gamma} + \frac{1-\gamma}{\gamma}\chi\right] \text{ for } S \in [S_{\min}, \underline{S}] && (5.63)
\end{aligned}$$

Case II: $S \in [\underline{S}, \overline{S}]$ $\mathfrak{E}$ has now full support: $E_{LB} = -\chi$, $E_{UB} = \chi$. Then:

$$\begin{aligned}
E[\mathfrak{R}|S] &= E[\mathfrak{R}|\frac{S}{\gamma} - \frac{1-\gamma}{\gamma}\chi \leq \mathfrak{R} \leq \frac{S}{\gamma} + \frac{1-\gamma}{\gamma}\chi] && (5.64)\\
&= \frac{S}{\gamma} \text{ for } S \in [\underline{S}, \overline{S}] && (5.65)
\end{aligned}$$

Case III: $S \in [\overline{S}, S_{\max}]$ Similar to case I again. $E_{LB} = \frac{S-\gamma(\mu+\sigma)}{1-\gamma}$, $E_{UB} = \chi$. Then:

$$\begin{aligned}
E[\mathfrak{R}|S] &= E[\mathfrak{R}|\frac{S-(1-\gamma)\chi}{\gamma} \leq \mathfrak{R} \leq R_{\max}] && (5.66)\\
&= \frac{1}{2}\left[R_{\max} + \frac{S}{\gamma} - \frac{1-\gamma}{\gamma}\chi\right] \text{ for } S \in [\overline{S}, S_{\max}] && (5.67)
\end{aligned}$$

Joint Density $g(S_H, S_L)$

The support of $g(S_H, S_L)$ is shown in Figure (5.14) and partitioned into three regions. Region (I) is described by the length $l = \sqrt{2}(S_{\max} - \overline{S})$ and the width $b = 2\sqrt{2}(1-\gamma)\chi$; Region (II) is given by the two areas $S_L \in [S_{\min}, \underline{S}], S_H \in [\underline{S}, \underline{S} + (1-\gamma)\chi]$ (II-A) and $S_L \in [\underline{S}, \underline{S} + (1-\gamma)\chi], S_H \in [S_{\min}, \underline{S}]$ (II-B); Region (III) is given by the two areas $S_L \in [S_H, \hat{S}], S_H \in [S_{\min}, \hat{S}]$ (III-A) and $S_L \in [S_{\min}, S_H], S_H \in [S_{\min}, \hat{S}]$ (III-B).

We focus on the case $S_k \leq \underline{S}$. If $\chi = (1-\gamma)/\gamma\sigma$, then half of the probability lies in (i) $S_H \leq \underline{S}$, $S_L \leq \underline{S}$; (ii) $S_H \in [\underline{S}, \overline{S}]$, $S_L \leq \underline{S}$; (iii) $S_L \in [\underline{S}, \overline{S}]$, $S_H \leq \underline{S}$. We solve the two-dimensional density $g(S_H, S_L)$ explicitely and find the following geometric figures in the three regions (I)-(III): Region I - prism; Region II - pyramid with triangular base; Region III - pyramid with a quadratic base. In order to determine the two-dimensional distribution $g(S_H, S_L)$ we proceed in two steps. First, we obtain the height h at $S_H = S_L = \underline{S}$ by using geometric methods. The volume of the distribution is normalized to unity: $V \overset{!}{=} 1 = I + 4II + 2III$. Then we determine $g(S_H, S_L)$ for the three regions shown in Figure (5.14).

Region I. First, we partition the support as shown in Figure (5.14). Then, $D = l + 2d$ and we can write it as $D = \sqrt{2}(S_{\max} - S_{\min}) = \sqrt{2}[\gamma(\mu+\sigma) + (1-\gamma)\chi - \gamma(\mu - \sigma) - (1-\gamma)\chi] = 2\sqrt{2}(\gamma\sigma + (1-\gamma)\chi)$. The length l of Region III is given as $l = \sqrt{2}(S_{\max} - \overline{S}) = 2\sqrt{2}(1-\gamma)\chi$. From this we obtain $l = 2\sqrt{2}(\gamma\sigma - (1-\gamma)\chi) \geq 0$ as $\sigma \geq (\frac{1-\gamma}{\gamma})\chi$. The width b of the prism is given as $b = 2\sqrt{2}(1-\gamma)\chi$ and the base thus is $A_{base} = \frac{1}{2}hb = h(1-\gamma)\chi$ and the volume V_{prism} is given as $V_{prism} = A_{base}l = h(1-\gamma)\chi \cdot 4(\gamma\sigma - (1-\gamma)\chi$.

Region II. The volume of a pyramid with triangular base is given as $V_{pyr,3} = \frac{1}{3}hA_{base}$ with $A_{base} = \frac{1}{2}(1-\gamma)\chi \cdot 2(1-\gamma)\chi = (1-\gamma)^2\chi^2$.

Region III. The volume of a pyramid with squared base is determined by $A_{base} = [2(1-\gamma)\chi]^2 = 4(1-\gamma)^2\chi^2$ to be $V_{pyr,4} = \frac{4}{3}h(1-\gamma)^2\chi^2$.

From the total volume $V_{total} = V_{prism} + 2V_{pyr,4} + 4V_{pyr,3} \overset{!}{=} 1$ we obtain for the height h:

$$h = \frac{1}{4\gamma(1-\gamma)\chi\sigma} \tag{5.68}$$

We are now interested in the two-dimensional density $g(S_H, S_L)$ in the region $S_H, S_L \in [S_{\min}, \underline{S}]$, which is Region III in Figure (5.14) and has the shape of a pyramid with squared base. The apex of the pyramid is at the top right corner (point C) of the base and has height h. This effectively partitions the base into two triangular regions A and B, as shown in Figure (5.6). The points D, C, E of the partitioned base and the apex H are given as:

$$C = \begin{pmatrix} \underline{S} \\ \underline{S} \\ 0 \end{pmatrix} \quad , \quad D = \begin{pmatrix} S_{\min} \\ S_{\min} \\ 0 \end{pmatrix} \quad , \quad E = \begin{pmatrix} S_{\min} \\ \underline{S} \\ 0 \end{pmatrix} \quad , \quad H = \begin{pmatrix} \underline{S} \\ \underline{S} \\ h \end{pmatrix} \tag{5.69}$$

We now can identify the plane that is determined by the points E, D and H:

$$\epsilon_0 = \begin{pmatrix} S_{\min} \\ \underline{S} \\ 0 \end{pmatrix} + \delta_0 \begin{pmatrix} 0 \\ S_{\min} - \underline{S} \\ 0 \end{pmatrix} + \delta_1 \begin{pmatrix} \underline{S} - S_{\min} \\ 0 \\ h \end{pmatrix} = \begin{pmatrix} S_{\min} + \delta_1(\underline{S} - S_{\min}) \\ \underline{S} - \delta_0(\underline{S} - S_{\min}) \\ \delta_1 h \end{pmatrix} \tag{5.70}$$

and interject it with the line k_0 that goes through the point $G = (S_H, S_L)$, $k_0 = (S_H, S_L, t)^t$ where $t = g(S_H, S_L)$.

We obtain for t:

$$t = h\frac{S_H - S_{\min}}{\underline{S} - S_{\min}} = \frac{1}{\kappa}(S_H - S_{\min}) \tag{5.71}$$

where $\kappa \equiv 4(1-\gamma)\gamma^2\chi\pi$ and $\pi \equiv 2\sigma\frac{1-\gamma}{\gamma}\chi$. Analogously, we obtain for $S_L \in [S_{\min}, \underline{S}], S_H \in [S_L, \underline{S}]$ (Region B):

$$g(S_H, S_L) = \frac{1}{\kappa}(S_L - S_{\min}) \tag{5.72}$$

Now, we consider Region II in Figure (5.14) and repeat the above calculation. Therefore, $S_L \in [S_{\min}, \underline{S}]$, $S_H \in [\underline{S}, \underline{S} + (1-\gamma)\chi]$. The system of three equations has more interaction now, as δ_1 depends on δ_0 as well and $t = g(S_H, S_L)$ thus depends on both S_H and S_L. Consider the points:

$$C = \begin{pmatrix} \underline{S} \\ \underline{S} \\ 0 \end{pmatrix} \quad , \quad D = \begin{pmatrix} \underline{S} + (1-\gamma)\chi \\ \underline{S} - (1-\gamma)\chi \\ 0 \end{pmatrix} \quad , \quad E = \begin{pmatrix} \underline{S} \\ S_{\min} \\ 0 \end{pmatrix} \quad , \quad H = \begin{pmatrix} \underline{S} \\ \underline{S} \\ h \end{pmatrix} \tag{5.73}$$

and define a plane $\epsilon_1 = \overrightarrow{OD} + \delta_0\overrightarrow{DE} + \delta_1\overrightarrow{DH}$:

$$\epsilon_1 = \begin{pmatrix} S_{\min} + (1-\gamma)\chi[3 - \delta_0 - \delta_1] \\ S_{\min} + (1-\gamma)\chi[1 - \delta_0 + \delta_1] \\ \delta_1 h \end{pmatrix} \tag{5.74}$$

which yields

$$g(S_H, S_L) = h\frac{(S_L - S_H) + (\underline{S} + S_{\min})}{\underline{S} - S_{\min}} \leq h \tag{5.75}$$

Likewise, one obtains for $S_L \in [\underline{S}, \underline{S} + (1-\gamma)\chi]$, $S_H \in [S_{\min}, \underline{S}]$:

$$g(S_H, S_L) = h\frac{(S_H - S_L) + (\underline{S} - S_{\min})}{\underline{S} - S_{\min}} \leq h \tag{5.76}$$

Conditional Expectation $E[\mathfrak{R}|S_H, S_L]$

The conditional expectation has the same mathematical structure as $g(S_H, S_L)$ for $S_k \in [S_{\min}, \underline{S}]$, $k \in \{H, L\}$ (Region III). We thus use the same geometric approach as before, with the height is now denoted as m instead of h and the reference point O being $R_{\min}$. The height m is obtained by observing that for $S_H = S_L = \overline{S}$: $E[\mathfrak{R}|S_H, S_L] = E[\mathfrak{R}|\overline{S}]$. In particular: $E[\mathfrak{R}|\underline{S}, \underline{S}] = \frac{\underline{S}}{\gamma} = R_{\min} + \frac{1-\gamma}{\gamma}\chi \equiv m$. The four points we now use to obtain the equations of the planes describing $E[R|S_H, S_L]$ are:

$$E = \begin{pmatrix} S_{\min} \\ S_{\min} \\ R_{\min} \end{pmatrix} \quad , \quad C = \begin{pmatrix} \underline{S} \\ S_{\min} \\ R_{\min} \end{pmatrix} \quad , \quad D = \begin{pmatrix} \underline{S} \\ \underline{S} \\ R_{\min} \end{pmatrix} \quad , \quad H = \begin{pmatrix} \underline{S} \\ \underline{S} \\ m \end{pmatrix} \tag{5.77}$$

from which we obtain for the plane $\epsilon_2 : \overrightarrow{OC} + \delta_0 \overrightarrow{OE} + \delta_1 \overrightarrow{CH}$ and the line $k_2 : (S_H, S_L, t)^t$:

$$t = R_{\min} + \frac{1}{2\gamma}(S_L - S_{\min}) = E[\mathfrak{R}|S_H, S_L] \; \forall S_H \in [S_{\min}, S_L] \tag{5.78}$$

Analogously we obtain for $S_H \in [S_{\min}, \underline{S}]$, $S_L \in [S_H, \underline{S}]$:

$$E[\mathfrak{R}|S_H, S_L] = R_{\min} + \frac{1}{\gamma}(S_H - S_{\min}) \; \forall S_L \in [S_H, \underline{S}] \tag{5.79}$$

Chapter 6

Conclusions for the Regulation of Systemic Risk

One of the most pressing questions in the aftermath of the financial crisis is how to deal with systemically important financial institutions (SIFIs). The purpose of this chapter is to evaluate the regulation proposals in the recently endorsed Basel III framework with respect to the main findings in this thesis and the liteature on systemic risk. A number of shortcomings in the current framework are analyzed and three measures for future reform are proposed: counter-cyclical risk-weights, dynamic asset value correlation multipliers, and enhanced transparency requirements for SIFIs.

The remainder of this chapter is organized as follows. After a brief introduction in section (6.1), section (6.2) gives an overview of the regulatory responses to the financial crisis. Section (6.3) outlines some shortcomings of Basel III and proposes a way forward with systemic risk regulation.

6.1 Introduction

The financial crisis of 2007/2008 unveiled the shortcomings in the regulation of systemic risk and exposed the moral hazard that is associated with systemically important financial institutions. Governments were forced to bail-out these large, complex and highly interconnected financial intermediaries as they feared the unforseeable consequences of their default. The G20 responded to the crisis with a new framework for banking regulation, commonly referred to as Basel III.[1] Basel III increases the quality and quantity of banking capital, introduces two liquidity ratios and one leverage ratio. However, the question if Basel III can effectively regulate systemic risk and resolve the moral hazard that is associated with systemically important financial institutions remains. To answer this question, this chapter evaluates the Basel III framework with respect to the main findings of this thesis and the literature on systemic risk .

6.2 The Regulatory Response to the Financial Crisis

In response to the financial crisis, the Basel Committee on Banking Supervision (2010a) has compiled a set of new global standards which is commonly referred to as Basel III. These standards were recently endorsed by the largest industrialized and developing countries at the G20 summit in Seoul. They will be implemented starting with January 1, 2013 and fully established by January 1, 2019. Basel III comprises changes in all three pillars of the former Basel II standards. The first

[1]Basel III comprises of a number of documents that the G20 leaders have agreed upon: Basel Committee on Banking Supervision (2010b), *"Basel III: A global regulatory framework for more resilient banks and banking systems"*, Basel Committee on Banking Supervision (2010c), *"Basel III: International framework for liquidity risk measurement, standards and monitoring"*, as well as the earlier document from Basel Committee on Banking Supervision (2010a), *"Report to the G20: The Basel Committee's response to the financial crisis"*. Downloaded from `http://www.bis.org/list/basel3/index.htm` on 12/29/2010.

pillar consists of minimum capital requirements, while the second pillar describes the banking supervision process and the third pillar aims to enforce market discipline through transparency of bank's risks. Although Basel II was not fully implemented by the time the financial crisis struck, it was agreed upon by the G20 leaders that it has to be reformed in order to cope with systemic risk as well.

6.2.1 Design and Main Features of Basel III

The cornerstone of Basel III are changes regarding the first pillar of Basel II. The aim is to reduce the probability of bank failures by improving banks' loss absorption capabilities. Besides extensions in capital requirements, an additional non-risk based leverage ratio and two liquidity ratios will be established in Basel III. Capital is about to increase both quantitatively and qualitatively. After a transition period, banks will be forced to hold 4.5% common equity instead of 2%. A stricter definition of common equity augments its quality and higher risk weights for several exposures intend to cover both on- and off-balance sheet risks.

The recent financial crisis revealed how crucial the break down of the interbank market is, as many banks faced difficulties to refinance themselves. Therefore, liquidity requirements are implemented to reduce insolvency problems arising from contagion via the interbank market. Under Basel III, banks will have to meet two liquidity ratios. Whereas the liquidity coverage ratio (LCR) follows a short-term approach, the net stable funding ratio (NSFR) addresses longer-term problems arising from illiquidity. Under the LCR banks will be required to hold a sufficient amount of liquid assets with a high quality to obviate short-term disruptions. The NSFR will include the entire balance sheet to prevent structural longer-term problems arising from liquidity mismatches. Details concerning both ratios are not yet specified.

The capital requirement under Basel II form a Tier 1 risk-based ratio which is defined as the ratio between a bank's core equity, i.e. its common equity and certain other financial instruments qualifying for equity, and its risk weighted assets. In the run-up to the crisis, the information content of this measure has been limited. Banks circumvented the constraint and increased both on- and off-balance sheet leverage levels but were able to report strong Tier 1 risk-based ratios at the same time. As high leverage levels increase a bank's probability of default, Basel III implements an additional non-risk based leverage ratio thus limiting incentives to circumvent capital requirements. Like the liquidity requirements, it is not agreed upon a concrete ratio. The Committee suggests to start the transition period with a minimum Tier 1 leverage ratio of 3%.

Beyond these increased requirements for banks, Basel III will improve the supervisory guidance of regulatory authorities under Pillar 2. The authorities' capacity to act will increase to enhance their ability to manage different kinds of risks, like liquidity, off-balance or concentration risks. Furthermore, conducting stress tests aims to assist the detection of systemic risks.

Pillar 3 comprises standards for market disclosure which will be raised in order to enhance transparency. On their websites, banks will have to report more details regarding their balance sheets like revealing the terms and conditions of all instruments of their regulatory capital base and explaining which deductions were applied. These requirements have to be fulfilled by the end of 2011.

Additionally, Basel III includes a macro prudential approach. The recent financial crisis has revealed that micro prudential regulation is insufficient to respond to systemic risks, as it focuses only on firm-specific risks. Macro prudential regulation thus seeks to stabilize the financial system by taking into account risks arising from the interactions between financial institutions. In order to prevent systemic risks, Basel III stipulates two kinds of capital buffers. In good times, banks will have to build up a capital conservation buffer of 2.5% so that the total common equity requirement rises to 7%. In times of distress this buffer can be scaled down to absorb losses. Depending on national circumstances, the authorities will be authorized to raise an additional countercyclical buffer of 0 to 2.5% in order to counteract excessive credit growth which might induce systemic risks.

6.2.2 Regulation of Systemically Important Financial Institutions

The cases of Lehman Brothers and AIG have highlighted how single financial institutions might trigger contagion effects or a common shock in the financial market and thus affect not only the banking sector but the economy as a whole. Hence, macro prudential regulation seeks to impose additional requirements on institutions which are systemically important, thus reducing their default probability. Potential tools for such additional requirements might be for instance capital surcharges, contingent capital or bail-in debt. At present, neither a definition of SIFIs nor details regarding these potential tools are specified in detail. The definition of the Basel Committee on Banking Supervision (BCBS) of SIFIs is expected in the near future is announced to include both quantitative and qualitative indicators. Moreover, the BCBS is currently conducting a survey to reveal how much additional loss absorbency potential an SIFI needs and to analyze which impact the different requirement tools might have on the financial system. The survey is expected to be published by mid-2011.

At their Seoul summit, the G20 (2010) outlined cornerstones of a framework to reduce the moral hazard risks posed by SIFIs and addresses the too-big-to-fail problem. This framework was developed in Financial Stability Board (2010a). The cornerstones of the framework are: (i) a resolution framework and other measures to ensure that all financial institutions can be resolved safely, quickly and without destabilizing the financial system and exposing the taxpayers to the risk of loss; (ii) a requirement that SIFIs and initially in particular financial institutions that are globally systemic should have higher loss absorbency capacity to reflect the greater risk that their failure poses to the global financial system;

(iii) more intensive supervisory oversight; (iv) robust core financial market infrastructure to reduce contagion risk from individual failures; (v) other supplementary prudential and other requirements as determined by the national authorities which may include, in some circumstances, liquidity surcharges, tighter large exposure restrictions, levies and structural measures. Special emphasis was put on globally systemically important financial institutions (G-SIFIs). The G20 agreed that they should be subject to a sustained process of mandatory international recovery and resolution planning. Furthermore, the G20 (2010) stress, that supervisors should have appropriate tools and powers to identify systemic risks at an early stage. This also highlights the importance of the Network Systemic Importance Index as developed in chapter (3) as a tool to identify SIFIs and impose prudential requirements that are commensurate with their systemic importance.

The Financial Stability Board (2010b) outlines in more detail how the intensity and effectiveness of SIFI supervision can be enhanced. The findings are summarized in ten recommendations relating to the mandates and independence of supervisory authorities; the ressources and supervisory powers necessary to fulfill the mandates, as well as accounts of improved techniques of banking supervision; recommendations for group-wide and consolidated supervision which relates to the supervision of a group of financial institutions; recommendations for continous and comprehensive supervision; information-sharing of home and host countries of globally active systemically important financial institutions; measures of forward looking macro-prudential surveillance; and the use of third party services by regulatory bodies.

Going forward, the G20 plan to strengthen the regulation and supervision of hedge funds, OTC derivatives and rating agencies. They asked the FSB to develop recommendations to strengthen the regulation of the shadow banking system by mid 2011. Meanwhile, various G20 member countries launched national legislative reforms that also address systemically financial institutions.

6.2.3 National Legislative Reforms

The financial crisis revealed the need for a reform of the financial regulatory framework. It became clear, that unregulated systemic risk can pose a major threat to financial stability and economic growth. However, most G20 countries do not yet have a formal definition of systemic risk (see International Monetary Fund et al. (2009)) and different countries have differing views on what systemic risk is, even on a non-formal level. Despite this fundamental problem, a number of governments reacted to the public pressure that was caused by the bail-out of supposedly systemically important financial institutions and proposed changes to the national regulatory frameworks. This chapter thus gives an overview of the legislative reforms and reform proposals in the United States, the Eurozone and the United Kingdom.

In the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act was signed into law on July 21, 2010. This act can be regarded as the broadest set of regulatory reforms since the reforms in response to the Great Depression. In over 2300 pages the Act comprises more than 240 rules across several federal agencies. Different aspects of the financial system are approached such as consumer protection, increasing transparency for derivatives or limits on proprietary trading and hedge funds. In order to address systemic risk the Dodd-Frank Act establishes the Financial Stability Oversight Council (FSOC). The main tasks of the FSOC are identifying systemically important institutions and gaps in regulation, collecting information and monitoring the financial services marketplace in order to identify potential risks. Both, systemically important non-bank financial institutions, as well as bank holding companies with more than $50 billion in assets are facing stricter regulation standards under the Dodd-Frank Act. These can include increased capital and liquidity requirements, leverage and concentration limits or enhanced public disclosures revealing how the institution could be resolved. Moreover, the FSOC possesses further tools like the ability to impose the issuing of contingent capital on distressed institutions. In case an institution is nevertheless in distress the Dodd-Frank Act provides the room for takeovers or liquidations.

The main critique on the Dodd-Frank Act with respect to considering systemic risk is that most of the details regarding stricter requirements are not constituted, yet, except for the leverage limit, which should not exceed 15 to 1. Acharya et al. (2010a) argues that marking institutions as systemically important enables these institutions competitive advantages (see e.g. Akram and Christophesen (2010) for an empirical verification) and incentivizes them to conduct excessive risk taking.

The European Parliament has given its final approval for a reform of the EU financial supervisory system on 22 September 2010.[2] The new legislation establishes a newly founded European Systemic Risk Board (ESRB) which will be hosted at the European Central Bank (ECB). It will be responsible for *"macro-prudential oversight of the financial system within the Community in order to prevent or mitigate systemic risks, to avoid episodes of widespread financial distress, contribute to a smooth functioning of the Internal Market and ensure a sustainable contribution of the financial sector to economic growth"*. The proposal by the European Commission further establishes a European System of Financial Supervisors, consisting of a network of financial supervisors who will work closely with the newly created European Supervisory Authorities (ESAs). The ESAs are created by the transformation of existing European supervisory committees into a European Banking Authority (EBA), a European Securities and Markets Authority (ESMA), and a European Insurance and Occupational Pensions Authority (EIOPA). The ESRB is an entirely new European body, but will not have any binding powers to impose measures on member states or national authorities. It rather acts as a standard setter which influences the action of policy makers. The ESRB will not be limited to macroprudential supervision of banks,

[2]The adapted resolutions can be found at http://www.europarl.europa.eu/

but rather monitors all types of entities or markets. It can issue warnings and recommendations that *"may address any aspect of the financial system which may generate a systemic risk [...] An essential role of the ESRB is to identify risks with a systemic dimension and prevent or mitigate their impact on the financial system within the EU"*.

In July 2010 the Government of the United Kingdom issued a consultation document on proposed changes to the UK regulatory framework. A more detailed proposal is expected early in 2011. HM Treasury (2010) confirms plans to replace the Financial Services Authority by a tripartite system consisting of the Financial Policy Committee (FPC), the Prudential Regulation Authority (PRA) and the Consumer Protection and Market Authority (CPMA) which all form subsidiaries of the Bank of England. The FPC will be responsible for macroprudential regulation by identifying systemic risks, deciding on macroprudential tools and recommending to the other authorities in order to reduce imbalances and weaknesses of the financial system, and to report to Parliament and the public in order to increase the action's transparency. As potential tools, the document considers countercyclical capital requirements, variable risk-weights, leverage limits, forward-looking loss provisioning, collateral requirements, and quantitative credit controls and reserve requirements. The focus of PRA will lie on the operational part of regulation and supervision by effectively coordinating macroprudential with microprudential regulation. The CPMA will be responsible for consumer protection and promoting confidence in the financial system. As information sharing among these authorities is essential a close cooperation is considered in the design of the authorities.

6.3 Policy Conclusions

A number of authors have critically analyzed the Basel III framework and proposed regulatory reform measures. Hellwig (2010) argues that there exist a number of asset correlations that went unnoticed prior to the crisis. Firstly, correlations arising from a common dependence on underlying macroeconomic factors, i.e. of credit risks in mortgages or mortgage-backed securities and other derivatives, were underestimated. And secondly, correlations of risks via similiar contracts, such as counterparty credit risks and underlying risks in derivatives, were insufficiently taken into account. This underestimation of correlations has drastic consequences, as banks were enabled by Basel II to conduct internal risk models in order to determine the appropriate amount of risk. Hellwig, however, points out that the empirical basis for this internal risk modelling is unsatisfactory: time series that are being used are often very short and do not allow reliable estimations of the underlying process; credit risk events are very rare, which makes them hard to estimate; these problems are amplified when it comes to the estimation of asset correlations. He further argues that the model-based approach amplified the interconnectivity in the financial system and thus contributed to systemic risk. Hellwig (2010) proposes two major changes to the system of banking regulation: (i) eliminate the risk-calibration of regulatory capital; and (ii) substantially higher regulatory capital.

Rochet (2010) argues that the explicit bail-out guarantees that were issued by the G20 to large financial institutions erode market discipline and create moral hazard. He further argues that the lack of resiliency of the interbank money market to the relatively small shocks from the sub-prime mortgage market is a major challenge for banking supervisors as banks were, prior to the crisis, deemed to be very resilient on the micro-level. The author emphasizes the major difficulties of identifying financial institutions that are too big to fail (TBTF) and would thus require additional supervisory oversight. The paper suggests to adopt central counterparty clearing for all "vital" market infrastructures (i.e. interbank transactions and derivatives) instead of opaque over-the-counter transactions. Furthermore, Rochet (2010) proposes that financial supervision should shift from protecting individual banks to protecting "platforms" (i.e. interbank markets, money markets, some derivative markets and large-value payment systems) and that the mandate of central banks should be refined accordingly.

Blundell-Wignall and Atkinson (2010) point out a number of shortcomings with the Basel III framework, part of which are rooted in Basel II. They criticize that promises in the financial system are not treated equally, regardless of where they are located. This allows for regulatory arbitrage. They further point out, that with increasing regulation in the banking sector, more capital will be invested in the unregulated shadow banking sector, as the cost of capital in the regulated sector increases. Blundell-Wignall and Atkinson (2010) show that the Basel II risk-weighting resulted in a *"perverse outcome in the crisis"* as banks with higher Tier 1 capital prior to the crisis generated higher losses when crisis struck. As Basel III brings only minor changes to the risk-weighting procedure, the danger of perverse incentives still exists. The authors further argue that the risk-weighting approach might not work well together with the leverage ratio. Blundell-Wignall and Atkinson (2010) propose to apply a quadratic minimum capital penalty for deviations from a benchmark portfolio in order to deal with lump-sum risks and argue that liquidity management should best be left to the market, as the crisis was primarily a crisis of solvency and confidence.

6.3.1 Shortcomings of the Existing Reform Proposal

While Basel III can be considered a necessary step forward, it has a number of shortcomings with respect to the regulation of SIFIs and systemic risk. Stronger capital requirements can help to enhance the resilience of the financial system to contagion effects, common shocks, and informational spillovers, as they effectively reduce counterparty risk. In this respect, the increased core capital requirements, as well as the increase in capital quality were steps in the right direction. This is especially the case for the leverage ratio and liquidity requirements. A number of problems remain, however.

(i) The core problem with capital requirements is their dependency on risk-weighted assets. As long as the risk-weights for interbank loans and other financial assets do not reflect the true risk associated with these assets, even the strongest capital requirements are rendered useless. In fact, the risk-weights currently implemented largely contributed to the creation of systemic risk as they incentivized banks to hold financial assets (interbank loans, derivatives, etc.) instead of real assets (corporate loans, corporate bonds, etc.) that have lower correlation. Basel III has missed the opportunity to reform the risk weights and rule them out as a source of systemic risk.

The asset value correlation (AVC) factor proposed for large financial institutions in Basel III is a global factor and does not take into account the different magnitudes of correlation of different assets. The correlation between two asset classes (i.e. the correlation between corporate loans and interbank loans) will in general be lower than the correlation of two assets of the same asset class. Banks thus have no incentive to diversify their portfolios but will rather specialize on holding assets of a certain class and gain profits from economies of scale and specialization, effectively creating portfolio lump risks. Portfolio lumpiness, however, is a significant source of systemic risk, as e.g. Georg and Poschmann (2010) show.

Therefore, the risk-weights and asset value correlation factor of Basel III fail to mitigate systemic risk. As banks lack the relevant information about the network structure of the financial system, they will necessarily underestimate the correlation of their portfolios and are thus unable to conduct optimal risk management. Only the supervisory authority is able to appropriately map the financial network in a macroprudential risk analysis. The network effect is amplified for SIFIs as the correlations between interbank loans from smaller banks to SIFIs will be larger, as it is the very definition of a SIFI that its default causes widespread failure in the financial system.

(ii) Basel III aims at regulating SIFIs by imposing additional capital requirements that are deemed to be commensurate with their systemic importance. The systemic importance of a bank, however, is a highly volatile quantity that can rapidly change over time. As it is impossible for banks to raise banking capital over night, they will be forced to hold as much banking capital as is required at the time of their largest systemic importance for the capital requirement to be effective. This argument makes it difficult for regulatory authorities to justify the additional requirements to the banks. Furthermore, capital requirements to prevent banks from gaining systemic importance can only be effective, if these requirements generate costs for the banks that are higher than the benefits from bail-out guarantees (see e.g. Akram and Christophesen (2010) for an analysis of gains from systemic importance). Otherwise, banks would still have an incentive to gain systemic importance. The benefits of bail-out guarantees can be estimated from two factors: (i) the amount of money governments had to spend on recent bail-outs; and (ii) the implicit gains that stem from the extraordinary monetary policy measures.[3] It seems therefore unlikely that imposing additional capital requirements for SIFIs works in practice. This raises the question of what is left of the promise to regulate banks that are too large, too interconnected, or otherwise of systemic importance. Basel III fails to provide a valid answer to that question.

(iii) Another problem with imposing additional capital requirements for SIFIs is, that the G20 yet failed to agree on a global lower bound of these requirements. This will lead to a race to the bottom amongst countries, as no country will voluntarily weaken its financial sector by imposing large capital requirements for systemically important financial institutions. I have argued that it is very difficult to properly measure the systemic importance of an individual financial institution and regulatory authorities will always have to justify additional capital requirements for those banks that they

[3] One example would be that banks were able to use the extended collateral standards of central banks and obtain central bank liquidity at a rate of 1% by depositing e.g. Greek sovereign bonds that pay a much higher interest.

deem to be of systemic importance. Without the appropriate measures of individual financial institutions, it is almost impossible for a regulatory authority to justify any additional capital charges of significant order. The Financial Stability Board (2010b) addresses the same problem with respect to the requirement that supervisory authorities be pro-active and intervene early during the build-up of systemic risks. It is stated that *"when supervisors take an early intervention approach, there are often no tangible risk indicators (i.e. losses) to confirm that this intervention is needed, so this makes it difficult to convince a firm and their boards that such measures are necessary to deal proactively with emerging areas of risk within a SIFI"*. The key question is, if it is generally possible to construct measures that detect systemic risks while they are building up. While the indicators currently available in the literature (see chapter 1.1.4 for an overview) are a huge step forward when compared to the literature before the crisis, they might still fail this particular task.

(iv) The different forms of systemic risk are interdependent and reinforce each other. However, informational spillovers are a rarely addressed issue in the G20 discussion on systemic risk. One of the few places where informational spillovers are mentioned is the Financial Stability Board (2010b), stating that *"Having a capital level that is too low vis-a-vis the risks being taken, especially for SIFIs, can lead to a highly vulnerable financial system. This shortfall contributed to the loss of confidence among counterparties, funds providers and investors"*. The enhanced capital requirements of Basel III will reduce the default probability of financial institutions. Therefore it will also reduce the risk of informational spillovers and herding behaviour, as market participants are aware of the higher resilience of the financial system. This will strengthen the trust amongst banks, but the question remains if it will prevent liquidity hoarding and fire-sales in a future crisis. The recent experience suggests that banks are well aware of the shortcomings of their risk-assessment and the devastating effects of informational contagion. This manifested with the insolvency of Lehman brothers in September 2008.

> The systemic impact of this particular insolvency was modest in terms of contagion effects and common shocks. But it was a signal to the remaining banks that they had underestimated the risks they had taken in their asset portfolios. The regulatory reform process thus has to focus on addressing informational spillovers as a relevant form of systemic risk and propose measures to address this issue.[4]

6.3.2 A Way Forward for Systemic Risk Regulation

The aforementioned shortcomings have to be addressed in the regulatory reform process in order to effectively regulate systemic risk. Some authors have made proposals about how the way forward with systemic risk regulation could look like. Rochet (2010) proposes a rather radical approach and suggests that financial supervision should shift from protecting banks to protecting what he calls *"platforms"*. These platforms are markets, such as the interbank market, money markets, some derivative markets, but also large value payment systems. This approach is appealing, but might be of purely academic interest, as it would require a completely different financial architecture, and as the author suggests himself, a new mandate for central banks and regulatory authorities. Hellwig (2010) proposes to eliminate the risk-calibration of regulatory capital altogether and a substantial increase in required capital. This would solve all problems with the current risk-weights, but does not seem to be a realistic solution as banks will lobby hard to prevent such a *"thorough overhaul"* of the financial system. Blundell-Wignall and Atkinson (2010) propose to apply a quadratic minimum capital penalty for deviations from a benchmark portfolio in order to deal with lump-sum risks. This proposal is appealing for two reasons: it would solve the lumpiness-problem of Basel II (and Basel III) and is more realistic than the rather radical approaches of Rochet (2010) and Hellwig (2010).

[4]An interesting remark is made by Haldane and May (2011) who argue that liquidity ratios will effectively limit liquidity hoarding shocks. While their point is arguably true, Acharya and Yorulmazer (2008) show that informational spillovers also increase the endogenous correlation of banks' assets.

While acknowleding that the crisis calls for a much more fundamental reform of the financial system than currently provided by Basel III, this paper tries to outline a realistic and viable way forward for systemic risk regulation. In order to address the identified shortcomings of Basel III, this paper proposes three measures.

(i) Risk-weights for interbank loans have to reflect the knife-edge property of interbank markets in some way. In normal times the low risk-weights for interbank loans are justified by the mutual insurance aspect of interbank markets. In times of crisis, however, interbank loans will amplify systemic risk and their respective risk-weights should be much larger. Thus, the static risk-weights as currently implemented in Basel III exhibit a pro-cyclicality with respect to systemic risk and a counter-cyclical risk buffer should be put in place. While Basel III proposed a counter-cyclical capital buffer, this is implemented as a global factor and does not change the incentive structure of the risk-weights. The effect of a counter-cyclical capital buffer could be realized by allowing national authorities to implement it as a counter-cyclical buffer on the risk-weights. Such a counter-cyclical risk-weight would counteract the time-dimension of systemic risk.

(ii) To enhance the risk-management capabilities of banks, the asset value correlation multiplier should be dynamic. Banks should be given a set of dynamic AVC for all asset classes (including cross sections) and then calculate their individual multiplier. This would enable banks to enhance their risk management and set an incentive for portfolio diversification. An additional advantage of such a dynamic multiplier is that it can be used as an effective regulatory tool in times of low economic growth but increasing systemic risk. In such times there will be a lot of political pressure on central banks to take measures stimulating growth. Even though most central banks are independent, a dynamic AVC would be a much more fine-tuned tool than just increasing the counter-cyclical buffer or imposing additional capital requirements on SIFIs. A further argument for the introduction of a dynamic multiplier is that the correlation of assets captures the cross-sectional dimension of systemic risk, and should thus be regulated accordingly. This line of argument is the rationale to distinguish between counter-cyclical risk-weights and a dynamic AVC multiplier as regulatory measures.

(iii) Basel III does not provide adequate measures to regulate systemically important financial institutions. This is a particular shortcoming and should be addressed in future regulation proposals. Instead of focussing on capital requirements, this paper proposes to focus on market transparency. I have argued above why informational spillovers played an important role in the recent financial crisis and that Basel III does not take this source of systemic risk into account. While increased capital buffers can help strengthen the trust amongst market participants, they are not sufficient to counteract the herding behaviour that was seen during the current crisis. In order to counteract informational spillovers, asymmetric information between market participants has to be reduced. It is thus necessary to emphasize the third pillar of Basel III and to enhance market transparency considerably. Especially banks that are considered to be of systemic importance should be required to publish more frequently more detailed information. A practical way to achieve this goal would be to introduce three categories of systemic importance, low, medium and high. This simple scheme would account for the high volatility of systemic importance. Banks that have a high systemic importance only a limited amount of time are considered to be of medium systemic importance while those who are almost always of high systemic importance are in the high group and the rest is in the low group.[5] Due to the enhanced reporting and data publication requirements for systemi-

[5]One could envisage a rule that each bank will be put into the next higher (lower) peer group if it has a higher (lower) ranking for two consecutive time periods. This would reduce the number of up- and downgrades and still detect structural changes when systemic risks are building up.

cally important financial institutions there is no use in keeping the names of the SIFIs secret. All market participants are aware who has which level of systemic importance and they are aware that this level might change over time. The regulators could publish a quarterly update on the systemic risk ranking. This time interval is frequent enough in order for banks to react to it and timely enough in order to detect the emergence of lump systemic risk at a given financial institution.

Such a simple scheme would allow different countries to use different measures of sytemic importance in order to take the country-specific details of their banking system into account. For banks that are of global systemic importance there should be an internationally agreed upon minimum requirement for reporting and data publication. In order for such a regulation scheme to be effective, it is necessary to have a transparent communication what criteria are taken into account when the systemic importance of an individual financial institution is measured. Note that this does not give rise to moral hazard, as each bank only knows its local properties but cannot say with certainty how the rest of the banking system evolves. Even if banks decide to gain systemic importance (i.e. if they want to benefit from implicit bail-out guarantees) they cannot be sure that other banks do not behave similar. Therefore all measures of systemic importance have to be relative measures in the sense that they measure the relative systemic importance of a bank with respect to other banks.

The approach of enforcing additional reporting and data publication of SIFIs (or those who are suspected to be SIFIs) is a much weaker approach than requiring banks to hold additional capital. As I have argued above, it takes banks some time to acquire new capital, especially in times when they most need it. Therefore additional measures have to be taken to prevent banks from trying to gain systemic importance. It is safe to assume that a bank with high systemic importance index over a long period of time is considered to be relevant for the system stability by other market participants. An insolvency of such a bank will thus give rise to considerable informational spillovers which are almost impossible to predict. Therefore, these banks are subject to implicit bail-out guarantees which should not come without a price. This price will not be imposed on the bank by other market participants. The systemic importance of a bank does not relate to its probability of default, which is the ultimate driver of refinancing costs for the bank. Therefore, it might prove useful to impose a levy or tax on systemic importance in order to set the appropriate incentives.

The proposed policy measures only sketch a way forward for systemic risk regulation. Some parts of the picture are still missing, as the regulation of the large shadow bank sector has not yet been discussed in detail. The measures aim to be realistic in the sense that they do not call for a complete overhaul of financial regulation, but rather try to improve the steps along the way that are already taken.

Deutsche Zusammenfassung

Das Ziel der vorliegenden Dissertation ist es, ein besseres Verständnis von systemischen Risiken auf Interbankenmärkten zu entwickeln. Die Bedeutung systemischer Risiken für die Stabilität des gesamten Finanzsystems ist durch die internationale Finanzkrise der Jahre 2007/2008 deutlich geworden, die zu einer der schwersten Rezessionen der letzten Einhundert Jahre geführt hat. Ausgehend von einer Krise auf dem US-Immobilienmarkt kam es in Folge der zunehmenden Verflechtungen zwischen Finanzinstituten zu enormen Verwerfungen auf den internationalen Kapitalmärkten. Diese erreichten ihren Höhepunkt mit dem Zusammenbruch der US Investmentbank Lehman Brothers im September 2008 und führten in den darauffolgenden Tagen zu einem beinahe vollständigen Zusammenbruch der Interbanken-Kreditmärkte. Banken sind auf diese gegenseitigen Kredite angewiesen um kurzfristig auftretende Liquiditätsschwankungen auf der Passivseite ihrer Bilanzen auszugleichen und die Aktivseite ausreichend zu diversifizieren. Ohne funktionierende Interbankenmärkte können Banken keine Fristentransformation vornehmen und die Realwirtschaft nicht mit langfristigen Krediten versorgen. Die Folge eines solchen Zusammenbruchs ist ein Rückgang der Investitions- und Produktionstätigkeit, reduzierte Handelsaktivität und steigende Arbeitslosigkeit.

Um die Stabilität des Finanzsystems zu gewährleisten waren Regierungen und Zentralbanken weltweit gezwungen auf noch nie dagewesene Sondermaßnahmen zurückzugreifen, von denen viele bis heute bestehen. Im Jahr 2009 hat der Internationale Währungsfonds die Gesamtkosten der Finanzkrise mit US$ 11.9 Trillionen beziffert, worin die Kosten für die Notmaßnahmen zur Rekapitalisierung von in Schieflage geratenen Finanzinstituten eingerechnet ist. Die Notmaßnahmen die in vielen Ländern notwendig waren um die nationalen Bankensysteme zu stabilisieren hatten erhebliche Auswirkungen auf die Haushalts- und Schuldensituation der einzelnen Länder. In der schlimmsten Phase der Krise (2007-2009) sind die öffentlichen Schulden der industrialisierten G20-Länder um etwa 20 Prozentpunkte angestiegen. Etwa 5.5 Prozentpunkte dieser Neuverschuldung stammen direkt aus den Stabilisierungsmaßnahmen für den Finanzsektor. Weitere 2 Prozentpunkte stammen aus Konjunkturpaketen welche die direkten Krisenfolgen abmildern sollten. Aus diesen Zahlen wird die Bedeutung des Themas der vorliegenden Arbeit deutlich.

Der Schweregrad der Krise wurde nicht nur durch die Tiefe der Krise hervorgerufen, sondern auch durch die Geschwindigkeit mit der sich die Krise entwickelte. Während der als *"great moderation"* bezeichneten Periode mit geringer Assetvolatilität, geringer Inflation und geringen Konjunkturzyklen entstanden systemische Risiken in Form von erhöhter Vernetztheit von Finanzinstituten und geringerer Transparenz von Finanzprodukten. Ab einem bestimmten Punkt war die Stabilität des Finanzsystems nicht mehr sichergestellt und die aufgestauten systemischen Risiken manifestierten sich. Dieses Eigenschaft von Finanzsystemen wurde von Haldane (2009) als "auf Messers Schneide", oder "robust-doch-fragil" bezeichnet und stellt ein wohlbekanntes Phänomen in der Analyse komplexer Systeme in der Biologie, Physik und Sozialwissenschaft dar.[6]

Um die Dynamik die diesem Verhalten zugrundeliegt zu verstehen, will die vorliegende Arbeit vier Fragen beantworten:

(Q1) Was sind die Ursachen und unterschiedlichen Manifestationen systemischer Risiken?

(Q2) Wie können systemische Risiken gemessen werden, insbesondere wenn sie

[6]Siehe hierzu auch Haldane and May (2011), sowie Battiston et al. (2009).

im entstehen sind?

(Q3) Wieviel tragen die einzelnen Formen systemischer Risiken zum Gesamtrisiko bei? Welches ist die dominierende Form systemischen Risikos?

(Q4) Sind die vorliegenden Vorschläge für eine Reform des internationalen Finanzsystems ausreichend um systemische Risiken in Zukunft wirksam zu unterbinden?

Die Struktur der vorliegenden Arbeit folgt diesen vier Fragen, die in nahezu allen Kapiteln der Arbeit in gewissem Umfang behandelt werden. Die einzelnen Kapitel setzen dennoch unterschiedliche Schwerpunkte. Während sich diese Einleitung auf Frage (Q1) fokussiert, wird die Frage (Q2) hauptsächlich in Kapitel (3) behandelt. Die beiden Kapitel (4) und (5) konzentrieren sich hauptsächlich auf die Frage (Q3), während die Frage (Q4) größtenteils in Kapitel (6) behandelt wird.

Die vorliegende Arbeit baut auf sechs Kapitel auf, welche unterschiedliche Aspekte systemischer Risiken in Interbankenmärkten behandeln. Nichtsdestotrotz geht Kapitel (2) etwas über den eigentlichen Fokus dieser Arbeit hinaus und wendet die Mikrofundierung des Bankenverhaltens welche in diesem Kapitel entwickelt wird auf ein Modell endogener Geldschöpfung an. In Kapitel (3) werden verschiedene Aspekte der Netzwerkstruktur des Südafrikanischen Interbankenmarktes als Anwendung eines realen Interbankennetzwerks analysiert. Darüber hinaus wird in diesem Kapitel ein Index zur Messung der Systemrelevanz einzelner Finanzinstitute als Baustein für eine umfassendere Makroprudenzielle Analyse entwickelt. Kapitel (4) beschreibt ein dynamisches Multi-Agenten Modell, basierend auf der Mikrofundierung des Bankenverhaltens aus Kapitel (2). Eine der Hauptaussagen dieses Kapitels ist, dass systemische Risiken in Form von gemeinsamen Gefährdungen gegenüber systemischen Risiken durch Interbanken-Ansteckungseffekte nicht nachrangig sind. Die beiden Formen systemischer Risiken wirken durch unterschiedliche Kanäle auf das Finanzsystem und verlangen nach unterschiedlichen, optimalen Reaktionen. Das Hauptergebnis dieses Kapitels wird in Kapitel (5) weiter untersucht, wo ein allgemeines Gleichgewichtsmodell eines

Bankensystems entwickelt wird, welches beide Formen systemischer Risiken in einem vereinheitlichten Modell umfasst. Das abschließende Kapitel (6) zieht die notwendigen Schlussfolgerungen für die Regulierung systemischer Risiken und untersucht das kürzlich verabschiedete Rahmenwerk Basel III im Hinblick auf die Ergebnisse der vorliegenden Arbeit.

Kapitel (2) entwickelt die Mikrofundierung des Banken- und Nichtbanken-verhaltens um den endogenen Geldschöpfungsprozess zu analysieren der durch die Wechselwirkung der verschiedenen Akteure auf den Märkten für Zentralbankgeld, Krediten und Bonds bestimmt wird. Das Modell erweitert den Ansatz von Bernanke and Blinder (1988) und modelliert die Entscheidungen über Gewinn- und Risikopräferenzen einer Bank mit einem Ansatz aus der Portfoliotheorie. Anschließend wird Value at Risk as Modellierungsansatz für die Liquiditätspräferenz einer Bank eingefhrt. Dieses Modell wird mit der Arbeit von Bofinger (2001) verknüpft, der ein Modell für den makroökonomischen Kreditmarkt entwickelt um den Geldschöpfungsprozess zu endogenisieren. Dieses kombinierte Modell wird um einen Firmen- und Haushaltssektor, sowie um die Zentralbank als Akteur erweitert. Den Einfluss von Zentralbankpolitik auf die Geldbasis wird abgeleitet und es wird gezeigt, dasss Zentralbankpolitik in der langen Frist weniger effektiv ist als in der kurzen Frist. Dies wirft die Frage nach der Wirksamkeit von Zentralbankpolitik auf und wird in Kapitel (4) weiter untersucht.

Kapitel (3) gibt einen Überblick über Netzwerktheorie als Werkzeug zur Bestimmung systemischer Risiken in Interbankennetzwerken und hat zwei Ziele. Erstens nimmt es eine Analyse der Struktur des Südafrikanischen Übernacht-Interbankenmarktes mit Methoden der Netzwerkthoerie vor. Hierbei wurden reale Daten des South African Multiple Options Settlement (SAMOS) System zwischen Februar 2005 und Juni 2010 verwendet. Einfache Maße für die Topologie eines Netzwerks werden vorgestellt und es wird gezeigt, dass der Südafrikanische Interbankenmarkt eine skalenfreie Topologie besitzt. Das zweite Ziel dieses Kapitels ist es, den Netzwerk-Systemrelevanz-Index (Network Systemic Importance Index - NSII) vorzustellen. Dieser basiert auf drei Maßen, welche die Bedeutung einer Bank innerhalb des Interbankennetzwerks bestimmen: Größe, Verbundenheit und Betweenness (Zentralität). Obwohl der Index nur ein Baustein einer umfassenderen Makroprudenziellen Analyse sein kann, umfasst er viele Eigenschaften welche die Systemrelevanz einer Bank bestimmen. Eine wichtige Eigenschaft des NSII ist, dass es sich hierbei um einen relativen Index handelt, der die Systemrelevanz einzelner Finanzinstitute relativ zueinander bestimmt und daher weniger anfällig für moral hazard ist. Es wird argumentiert wieso der NSII ein geeignetes Maß zur Bestimmung der Systemrelevanz einer Bank ist und daher dazu verwendet werden kann eine Steuer oder Abgabe auf Systemrelevanz zu erheben.

Die Finanzkrise hat deutlich gemacht dass es wichtig ist systemische Risiken sowohl qualitativ, als auch quantitativ zu verstehen, um die Stabilität des Finanzsystems zu garantieren. Die Krise hat damit auch gezeigt, dass die Struktur und Dynamik von Interbankenmärkten berücksichtigt werden muss, wenn die Widerstandsfähigkeit des Finanzsystems analysiert wird. In Kapitel (4) wird daher ein dynamisches Multi-Agenten Modell systemischer Risiken in Interbankenmärkten entwickelt. Dieses Modell stellt die dynamische Verallgemeinerung des statischen Modells des Bankenverhaltens aus Kapitel (2) dar. Multi-Agenten Simulationen eignen sich zur Analyse dynamischer Effekte besonders gut und wurden bereits etwa von Iori et al. (2006), sowie von Nier et al. (2007) hierzu verwendet. Die in der Literatur existierenden Modelle haben jedoch eine Reihe von Mängeln und eignen sich nur bedingt für die Beantwortung der in der vorliegenden Arbeit aufgeworfenen vier Fragen (Q1)-(Q4). Insbesondere wurde in der Literatur stets von sicheren Investitionen und häufig von fixen Depositen ausgegangen. Außerdem wurde stets eine exogen vorgegebene, fixe Netzwerkstruktur verwendet, wodurch eine Analyse vieler dynamischer Effekte gar nicht möglich ist. In diesem Kapitel werden daher sowohl riskante Investitionen, als auch Depositenfluktuationen als Auslöser für Liquiditätsschwankungen (und damit als mögliche

Ursachen von Illiquidität und Insolvenz einer Bank) verwendet. Darüber hinaus bildet sich die Netzwerkstruktur des Interbankenmarktes in gewissem Sinne endogen heraus, so dass viele Aspekte realer Interbankennetzwerke gut abgebildet werden. Es wird die Wirksamkeit von Zentralbankpolitik untersucht und in Einklang mit Kapitel (2) gezeigt, dass diese in der langen Frist weniger effektiv ist als in der kurzen Frist. Es werden unterschiedliche Netzwerktopologien miteinander verglichen und gezeigt, dass in Zufallsgraphen der Zusammenhang zwischen dem Grad der Vernetztheit und der Instabilität des Finanzsystems nicht monoton ist. Skalenfreie Netzwerke erweisen sich in der Analyse stabiler als Kleine-Welt Netzwerke, die wiederum stabiler sind als zufällige Netzwerke. Das in diesem Kapitel vorgestellte Modell umfasst viele Aspekte der Dynamik realer Interbanknetzwerke und kann daher genutzt werden um die Auswirkung unterschiedlicher Formen systemisher Risiken miteinander zu vergleichen. Es wird gezeigt, dass gemeinsame Gefährdungen, entgegen ihrer Bedeutung in der Literatur, die größere Bedrohung für die Finanzstabilität darstellen und bei der Regulierung systemischer Risiken berücksichtigt werden müssen.

Dieses Ergebnis wird in Kapitel (5) im Rahmen eines allgemeinen Gleichgewichtsmodells weiter untersucht. Basierend auf dem Modell von Diamond and Dybvig (1983) existiert eine breite Literatur, welche die Auswirkungen einzelner Formen systemischer Risiken untersucht. Allen and Gale (2000) und Freixas et al. (2000) untersuchen Ansteckungseffekte in Interbankenmärkten, während Dasgupta (2004) den optimalen Grad der Verneztheit auf diesen Märkten bestimmt. Gemeinsame Gefährdungen wurden etwa von Acharya (2009) untersucht, aber bisher existiert kein Modell in der Literatur, welches beide Formen gemeinsam analysiert. Diese Lücke wird in diesem Kapitel geschlossen und wir zeigen, dass es zu nichttrivialen Wechselwirkungseffekten zwischen den unterschiedlichen Formen systemischer Risiken kommen kann. Insbesondere können die einzelnen Effekte prozyklisch wirken und stellen damit eine besondere Herausforderung für die Regulierung systemischer Risiken dar.

Im abschliessenden Kapitel (6) wird das neue Basel III-Rahmenwerk im Lichte der Erkenntnisse dieser Arbeit analysiert. Es werden unterschiedliche Schwachstellen aufgezeigt und Vorschläge für weitere Reformschritte zur Regulierung systemischer Risiken herausgearbeitet. Hierdurch wird die vorliegende Arbeit abgerundet und die notwendigen Schlussfolgerungen aus den theoretischen Überlegungen der Kapitel (2) bis (5) gezogen.

Promotionserklärung

Erklärung gemäß §4 Abs. 1 Pkt. 3 PromO

Hiermit erkläre ich,

1. dass mir die geltende Promotionsordnung bekannt ist;

2. dass ich die Dissertation selbst angefertigt, keine Textabschnitte eines Dritten oder eigener Prüfungsarbeiten ohne Kennzeichnung übernommen und alle von mir benutzten Hilfsmittel, persönlichen Mitteilungen und Quellen in meiner Arbeit angegeben habe;

3. dass ich bei der Auswahl und Auswertung des Materials sowie bei der Herstellung des Manuskriptes keine unzulässige Hilfe in Anspruch genommen habe;

4. dass ich nicht die Hilfe eines Promotionsberaters in Anspruch genommen habe und dass Dritte weder unmittelbar noch mittelbar geldwerte Leistungen von mir für Arbeiten erhalten haben, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen;

5. dass ich die Dissertation noch nicht als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht habe;

6. dass ich nicht die gleiche, eine in wesentlichen Teilen ähnliche oder eine andere Abhandlung bei einer anderen Hochschule bzw. anderen Fakultät als Dissertation eingereicht habe.

Jena, den 30 März 2011

Pierre Georg Georg

Bibliography

V. V. Acharya, T. F. Cooley, M. Richardson, R. Sylla, and I. Walter. *A Critical Assessment of the Dodd-Frank Wall Street Reform and Consumer Protection Act.* VoxEU.org, 20.10.2010, 2010a. URL http://www.voxeu.org/index.php?q=node/5692.

Viral Acharya. A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255, 2009.

Viral Acharya and Tanju Yorulmazer. Cash-in-the-market pricing and optimal resolution of bank failures. *Review of Financial Studies*, 21:2705–2742, 2008.

Viral V. Acharya and Alberto Bisin. Counterparty risk externality: Centralized versus over-the-counter markets. Working Paper June 2010, New York University Department of Economics, 2010.

Viral V. Acharya and Tanju Yorulmazer. Information contagion and interbank correlation in a theory of systemic risk. CEPR Discussion Papers 3473, C.E.P.R. Discussion Papers, 2003.

Viral V. Acharya, Lasse H. Pederson, Thomas Philippon, and Matthew P. Richardson. *Restoring Financial Stability: How to Repair a Failed System*, chapter Regulating systemic risk, pages 283–303. Wiley, Hoboken, NJ, 2009.

Viral V. Acharya, Lasse H. Pederson, Thomas Philippon, and Matthew P. Richardson. Measuring systemic risk. *Federal Reserve Bank of Cleveland, Working Paper*, 2, 2010b.

Tobias Adrian and Markus K. Brunnermeier. Covar. *Federal Reserve Bank of New York staff report*, (348), 2009.

Tobias Adrian and Hyun Song Shin. Liquidity and leverage. *Journal of Financial Intermediation*, 19(3):418–437, 2010.

Toni Ahnert and Co-Pierre Georg. Systemic interaction risk. Technical report, Social Science Research Network, 2011. Available at SSRN: http://ssrn.com/abstract=1773915.

David Aikman, Piergiorgio Alessandri, Bruno Eklund, Prasanna Gai, Sujit Kapadia, Elizabeth Martin, Nada Mora, Gabriel Sterne, and Matthew Willison. Funding liquidity risk in a quantitative model of systemic stability. Bank of England working papers 372, Bank of England, 2009.

Q. Farooq Akram and Casper Christophesen. Interbank overnight interest rates: gains from systemic importance. Working Paper 2010-11, Norges Bank, 2010.

F. Allen, E. Carletti, and D. Gale. Interbank market liquidity and central bank intervention. *Journal of Monetary Economics*, 56(5):639–652, 2009.

Francis Allen and Douglas Gale. Financial contagion. *Journal of Political Economy*, 108:1–33, 2000.

Franklin Allen and Ana Babus. Networks in finance. *Wharton Financial Institutions Center Working Paper*, 08-07, 2008.

Franklin Allen, Ana Babus, and Elena Carletti. Financial connections and systemic risk. Economic Working Papers ECO2010/26, European University Institute, 2010.

George-Marios Angeletos and Iván Werning. Crises and prices: Information aggregation, multiplicity, and volatility. *The American Economic Review*, 96(5): pp. 1720–1736, 2006.

Mauricio Arias, Juan Carlos Mendoza, and David Alejandro Pérez. Applying covar to measure systemic market risk: the colombian case. Temas de estabilidad financiera, Banco de la Republica de Colombia, 2010.

L. Bajec and J. Graf Lambsdorff. There is no bank lending channel! *Passau Economic Discussion Papers*, 46, 2006.

O. Bandt, P. Hartmann, and J.-L. Peydró. Systemic Risk in Banking: An Update. *The Oxford Handbook of Banking (Oxford University Press, UK)*, 2009.

Albert-László Barabási and Réka Albert. Emergence of scaling in random networks. *Science*, 286:509–512, 1999.

Basel Committee on Banking Supervision. The basel committee's response to the financial crisis. Report to the G20, Bank for International Settlements, October 2010a.

Basel Committee on Banking Supervision. Basel III: A global regulatory framework for more resilient banks and banking systems. Basel iii document, Bank for International Settlements, December 2010b.

Basel Committee on Banking Supervision. Basel III: International framework for liquidity risk measurement, standards and monitoring. Basel iii document, Bank for International Settlements, December 2010c.

Stefano Battiston, Domenico Delli Gatti, Mauro Gallegati, Bruce C. Greenwald, and Joseph Stiglitz. Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. NBER Working Papers 15611, National Bureau of Economic Research, Inc, 2009.

Christopher Becher, Stephen Millard, and Kimmo Soramäki. The network topology of chaps sterling. Bank of England working papers 355, Bank of England, 2008.

B. Bernanke and A. S. Blinder. Credit, money, and aggregate demand. *American Economic Review, Papers And Proceedings*, 78:435–439, 1988.

Martin Blåvarg and Patrick Nimander. Interbank exposures and systemic risk. In *Risk measurement and systemic risk*. Bank for International Settlements, 2002.

Adrian Blundell-Wignall and Paul Atkinson. Thinking beyond Basel III: Necessary Solutions for Capital and Liquidity. *OECD Journal: Financial Market Trends*, 2010(1), 2010.

P. Bofinger. *Monetary Policy: Goals, Institutions, Strategies, And Instruments*. Oxford University Press, Oxford, 2001.

Frederic Boissay. Liquidity and financial fragility. Forthcoming paper, 13th Conference of the ECB-CFS Research Network on Macro-Prudential Issues, 2010.

Claudio Borio. Implementing a macroprudential framework: Blending boldness and realism. Keynote speech at the HKIMR-BIS conference "Financial Stability: Towards a Macroprudential Approach", Bank for International Settlements, 2010.

Michael Boss, Helmut Elsinger, Martin Summer, and Stefan Thurner. The network topology of the interbank market. *Quantitative Finance*, 4(6):677–684, 2004.

Nicola Brink. Note on the global financial market turmoil and central bank intervention - a south african perspective. Financial stability report, South African Reserve Bank, March 2009.

Nicola Brink and Co-Pierre Georg. Systemic risk in the south african interbank overnight market. Discussion Paper DP/11/01, South African Reserve Bank, 2011a.

Nicola Brink and Co-Pierre Georg. Assessing systemic risk in the south african interbank market. Special Note in the Financial Stability Review April, South African Reserve Bank, 2011b.

Christian T. Brownlees and Robert Engle. Volatility, correlation, and tails for systemic risk measurement. Working paper, New York University, 2010.

Markus Brunnermeier, Andrew Crockett, Charles Goodhart, Avi Persaud, and Hyun Song Shin. The fundamental principles of financial regulation. *Geneva Reports on the World Economy*, 11, 2009.

Markus K. Brunnermeier. Deciphering the liquidity and credit crunch 2007-08. NBER Working Papers 14612, National Bureau of Economic Research, Inc, December 2008. URL http://ideas.repec.org/p/nbr/nberwo/14612.html.

Daniel O. Cajueiro and Benjamin M. Tabak. The role of banks in the brazilian interbank market: Does bank type matter? Working Paper 130, Banco Central do Brasil, Research Department, 2007.

Javier Marquez Diez Canedo and Serafin Martinez Jaramillo. A network model of systemic risk: stress testing the banking system. *Intelligent systems in accounting, finance and management*, 16:87–110, 2009.

Olli Castrén and Ilja Kristian Kavonius. Balance sheet interlinkages and macro-financial risk analysis in the euro area. *European Central Bank Working Paper Series*, No. 1124, December 2009, 2009.

Stephen G. Cecchetti. Crisis and responses: The federal reserve in the early stages of the financial crisis. *Journal of Economic Perspectives*, 23(1):5175, 2009.

Jorge A. Chan-Lau. Regulatory capital charges for too-connected-to-fail institutions: A practical proposal. IMF Working Papers 10/98, International Monetary Fund, 2010.

Eui Jung Chang, Eduardo José Araùjo Lima, Solange M. Guerra, and Benjamin M. Tabak. Measures of interbank market structure: An application to brazil. *Brazilian Review of Econometrics*, 28(2):163–189, 2008.

Victoria Chick and Sheila Dow. Monetary policy with endogenous money and liquidity preference: a nondualistic treatment. *Journal of Post Keynesian Economics*, 24(4):587–607, 2002.

Rodrigo Cifuentes, Hyung Song Shin, and Gianluigi Ferruci. Liquidity risk and contagion. *Journal of the European Economic Association*, 3:556–566, 2005.

R. Cont and A. Moussa. Too interconnected to fail: contagion and risk in financial networks. Working paper, Columbia Center for Financial Engineering, 2009.

Amil Dasgupta. Financial contagion through capital connections: A model of the origin and spread of bank panics. *Journal of the European Economic Association*, 2(6):1049–1084, 2004.

Gianni De Nicolo and Myron L. Kwast. Systemic risk and financial consolidation: Are they related? *Journal of Banking & Finance*, 26(5):861–880, May 2002. URL http://ideas.repec.org/a/eee/jbfina/v26y2002i5p861-880.html.

Hans Degryse and Gregory Nguyen. Interbank exposures: An empirical examination of contagion risk in the belgian banking system. *International Journal of Central Banking*, 3(2):123–171, 2007.

D.W. Diamond and P.H. Dybvig. Bank runs, deposit insureance and liquidity. *Journal of Political Economy*, 91:401–419, 1983.

Larry Eisenberg and Thomas H. Noe. Systemic risk in financial systems. *Management Science*, 47(2):236–249, 2001.

European Central Bank. The concept of systemic risk. Special feature in the december financial stability report, 2009.

European Central Bank. Analytical models and tools for the identification and assessment of systemic risks. Financial stability review, European Central Bank, June 2010a.

European Central Bank. Financial Networks and Financial Stability. Special Issue in the Financial Stability Review June 2010, 2010b.

Chitru S. Fernando. Commonality in liquidity: Transmission of liquidity shocks across investors and securities. *Journal of Financial Intermediation*, 12:233–254, 2003.

Financial Stability Board. Progress of financial regulatory reforms. Letter to G20 leaders, Financial Stability Board, November 2010a.

Financial Stability Board. Intensity and effectiveness of sifi supervision. Recommendations for enhanced supervision, Financial Stability Board, November 2010b.

Financial Stability Board, International Monetary Fund, and Bank for International Settlements. The financial crisis and information gaps. Report to the G-20 Finance Ministers and Central Bank Governors October, Financial Stability Board and International Monetary Fund and Bank for International Settlements, 2009a.

Financial Stability Board, International Monetary Fund, and Bank for International Settlements. Guidance to assess the systemic importance of financial institutions, markets and instruments: Initial considerations–background paper. Report to the G-20 Finance Ministers and Central Bank Governors October, Financial Stability Board and International Monetary Fund and Bank for International Settlements, 2009b.

Tom Fong, Laurence Fung, Lillie Lam, and Yu Ip-wing. Measuring the interdependence of banks in Hong Kong. Working Papers 0919, Hong Kong Monetary Authority, 2009.

G. Fontana. Rethinking endogenous money: A constructive interpretation of the debate between horizontalists and structuralists. *Metroeconomica*, 55(4): 367–385, 2004.

Xavier Freixas and Cornelia Holthausen. Interbank market integration under asymmetric information. *Review of Financial Studies*, 18:459–90, 2005.

Xavier Freixas, Bruno M Parigi, and Jean Charles Rochet. Systemic risk, interbank relations, and liquidity provision by the central bank. Technical Report 3, 2000.

Xavier Freixas, Antoine Martin, and David Skeie. Bank liquidity, interbank markets, and monetary policy. *Federal Reserve Bank of New York Staff Report*, 371, 2010.

Craig Furfine. Interbank exposures: quantifying the risk of contagion. Bank for International Settlements Working Papers 70, Bank for International Settlements, 1999.

Craig Furfine. Banks monitoring banks: Evidence from the overnight federal funds market. *Journal of Business*, 74:33–58, 2001.

G20. The Seoul Summit Document. Technical report, The G20 Seoul Summit 2010, 2010.

Silvia Gabrieli. The functioning of the european interbank market during the 2007-08 financial crisis. CEIS Research Paper 158, Tor Vergata University, CEIS, May 2010.

Silvia Gabrieli. The microstructure of the money market before and after the financial crisis: a network perspective. CEIS Research Paper 181, Tor Vergata University, CEIS, 2011.

Prasanna Gai and Sujit Kapadia. Contagion in financial networks. Discussion Paper 1231, Bank of England, 2008.

Prasanna Gai and Sujit Kapadia. A network model of super-systemic crises. *Central Bank of Chile, Working Papers*, 542, 2009.

Céline Gauthier, Alfred Lehar, and Moez Souissi. Macroprudential regulations and systemic capital requirements. Working Paper 2010-4, Bank of Canada, January 2010.

R.G. Geldos and J. Roldós. Consolidation and market structure in emerging market banking systems. *Emerging Markets Review*, 5:39–59, 2004.

Co-Pierre Georg. The effect of the interbank network structure on contagion and financial stability. Graduate School "Global Financial Markets - Stability and Change" Working Papers 12, University of Jena, 2010.

Co-Pierre Georg. Basel III and systemic risk regulation - what way forward? Graduate School "Global Financial Markets - Stability and Change" Working Papers No. 16, University of Jena, 2011.

Co-Pierre Georg and Markus Pasche. Endogenous money – on banking behaviour in new and post keynesian models. *Jena Economic Research Papers*, 2008-65, 2008.

Co-Pierre Georg and Jenny Poschmann. Systemic risk in a network model of interbank markets with central bank activity. Jena Economic Research Papers 2010-33, University of Jena, 2010.

Marvin Goodfriend and Robert G. King. Financial deregulation, monetary policy and central banking. *Federal Reserve Bank of Richmond Economic Review*, 74: 3–22, 1988.

A. G. Haldane. Rethinking the financial network. Speech at "Financial Student Association", Amsterdam, 28.04.2009., 2009.

Andrew G. Haldane and Robert M. May. Systemic risk in banking ecosystems. *Nature*, 469:351–355, 2011.

F. Heider, M. Hoerova, and C. Holthausen. Liquidity hoarding and interbank market spreads: The role of conterparty risk. European Central Bank. Technical report, European Central Bank, 2009.

T. Hellmann and J. Stiglitz. Credit and equity rationing in markets with adverse selection. *European Economic Review*, 44:281–304, 2000.

Martin F. Hellwig. Capital regulation after the crisis: Business as usual? Working Paper Series of the Max Planck Institute for Research on Collective Goods 2010-31, Max Planck Institute for Research on Collective Goods, 2010.

HM Treasury. A new approach to financial regulation: judgement, focus and stability. Hm treasury document, July 2010.

C.-F. Huang and Robert H. Litzenberger. *Foundations for Financial Economics.* North-Holland, 1988.

Xin Huang, Hao Zhou, and Haibin Zhu. A framework for assessing the systemic risk of major financial institutions. BIS Working Papers 281, Bank for International Settlements, 2009a.

Xin Huang, Hao Zhou, and Haibin Zhu. Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis. Finance and Economics Discussion Series 2009-44, Board of Governors of the Federal Reserve System (U.S.), 2009b.

IMF Staff Note. Fiscal implications of the global economic and financial crisis. IMF Staff Position Note SPN/09/13, International Monetary Fund, 2009.

International Monetary Fund. Assessing the systemic implications of financial linkages. Global financial stability report, April 2009.

International Monetary Fund. World economic outlook. Technical Report April, 2010.

International Monetary Fund, Bank for International Settlements, and Financial Stability Board. Guidance to assess the systemic importance of financial institutions, markets and instruments: Initial considerations. *Briefing Paper for the G20 Finance Ministers and Central Bank Governors*, October, 28, 2009.

G. Iori, S. Jafarey, and F.G. Padilla. Systemic risk on the interbank market. *Journal of Economic Behavior & Organization*, 61(4):525–542, 2006.

Giulia Iori, Giulia De Masi, Ovidiu Vasile Precup, Giampaolo Gabbi, and Guido Caldarelli. A network analysis of the italian overnight money market. *Journal of Economic Dynamics and Control*, 32(1):259–278, 2008.

Arvind Krishnamurthy. The financial meltdown: Data and diagnoses. Northwestern working paper, Northwestern University, 2008.

Dan Ladley. Contagion and risk-sharing on the inter-bank market. Discussion Papers in Economics 11/10, Department of Economics, University of Leicester, 2011.

Marc Lavoie. *Foundations of Post-Keynesian Economic Analysis*. Edward Elgar, Aldershot, 1992.

Marc Lavoie. A post-keynesianamendment to the new consensus on monetary policy. *Metroeconomica*, 57(2):165–192, 2006.

A. Lehar. Measuring systemic risk: A risk management approach. *Journal of Banking and Finance*, 10:2577–2603, 2005.

Yaron Leitner. Inducing agents to report hidden trades: a theory of an intermediary. Working Papers 09-10, Federal Reserve Bank of Philadelphia, 2009.

Michele Lenza, Huw R. Pill, and Lucrezia Reichlin. Monetary policy in exceptional times. *CEPR Discussion Paper*, 2010.

N. Gregory Mankiw and David Romer. *New Keynesian Economics. Vol. 1: Imperfect competition and sticky prices + Vol. 2: Coordination Failures and Real Rigidities*. MIT Press, Cambridge Mass./London, 1991.

Michele Manna and Carmela Iazzetta. The topology of the interbank market: developments in italy since 1990. Temi di discussione (Economic working papers) 711, Bank of Italy, Economic Research Department, May 2009.

Sheri Markose, Simone Giansante, Mateusz Gatkowski, and Ali Rais Shaghaghi. Too interconnected to fail: Financial contagion and systemic risk in network model of cds and other credit enhancement obligations of us banks. *University of Essex Discussion Paper Series*, 683, 2010.

Christoph Memmel and Ingrid Stein. Contagion in the german interbank market. Working paper, Deutsche Bundesbank, 2008.

Frederic S. Mishkin. *The Economics of Money, Banking, and Financial Markets*. Addison-Wesley, Boston et al., 2006.

Paolo Emilio Mistrulli. Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. Temi di discussione (Economic working papers) 641, Bank of Italy, Economic Research Department, 2007.

Basil J. Moore. *Horizontalists and verticalists: the macroeconomics of credit money*. Cambridge University Press, New York, 1988.

Stephen Morris and Hyun Song Shin. Unique equilibrium in a model of self-fulfilling currency attacks. *The American Economic Review*, 88(3):pp. 587–597, 1998.

Stephen Morris and Hyun Song Shin. Rethinking multiple equilibria in macroeconomic modelling. (1260), June 2000.

Erland Nier, Jing Yang, Tanju Yorulmazer, and Amadeo Alentorn. Network models and financial stability. *Journal of Economic Dynamics and Control*, 31:2033–2060, 2007.

Erland Nier, J Yang, T Yorulmazer, and A Alentorn. Network models and financial stability. Working Paper 346, Bank of England, 2008.

E. Nissan. Comparing bank concentration across developing and developed countries. *Journal of Global Business*, 15(28):15–24, 2004.

T. I. Palley. Endogenous money: What it is and why it matters. *Metroeconomica*, 53:152–180, 2002.

T. I. Palley. Macroeconomics without the LM: A post-keynesian perspective. Technical Report 179, Political Economy Research Institute Working Paper, 2008a.

T. I. Palley. Endogenous money: Implications for the money supply process, interest rates, and macroeconomics. Technical Report 178, Political Economy Research Institute Working Paper, 2008b.

Ana Petrovic and Ralf Tutsch. National rescue measures in response to the current financial crisis. Legal Working Paper Series No 08 / July 2009, European Central Bank, 2009.

R. Pollin. Two theories of money supply endogeneity: some empirical evidence. *Journal of Post Keynesian Economics*, 13(3):366–396, 1991.

Jean-Charles Rochet. Commentary: Systemic risk: Changing the regulatory perspective. *International Journal of Central Banking*, 6(34):259–276, 2010.

Jean-Charles Rochet and Jean Tirole. Interbank lending and systemic risk. *Journal of Money, Credit and Banking*, 28(4):733–762, 1996.

Louis-Philippe Rochon. *Credit, Money, and Production: An Alternative Post-Keynesian Approach*. Edward Elgar, Cheltenham, 1999.

Mara Rodriguez-Moreno and Juan Ignacio Pea Snchez de Rivera. Systemic risk measures: the simpler the better. Open Access publications from Universidad Carlos III de Madrid, Universidad Carlos III de Madrid, 2010.

P. Romer. Keynesian macroeconomics without the LM curve. *Journal of Economic Perspectives*, 14:149–169, 2000.

Angelika Sachs. Completeness, interconnectedness and distribution of interbank exposures: A parameterized analysis of the stability of financial networks. Discussion Paper Series 2: Banking and Financial Studies 2010,08, Deutsche Bundesbank, Research Centre, 2010.

Bernd Schwaab, André Lucas, and Siem Jan Koopman. Systemic risk diagnostics. Discussion Paper TI 10-104/DSF 2, Duisenberg school of finance - Tinbergen Institute, 2010.

Miguel A. Segoviano Basurto and C. A. E. Goodhart. Banking stability measures. IMF Working Papers 09/4, International Monetary Fund, 2009.

George Sheldon and Martin Maurer. Interbank lending and systemic risk: An empirical analysis for switzerland. *Swiss Journal of Economics and Statistics (SJES)*, 134(IV):685–704, 1998.

Kimmo Soramäki and Marco Galbiati. An agent-based model of payment systems. *Bank of England working paper*, 352, 2008.

J. Stiglitz and A. Weiss. Credit rationing in markets with impferfect information. *American Economic Review*, 17:393–410, 1981.

Benjamin Miranda Tabak, Solange Maria Guerra, and Rodrigo Andres De Souza Penaloza. Banking concentration and the price-concentration relationship: the case of Brazil. *International Journal of Accounting and Finance*, 1(4):415–435, 2009.

Nikola Tarashev, Claudio Borio, and Kostas Tsatsaronis. The systemic importance of financial institutions. *BIS Quarterly Review*, September:75–87, 2009.

John B. Taylor. Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39:195–214, 1993.

J.B. Thomson. On systemically important financial institutions and progressive systemic mitigation. *Federal Reserve Bank of Cleveland, Policy Discussion Papers* , 27, 2009.

Harald Uhlig. A model of a systemic bank run. *Journal of Monetary Economics*, 57(1):78–96, 2010.

Christian Upper and Andreas Worms. Estimating bilateral exposures in the german interbank market: Is there a danger of contagion? *European Economic Review*, 48:827–849, 2004.

Iman van Lelyveld and Franka Liedorp. Interbank contagion in the dutch banking sector. DNB Working Papers 005, De Nederlandsche Bank, Research Department, 2004.

Jürgen von Hagen. The monetary mechanics of the crisis. Technical Report 2009/08, Bruegel Policy Contribution, 2009.

Wolf Wagner. In the quest of systemic externalities: A review of the literature*. *CESifo Economic Studies*, 56(1):96–111, 2010.

Jack E. Wahl and U. Broll. Value at risk and bank equity. *Jahrbücher für Nationalökonomie und Statistik*, 223:129–135, 2003.

Duncan J. Watts and Steven H. Strogatz. Collective dynamics of 'small-world' networks. *Nature*, 393:440–442, 1998.

Simon Wells. Financial interlinkages in the United Kingdom's interbank market and the risk of contagion. Bank of England Working Papers 230, Bank of England, 2004.

Karl Whelan. Containing systmic risk. *UCD Centre for Economic Research Working Paper Series*, WP09/27, 2009.

Michael Woodford. *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press, 2003.

L. Randall Wray. Endogenous money: Structuralist and horizontalist. Technical Report 512, The Levy Economics Institute Working Paper Series, 2007.

Chen Zhou. Are banks too big to fail? DNB Working Papers 232, Netherlands Central Bank, Research Department, December 2009. URL http://ideas.repec.org/p/dnb/dnbwpp/232.html.