MODELLING AND ANALYSIS OF FINANCIAL NETWORK DYNAMICS

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A dissertation submitted
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Alexandrina Braack

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Abstract

The investigation of financial networks has been given more attention over the recent years and is generating even greater interest. This dissertation pertains to the research activities with focus on the analysis and modeling of financial network dynamics and complex relationships between financial institutions, central banks and other participants of the financial markets. We develop a simulation-based financial network model, reproducing a stylized financial system, which is affected by strong idiosyncratic or systematic external shocks. We use this model to analyze the interaction between banks, different economic sectors, and the central bank.

The distinctive character of the presented model is that banks are affected by the initial distress depending on their individual asset structure, due to the fact that banks, real economy segments and the central bank are connected by various credit and investment links building a multi-layer network structure. In comparison to existing models and scientific contributions in this area,

our model merges many different facets and characteristics of financial network into one single comprehensive model. Besides common borrower-lender relations, the so-called asset based financial network model includes the securitization of debts distinguishing between covered bonds and collateralized debt obligations, allowing us to analyze various network structures. Moreover, the model takes account of the regulatory capital and liquidity requirements, as well as the risk of deposit withdrawals, interbank trading and possible supportive activities by the central bank.

Besides the effect of capitalization on banking system stability, we analyze the impact of risk preferences of the banking sector with respect to its investments. In view of the initial shock, we focus on its intensity and concentration. We look at the effect of degree of connectivity and heterogeneity within banking systems. Furthermore, we analyze effects of size of interbank networks and their heterogeneity on vulnerability of whole networks and their single areas. In this context, a core-periphery network structures are studied. We explore effects of the loss of confidence in the banking system, connected to deposit withdrawals. Furthermore, we analyze the influence of certain properties connected to the regulatory framework. In this context, we look at the impacts of tightening regulatory capital restrictions and disparate capital requirements. Thereby we consider the case that all banks are treated equally, and the case of required capital assuming that systemically important banks faced the capital surcharge. Furthermore we look at the risk adjusted capital requirements compared to the 'flat' capital adequacy. Analyzing liquidity effects, we focus on initial liquidity endowment within banking systems and liquidity provided by central banks during financial crises.

The simulation experiments and results presented in this thesis show how diverse characteristics of the network itself and its environment as well as the properties of the systemic event exert influences on the dynamics within the network and thus on systemic risk. The tangible results often depend on a broad spectrum of factors.

The results of this work underline that an effective monitoring and regulating of banking systems have to be based on a deep understanding of financial products and current developments in the financial markets, transparency of bank books to the greatest possible extent and a continuous development of sophisticated models using this knowledge and data.

”The truth is rarely pure and never simple.”
— Oscar Wilde, *The Importance of Being Earnest*

To my sons…

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Glossary

ABN Asset Based Network

ABS Asset Backed Securities

BCBS Bank of International Settlements

BIS Basel Committee on Banking Supervision

CAR Capital Adequacy Ratio

CB Covered Bonds

CDO Collateralized Debt Obligations

CP Core-Periphery (network)

D-SIB Domestic Systemic Important Banks

ECB European Central Bank

ERP Erdös-Rényi Probability

G-SIB Global Systemic Important Banks

HR High Risk

IRS sensitivity (of capital requirements) to the individual risk

LCR Liquidity Coverage Ratio

LR	Low Risk
NSFR	Net Stable Funding Ratio
OTC	off-exchange-trading market (Over-the-counter)
RA	Risk Assets
RWA	Risk Weighted Assets
SIB	Systemic Important Bank
SPV	Special Purpose Vehicle
SRS	sensitivity (of capital requirements) to the systemic risk

Introduction

0.1 Motivation

The term 'financial crisis' is often defined a situation in which some financial institutions or assets rapidly lose their value. Until recently, financial crises were associated with bank runs, stock market crashes, bursting of bubbles or currency crises. The financial crisis that started in 2007 in the USA real estate market opened up entirely new dimensions. Many banks that had contributed to the excessive mortgage lending to customers of low credit standing went bankrupt within a short period of time. The so-called sub prime crisis spread rapidly due to the refinancing of the loans by pooling and securitization of receivables as well as by the short term liquidity traded on the interbank markets. Soon after the start of the crisis the interbank market had almost completely dried up, activating a further spiral of liquidity problems. Cost-intensive interventions of a large number of central banks and governments, taken to rescue distressed banks, seemed to be necessary to prevent a deepening global financial crisis. Consequently, the substantial over-indebtedness of individual countries caused several economic and government crises. However, the impacts of the last financial crisis and of the associated monetary policies are still not completely clear.

One question that has arisen during the crisis is: Could the financial crisis that started in August 2007 and the subsequent contagion effects have been predicted by modern macroe-

conomic models and early warning systems? Davis et al. (2008), for example, worked on similar questions in order to evaluate the power of early warning systems. They found that the US sub-prime crisis was only partly foreseen and that some of the consequences like the risk of contagion and the subsequent negative externalities for financial stability had been overlooked. One of the results of their work is that the latest financial crisis had some features that were rather atypical for the average banking crisis. This finding can explain, at least in part, the failure of the macroeconomic models and early warning systems which were used at the central banks and other institutions before and during the crisis. In particular, the role of financial intermediaries has long been neglected in macroeconomic models, which considered banks and broker-dealers as passive players, see Brunnermeier(2009). Similarly, the financial sector has played only a very rudimentary role in the prevailing macroeconomic models. Phenomena like speculative bubbles, overinvestment, the effects of balance sheet changes, as well as liquidity and the domino effects of bank bankruptcies haver been excluded a priori, as emphasized by Lux(2016).
The other often discussed question is whether the ensuing domino effect could have been restricted or even avoided by better regulation. One of the problems in this context is that it is often fairly uncertain whether the implementation of concrete policies, proposals and activities in order to make financial systems more resistant would lead to satisfactory results. The effectiveness of such efforts will depend on the number of factors, not at least because of the complexity of financial systems, interdependencies within them and many conceivable externalities.

A number of studies in recent years have shown that network structures play an important role for financial system stability. But interbank networks and their effects have been neither sufficiently investigated nor adequately included in further analyses, as underlined by Lux(2009). However, in recent years the role of financial networks in economic research has been growing in importance. The research activities mainly move in two principal directions: empirical studies of interbank markets and network modeling, which is either analytical or simulation-based. However, attempts are often made to combine the findings of both research activities. The simulation-based models, for example, often apply network topologies characterized by empirically discovered properties.

One of the first theoretical works dealing with financial networks is the research of Eisenberg and Noe (2001), which presented an abstract approach for the modeling of financial systems. The authors developed a clearing financial network model which meets the usual requirements on clearing vectors imposed by bankruptcy law: proportional repayments of liabilities in default, limited liability, and absolute priority. In this context, the endogenously-determined clearing vectors represent a specification of the payments made by each of the nodes in the network. The model clears the financial system and provides the systemic risk information solving a static clearing problem. Some years before, Sheldon and Maurer (1998) estimated a matrix of interbank loans for Switzerland based on the principle of entropy maximization. Closely related to this research, Upper and Worms (2002) estimated the bilateral credit relationships for the German banking system by using the same approach. Using the techniques developed in these papers, Elsinger, Lehar and Sommer (2002) suggested a new approach to risk assessment for banks by using standard risk management techniques in combination with a network model of interbank exposures and individual bank data usually collected at the central bank. Cifuentes (2002) analyzed the link between banking concentration and systemic risk. Cifuentes et al. (2005) engaged in intensive follow-up work on liquidity risk in a system of interconnected financial institutions when these are subject to regulatory solvency constraints and are forced to sell their assets to meet the requirements.

During the financial crisis that began back in August 2007 and in the face of the increasing linkages between banks, it became clearer that the risk assessment of banking system stability should be at the level of the system rather than at the level of individual institutions. There seems to have been rising interest in understanding the risk of contagion and its consequences over the last decade. The use of network models for this purpose has grown in popularity. Their methodology and technology are being developed in several directions, one of which is the model family explicitly including the highly simplified balance sheets of banks. Such models differ from one another by design of the network and its topology, definition of the initial shock, contagion mechanisms and further dynamic processes. In particular, Nier et al. (2007) simulated effects of a shock to the system resulting from the failure of one or more randomly chosen financial institutions. May and Arinaminpathy (2010) explored a mathematical model of a simplified banking system and studied the interplay between the properties of individual banks and the dynamical processes in the system. They discussed results in relation to potential regulations aimed at reducing systemic risk.

There has been a large amount of literature related to the scope of the present dissertation over the past few years. The overview on the most closely related literature will be presented in section 0.3 after introducing the scope of the dissertation. Furthermore, the most important single subjects related to the present work will be discussed in the appropriate places in subsequent chapters.

As much as has already been covered over recent years, many more open questions remain in order to understand the interaction of banks and other actors of the financial systems and its consequences.

0.2 Scope of the dissertation

The focus of this dissertation is on the simulation-based financial network analyses. Here we try to move forward in a new direction, developing the dynamic asset based network model (ABN-model). In the financial network models that we know, the exogenous shock mostly directly affects one or more banks. Normally, the source of the shock is then either not specified or given by a failure of the external (non-financial) sector without further specification. Initially affected banks are chosen randomly or on the basis of their specific properties such as balance sheet totals. The asset structure of individual banks with respect to the priority of their assets and portfolio diversification or risk is not usually considered.

In contrast to previous work, we consider a diversified real sector (here termed 'external sector') as a part of the network, characterized by the heterogeneous risk and financing structures of individual segments including the heterogeneous securitization techniques. Furthermore, the segment-specific degrees of diversification, in terms of the number of banks sharing the financing of any segment, implies a heterogeneous structure of the banking sector in the model. These properties allow a more differentiated analysis of the systemic risk, in particular regarding the characteristics of the initial shock.

For the construction of the ABN-model we found the inspiration in the network model presented by Nier et al.(2007) in [53]. However, we refined the central properties of the financial network and introduced further dynamics. Like Nier et al. and many others, we identify the external sector as the source of the initial shock and determine the intensity of the initial shock as the (unexpected) default rate of external loans. However, the ABN-model's specificity is found in the differential treatment of external segments concerning the stress scenarios and thus in the distribution of defaults across external segments. Moreover, because of the heterogeneous asset structure of the banking system, the affectedness of a single bank does not primarily depend on its properties such as size or interconnectivity, but on its asset structure. Banks holding non-performing assets will be directly affected. Thereby, the degree of the initial affectedness for a single bank depends on its share of non-performing assets and on the risk degree of its investments. Furthermore, banks may be also affected by the loss transfer via interbank credit links or by the withdrawal of deposits. Moreover, they may be forced to sell their assets at fire-sale prices in the case of liquidity shortage and thus face further losses from fire-sales. Further, the ABN-model includes the securitization of debts using two classes of debt securities: covered bonds (CB) and collateralized debt obligations (CDO). Moreover, it takes account of the risk adjusted capital requirements and liquidity reserve deposits, and

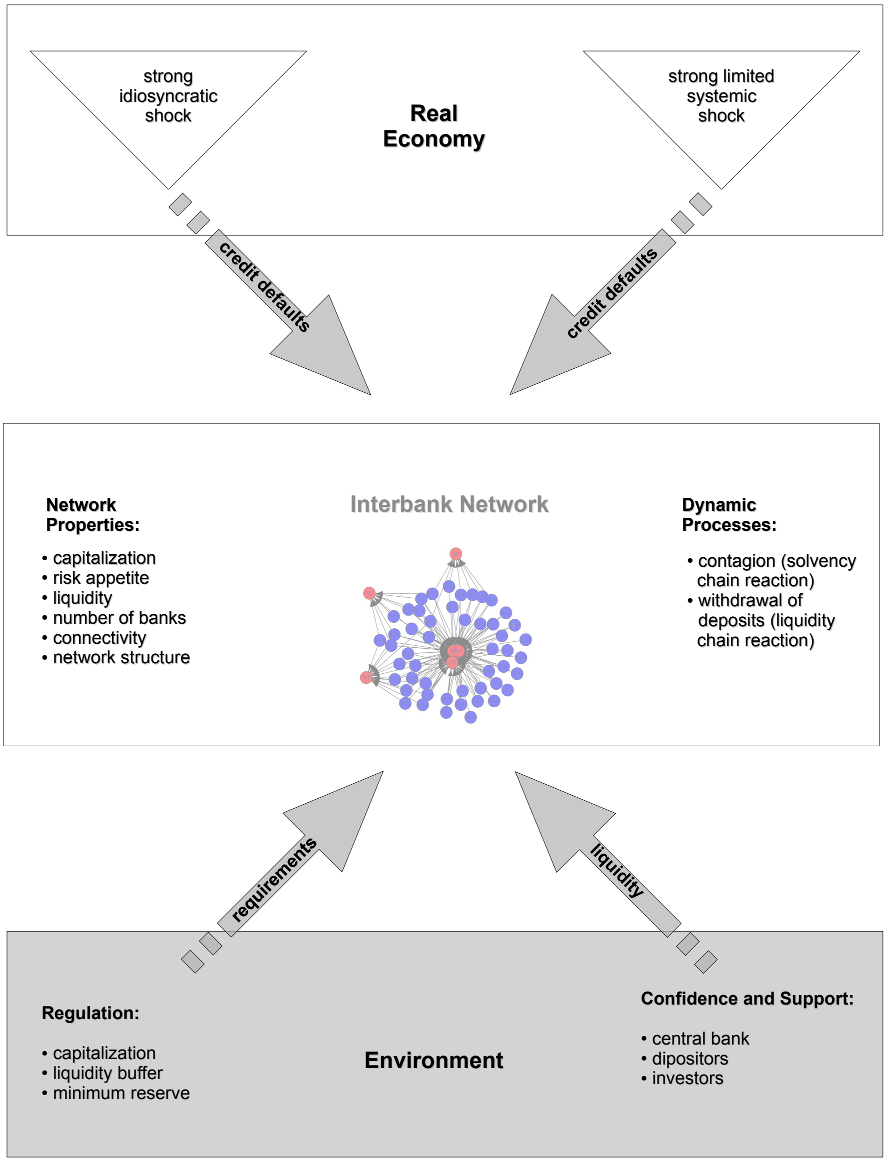


Figure 1: Graphical representation of the scope of the dissertation.

comprises the central bank with its supporting role.

The scope of the analyses is illustrated in the Fig.1 and will be briefly described here.

The focus of the analysis is the systemic risk according to the definition of O. de Bandt and P. Hartmann (2000) in the ”narrow” sense (please refer to section 1.1.1), implying the failures of one or many financial institutions caused by strong idiosyncratic or limited systematic shocks, being accompanied by the subsequent shock transmission processes and further dynamics within the network. Consequently, bank defaults can be triggered directly or indirectly, as a result of contagion and the subsequent dynamic processes like withdrawals of deposits. The wide systematic shocks, leading to wide systemic events by affecting many markets and financial institutions simultaneously and causing the systemic crisis, are not the focus of this research.

We consider the real economy as trigger of such initial shocks, which subsequently lead to loan losses to banks concerning one or more banks initially to various degrees. Thereby we study two main network dynamics triggered by such unexpected loan losses: solvency and liquidity chain reactions. These dynamics are designed as iterative processes, which may take very different forms depending on the network properties and the environment in which the network is situated. To analyze the environmental impact we take a look at the regulatory requirements like capital adequacy and liquidity requirements, as well as at depositor and investor confidence in the banking system and the stabilizing support for troubled financial institutions by the central bank.

We do not limit ourselves to the banking systems, but consider the financial system as a whole. The economy we deal with consists of three elements: firstly the real economy including a number of different sectors, secondly the banking system regarded as a dynamic network, and thirdly the central bank. Analyzing the impact of the shocks and processes that follow, we primarily focus on the resilience of the banking system, but we also consider the losses in the economy as costs of the systemic risk including both, losses to banks and non-banks (externals). We consider expected credit losses to banks as operating losses that will be normally covered by margin requirements and the default fund. The main purpose of bank equity is to cover losses that are greater than expected. From this perspective, shocks regarded here are connected only to unexpected losses. We regard the losses of bank capital besides the losses to non-banks as costs of systemic risk for the following reasons: since the stockholders of financial institutions are often representatives from a variety of industries, private persons or even public authorities, a drastic reduction of the equity value may be able to trigger further shocks in the economy. Furthermore, banks that experience distress are required to reinforce their capital to meet the regulatory solvency ratios. In case of doubt, banks may be obliged to heavily reduce their lending to the real economy or even to cease lending altogether because of capital shortage.

The main objective of the present work is to show that simulation experiments could provide a general guide to developments in complex networks like a financial system. However, the tangible results often depend on a broad spectrum of factors like network topology and dynamic processes, properties of nodes and, not least, shock specification. Furthermore, the specific asset structures of banks and their interconnectedness are of great importance for the reliability of the results and have to be included in the network modeling. The asset based approach for the financial network modeling should allow us to analyze the stability of the financial system and other consequences due to the various economic developments related to certain industrial branches or countries. Furthermore, by using the proposed approach, the effects of regulatory requirements and monetary policies can be evaluated taking into account various characteristics of the banking system as well as of the potential shocks. Moreover, we believe that the impact of macro-economic shocks on the stability of the banking system can be appreciated in a feasible and realistic way by combining the asset based network approach and the real data. However, even with a lack of concrete data, some interesting and stable observations in terms of the systemic risk could be made by using the ABN-model for various simulation experiments. We will observe, for example, that the support by the central bank, providing additional liquidity during the crises, can reduce bank losses and their defaults and even the losses transmitted from banks to externals, while an increasing liquidity reserve of banks could deepen the contagion process and raise losses to both: banks and externals, particularly if withdrawals of deposits are triggered by a loss of confidence and are solvency based. Furthermore, we will see that the increasing heterogeneity of better capitalized banking systems tends to have negative effects on their resilience, while the increasing heterogeneity in less well capitalized systems shows rather stabilizing effects. Moreover, differences between core and periphery have mostly clear opposing effects on the core and periphery banks. Further, we will observe that an equal increase in the equity ratio for all banks tends to stabilize the banking system more effectively than capital surcharges for systemically important financial institutions only, even if the total increase of banking capital in the system occurs to the same extent.

In the present PhD-project we concentrate on developing the mentioned asset based network approach, the implementation of the according simulation-based model in the programming language `C++`, as well as the simulation analyses of a number of characteristics of the financial network and its environment in terms of systemic risk. The dissertation is organized as follows. Chapter 1 deals with the systemic risk in financial systems from a theoretical perspective. The asset-based approach and the derived model are the integral part of the dissertation and will be presented in detail in chapter 2. Chapter 3 describes the methodology of simulation experiments used in the following analyses. Chapters 4 to 9 are dedicated to the analysis of various properties of the financial networks and individual banks, as well as to the regulatory environment. We will first address the question of how system stability would be affected by the increasing intensity and concentration of the initial event in chapter 4 and show that the resistance of a banking system is connected to two opposite effects: the positive one related to the sharing of losses across banks, and the negative effect caused by growing contagion. Thus, the answer to the question of whether the banking system is more resistant against idiosyncratic events than against broader distributed shocks depends on the magnitude of the initial shock and capitalization level of the banking system, among others. Chapter 5 investigates the risk-taking capability of banking systems. In this context we will look at the capitalization level of banks and their risk appetite. We will see that increasing the equity of banks has a positive impact on their resilience against systemic events, in general. However, we will recognize that for low levels of capital, slightly increasing capital can worsen contagion. Further, we will analyze the impact of risk preferences of the banking sector with regard to the risk of their investments and show that this impact is not unique. Moreover, the effects of risk appetite of banks depend, inter alia, on the capital requirements and properties of systemic events. Chapter 6 deals with the relationship between systemic risk and some properties of the network structure from different points of view. In particular, we will look at the degree of connectivity and the heterogeneity of the banking system. We will observe that higher connectivity can be positive or negative for system resilience, depending on the capitalization level of banks, magnitude of the initial shock, and even on the level of the interbank connectivity degree. Moreover, the effect of the size of interbank networks will be analyzed. We will see two contrary effects, related to the increasing granularity and sharing of losses. Furthermore, we will study the impact of increasing heterogeneity, considering three-tiered core-periphery networks. Chapter 7 has a focus on the liquidity risk, related to the loss of confidence in a banking system. Here we will discover that under some circumstances, a marginal loss of confidence would lead to heavy losses for banks and externals and substantially destabilize the banking system. Chapter 8 explores the implications of the risk adjusted capital requirements and of a capital surcharge for systemically important banks. With regard to risk adjusted capital requirements, we will show that such requirements could make the banking system more vulnerable to unexpected shocks, compared to flat capital requirements. This would be the case if capital relief for lower risk banks given by risk adjusted capital adequacy in relation to flat capital requirements is larger than the real risk difference, which implies the underestimation of risk by banks or by regulatory capital requirements. We will turn to liquidity management instruments in Chapter 9. In particular, we will look at how the system stability will be affected by increasing liquidity buffers or reserve and how it will be influenced by the willingness of the central bank to support the banking system in order to prevent a further mounting financial turmoil. We will observe the rather destabilizing effects of increasing liquidity endowment of banks, while the supportive role of the central bank tends to stabilize the system, especially if it is quite well capitalized as a whole. Chapter 10 concludes and underlines the importance of the discussed results for further research and regulatory activities.

0.3 Related literature

The presented work contributes to some strands of literature related to the systemic risk in financial systems and financial network modeling, which are presented in the tabular overview below. The emphasis is placed on the most relevant aspects concern the scope of this dissertation.

Key elements of the systemic risk

references	subject	results
De Bandt and Hartmann (2000)	proposed a concept of systemic risk regarding the *"strong" systemic event* as the key element in the definition of systemic risk which includes *shocks* and *propagation mechanisms* itself	besides the various forms of external effects also the contagion effects are being treated as the core of the systemic risk
Upper (2011)	reviewed the methodologies behind simulation methods to test for contagion in interbank markets restricting his attention to papers published until 2011 dealing with contagion driven by defaults on interbank lending.	underlined the shortcomings in the financial contagion modeling: common assumption that banks do not react after a shock has occurred, focus on the failure of an individual bank rather than common shocks and absence of behavioural foundations

Topology of banking systems

references	subject	results
Sheldon and Maurer (1998)	estimated a matrix of interbank loans for Switzerland based on known marginal loan distributions and the principle of entropy maximization.	domestic interbank lending is not the foremost threat to financial market stability in Switzerland – the domestic interbank loans are quantitatively less important in Switzerland than cross-border interbank loans
Upper and Worms (2002)	estimated the bilateral credit relationships for the German banking system	contagion risk depends on the topology of the interbank linkages
Müller (2006)	analyzed the Swiss interbank market with respect to the contagion potential using data on bilateral bank exposures and credit lines, considered the effect on solvency and liquidity of a complete unwinding of interbank lending	there is substantial potential for contagion via exposure and credit lines in the market; a lender of last resort intervention could remarkably reduce the negative spill-over effects on the liquidity and solvency; the structure of the interbank market is substantial for its resilience: centralized markets are more vulnerable to contagion
Fricke and Lux (2015 a,b), Finger, Fricke and Lux (2013)	analyzed data for the Italian interbank network based on overnight loans collected by the e-MID trading platform during 1999-2010 and explored the network topology	networks appear to be random on a daily base, but contain significant non-random structure on a higher aggregation level; core-periphery structure provides a better fit for analyzed interbank data; the identified core is quite stable over time with the majority of core banks can be classified as intermediaries; the data are best described by negative binomial distributions
Iman van Lelyveld and Daan in 't Veld (2012)	investigated the network structure of interbank markets using data for the Netherlands	found a significant core periphery structure
Tellez (2013)	analyzed the network of exposures between Australian authorized deposit-taking institutions	despite of the network complexity and core periphery structure, the author underlined the low density of the banking network

Financial network modelling

references	subject	results
Eisenberg and Noe (2001)	developed an algorithm that clears the financial system and provides information on the systemic risk	abstract approach for banking networks solving a static clearing problem
Nier et al. (2007)	modeled the contagion mechanisms as a simulation model and analyzed the risk of knock-on defaults triggered by the initial bank default depending on some bank properties and the financial network structure	M-shaped graph describes the non-linear relationship between contagion and the level of interconnectivity of banks reflecting the interplay of two opposite effects of increasing connectivity: increasing number of channels for shock transmission and increasing resistance to contagion by sharing losses across a larger number of counterparts
May and Arinaminpathy (2010)	explored a mathematical model of a simplified banking system and studied the interplay between the properties of individual banks and the overall dynamical behaviour of the system, using analytic mean-field approximations for the network	provided a mathematical explanation for simple dynamics in 'banking ecosystems
Montagna and Kok (2013)	developed an agent-based multi-layered interbank network model based on a sample of large EU banks offering a holistic approach to interbank contagion and proposed a systemic importance measure based on a multi-layered network model	taking into account that banks are related to each other in various market segments, the contagion effects can be substantially larger than the sum of the contagion-induced losses when considering the market segments individually
Lengnick, Krug and Wohltmann (2013)	explored an agent-based and stock flow consistent model of a monetary economy and analyzed the impact of interbank lending on the financial stability	interbank lending stabilizes the economy, normally, but amplifies systemic instability during crises; even with no interbank market, indirect contagion can lead to propagation of bankruptcies
Montagna and Lux (2016)	introduced a probabilistic model combining such important known quantities like the size of the banks with a realistic network structure	the approach enables to analyze impacts of idiosyncratic shocks and contagion for banking networks with only some key statistics and statistical regularities are known

Scientific publications emphasized below reflect useful insights from the financial network analyses with a focus on various aspects considered in this dissertation.

Degree of interconnectedness within the banking systems

references	subjects	statements
Allen and Gale (2000); Freixas et al. (2000); Haldane and May (2011); Acemoglu et al. (2015)	analyzed the financial contagion in banking systems and the resilience of the system to the insolvency of any individual bank depending on the interconnectivity degree	at a low magnitude and a low number of negative shocks, a more equal distribution of interbank liabilities leads to a less fragile financial system
Cifuentes et al. (2002, 2005)	intensive follow-up work on liquidity risk in a interconnected banking network, when banks are forced to sell their assets to meet the solvency and liquidity requirements	systemic resilience and bank interconnections are non-monotonically related – more interconnected systems may be riskier than less connected systems; liquidity buffers play a similar role as capital buffers and can be more effective
Nier et al. (2007)	studied the impact of connectivity as well as the interplay between connectivity and net worth	negative nonlinear relationship between contagion and capital: in undercapitalized networks, a further increase of connectivity increases the contagion; in better capitalized networks systemic risk increases or decreases with increase of connectivity, depending on the initial level
Battiston et al. (2009)	investigated the effect of the network connectivity	the relationship between connectivity and systemic risk is decreasing if the degree of connectivity is (relatively) low and increasing when it becomes high
Cont and Moussa (2010)	studied a specific case of powerlaw network based on a scalefree simulation	increasing connectivity may significantly increase contagion; contagion is very sensitive to the network structure properties, especially to the level of connectivity and concentration; more heterogeneous networks in degrees and exposures are more resilient to contagion

Systemic event properties

references	subjects	statements
Furfine (2003)	looked at the role of liquidity in the contagion process, considering the case where the largest lender in the federal funds market is unable to lend	illiquidity may not only amplify contagion but also cause it
Gai and Kapadia (2010)	examined the effects of initial shocks with various magnitude in a financial network model	similar shocks could have very different consequences for the financial system depending on whether or not the shock hits at a particular pressure point in the network structure. Moreover, when capital buffers have been eroded to critical levels, the level of contagion risk could increase extremely rapidly
Acemoglu et al. (2015)	studied the relationship between the financial network architecture and the likelihood of systemic failures due to counterparty risk.	as the magnitude or the number of negative shocks crosses certain thresholds, more financial interconnections are no longer a guarantee for stability

Heterogeneity of the banking structure

references	subjects	statements
Haldane and May (2011) ; Haldane and Kapadia (2011)	studied the impact of heterogeneity	that homogeneous banking systems clearly make each individual bank safer but amplify the systemic risk.
Battiston et al. (2012)	investigated how the size of the default cascade is affected by the initial distribution of robustness and by the level of risk diversification in the network	the effect of diversification is not unique, but depends crucially on the allocation of assets and liabilities across agents and the exposure structure
Hofmann de Quadros et al. (2014)	analyzed various types of interbank network	more connected networks with high concentration of credits are more resilient to contagion

Systemic importance of banks

references	subjects	statements
Brownlees and Engle (2012)	privided a systemic risk measure, defined as a banks contribution to the deterioration of the capitalization of the financial system as a whole during a crisis	*bank size* and especially *organizational complexity* are significant for systemic risk of financial institutions
Laeven, Ratnovski and Tong (2014)	provide an economic foundation for the debate on bank size, as well as on activities and complexity of large banks, using data of 52 countries.	large banks, on average, create more individual and systemic risk, especially if having insufficient capital or unstable funding, engaging more in market activities or being more complex.
Varotto and Zhao (2014)	analyzed systemic risk for US and European banks from 2004 to 2012	common systemic risk indicators are primarily driven by bank size and focused on the fact that smaller banks may still pose considerable systemic threats; banks balance sheet characteristics can help to forecast its systemic importance; the systemic risk of different financial networks appears to be driven by different factors

Confidence in banking systems

references	subject	results
Feijen and Perotti (2005)	devoted to the issue of investor protection	under weak regulatory institutions, financial liberalization is often followed by financial crises; industry exit rates and profit margins after banking crises are higher in the most corrupt countries
Galindo and Micco (2007)	studied relationship between creditor protection and the response of credit to external shocks by using a panel constructed gathering information (1990-2004) for a broad set of countries	detected the empirical support for the idea that weak creditor protection makes credit markets more volatile
Dailami and Masson (2009)	considered ways of measuring investor and consumer confidence; analyzed and explained the evolution of confidence	underlined the connection between the willingness of investors to allocate assets to equities, and their risk appetite and confidence; postulated four dimensions of investor confidence: market volatility, market performance, macroeconomic news, and government responses

Regulatory requirements and crisis prevention

references	subjects	statements
Elsinger, Lehar and Sommer (2002)	suggested a new approach to risk assessment for banks by using standard risk management techniques in combination with a network model of interbank exposures and individual bank data usually collected at the central bank; applied the model to Austrian bank data set	correlated exposures of banks are the main source of systemic risk and contagion is of secondary importance if bankruptcy costs are low and an effective strategy to tackle the crisis exist; funds for a lender of last resort that are needed to stop contagion can be surprisingly small
Heid, Porath and Stolz(2003)	examined the impact of capital requirements on capital and risk levels of German savings banks	found evidence that banks response to regulatory requirement adjustment depends on the amount of capital buffer, defined by capital the bank holds in excess of the regulatory minimum
Cont and Moussa (2010)	studied the impact of capital requirements in limiting the extent of systemic risk and default contagion in a network context	targeting the creditors of the most contagious institutions is a more effective procedure than increasing capital ratios for all institutions in the network equally
Brei and Gambacorta (2014)	analyzed, how the risk-weighted regulatory capital ratio and the Basel III leverage ratio behave over the cycle, using a large data set for the period 1995-2012	both ratios are countercyclical with a tighter constraint for banks in booms and a looser constraint in recessions; the leverage ratio is significantly more countercyclical than the risk-weighted regulatory capital ratio; exposure measures, total and risk wighted assets are positively correlated with cycle indicators; correlation is lower during the crisis because of a sharp lending and investment reduction during the crisis
Krug, Lengnick and Wohltmann (2014)	analyzed the impact of Basel III's components on financial stability by using a stock-flow consistent agent-based model	positive impact of the synergistic interaction of microprudential instruments is considerably larger than the sum of the individual contributions to stability, but surcharges on SIBs contribute to complexity of the regulatory framework without improving the resilience of the system

Chapter 1

Systemic risk in financial systems

1.1 Definition of systemic risk

Before the financial crisis which began in 2007, there was widespread belief that the stability of the financial systems would be ensured if banks and financial institutions did not take excessive risk. Hence, the focus of the banking regulators and the supervisory authorities and institutions was on microprudential regulation, that primarily tried to ensure that no individual bank or other financial institution took on risks that were too large. On the basis of the experience, scientific findings and discussions over the last years, it could be said that the financial regulation bodies failed to prevent a financial crisis not least by ignoring systemic risk. There must be no doubt that examining vulnerabilities of the financial system as a whole should be a necessary amendment of the microprudential regulation and supervision.

Despite the growing popularity of the term 'systemic risk', there is no clear definition of what is meant by it. One explanation is that systemic risk is a broader term and does not relate solely to economics or the financial markets. According to Kambhu, Weidman and Krishnan (2007), systemic risk can be regarded as a generic problem and one of high importance to many environmental and engineering sciences. For example, "*atmospheric scientists examine such questions in the context of climate change, as do fishery managers concerned with the sudden collapse of certain economically important fish stocks"* (see [40], p.6). However, even within the limitation of financial systems, systemic risk is a multifaceted phenomenon and difficult to define precisely. In particular, this expression comprises financial institutions being affected by sufficiently adverse shocks, which may simultaneously take a significant part of them down and have a negative impact on the supply of credit to the real sector, see Martinez (2012). This consideration represents the "*... traditional view of systemic risk, assuming that systemic risks are exogenous in the sense that as long as financial institutions and firms are responsible in their choice of investments, captures the effects of exogenous shocks, the financial system will be stable"*, as stated by Franklin Allen in the INQUIRE Conference (November 4, 2014). However, while some triggers of systemic risk are exogenous, many are endogenous depending on the financial network structures as well as on the government and central bank policies. "*Developments in the financial system can cause a seizing-up or breakdown of this system and trigger massive damages to the real economy. Such developments can stem from the failure of large and interconnected institutions, from endogenous imbalances that add up over time, or from a sizable unexpected event...."*(e.g. Clare Distinguished Lecture in Economics and Public Policy by Jean-Claude Trichet, organized by the Clare College, University of Cambridge, Cambridge, 10 December 2009). For example, lowering interest rates as endogenous effect at a time when property prices are rising rapidly can lead to a real estate bubble, the bursting of which could initiate a deep financial crisis with very serious consequences for the entire economy.

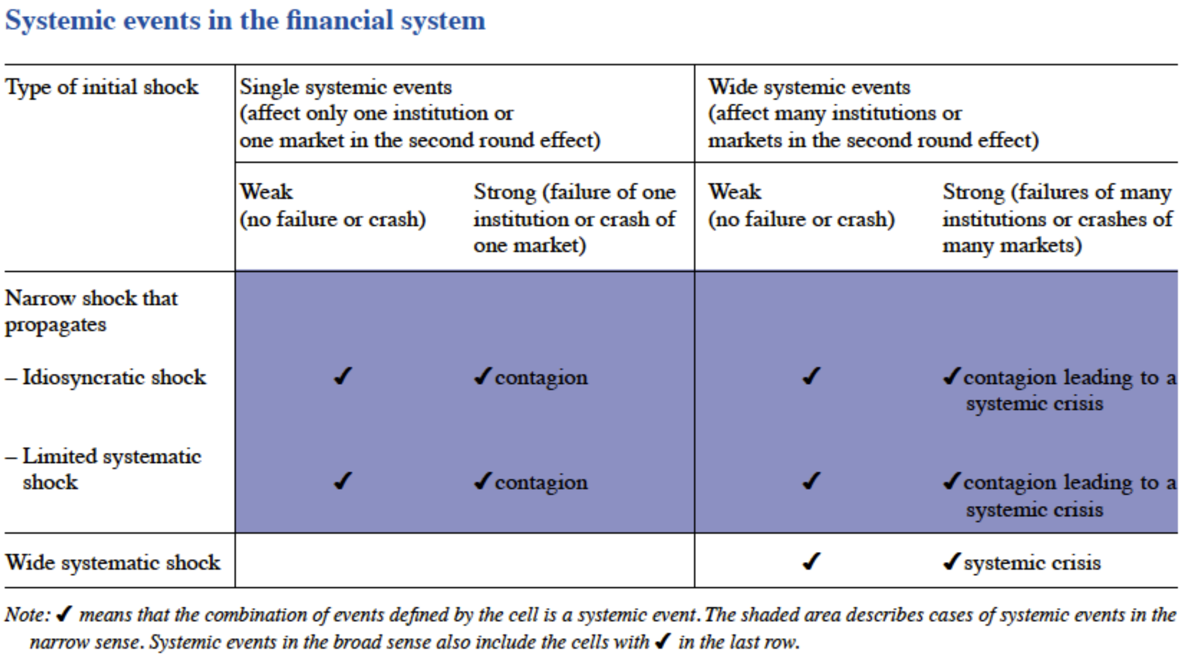
In accordance to the European Central Bank (2010), systemic risk can be defined as "*a risk of financial instability so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially"*.

According to de Bandt et al. (2009), the systemic risk with regard to financial systems can be considered as a result of market imperfections, namely, as "*the likelihood of multiple failures of financial institutions that poses significant problems to the financial stability*", see [19]. This definition has been further clarified in O. de Bandt and P. Hartmann (2000), where the authors presented a concept of systemic risk as basic economic concept for the understanding of financial crises. Thereby, they are regarding the *'strong' systemic event* as the key element in the definition of systemic risk which includes two important elements itself, *shocks* and *propagation mechanisms.* This approach, besides considering the various forms of external effects, takes into account the contagion effects as being core to systematic risk.

This definition of the systemic risk is in line with the scope of the present work. Therefore, the mentioned concept and, in particular, the key elements of the systemic event (shock and shock propagation mechanisms) will be treated in the following sections in accordance with O. de Bandt and P. Hartmann (2000).

1.1.1 Systemic event

The first element of a (strong) systemic event is either an idiosyncratic or a systematic initial shock which leads to the failures of one or many institutions or crashes of one or many markets. O. de Bandt and P. Hartmann define the strong systemic event being 'idiosyncratic' that concerns one institution, market or system independently from others and spreads to the others via contagion (domino effect), while widespread 'systematic shocks' affect many institutions or markets at the same time. In our opinion, it depends on the perspective of the observer, what kind of systemic event one is facing or speaking about, especially with regard to the definition of the system or to the source or trigger of the initial shock. For example, the financial crisis had been triggered by a particular problem in only one - say real estate - market, strongly affecting several banks simultaneously which were able to transmit the losses to the financial markets themselves. From the perspective of the entire economy, we would see a single segment (real estate in this case)



Systemic events in the financial system

Type of initial shock	Single systemic events (affect only one institution or one market in the second round effect)		Wide systemic events (affect many institutions or markets in the second round effect)	
	Weak (no failure or crash)	Strong (failure of one institution or crash of one market)	Weak (no failure or crash)	Strong (failures of many institutions or crashes of many markets)
Narrow shock that propagates				
– Idiosyncratic shock	✓	✓contagion	✓	✓contagion leading to a systemic crisis
– Limited systematic shock	✓	✓contagion	✓	✓contagion leading to a systemic crisis
Wide systematic shock			✓	✓systemic crisis

Note: ✓ means that the combination of events defined by the cell is a systemic event. The shaded area describes cases of systemic events in the narrow sense. Systemic events in the broad sense also include the cells with ✓ in the last row.

Figure 1.1: Systemic events. Graphic reproduced from De Bandt and Hartmann (2000)

getting into trouble due to the initial shock independently of other markets and speak of an idiosyncratic shock. But from the perspective of the financial market we would consider the fact that several banks have been affected by the turmoil in the real estate market, propagating the shock to the entire economy, and speak of a limited systematic shock. Defining the real estate market as the system we would take the turmoil into consideration and come to the conclusion that many regions are affected.

The work of O. De Bandt and P. Hartmann provides the concept of systemic risk based on the definition of systemic events in the 'narrow' and 'broad' senses, respectively. Systemic events in the broad sense include wide systematic shocks leading to systemic crisis in addition to the characteristics of the systemic events in the narrow sense, as it can be seen in Fig.1.1. Such negative shocks are often 'uninsurable' or not diversifiable. This distinction is important with respect to the crisis management instruments, which might be different. According to Kambhu, Weidman and Krishnan (2007), " *a detailed understanding of what constitutes systemic risk is important to forming a regulatory regime that balances costs* *and benefits. Indeed, in all the roles policymakers fill in preventing systemic events and mitigating systemic risk, a proper analytical framework is crucial for defining the correct scope and mode of action. For central bankers in particular, a clear method for identifying systemic risk and the onset of systemic events is critical for decision making on whether and how to intervene"* (see [40], p.10). O. De Bandt and P. Hartmann (2000) explain that, "*bank crises emerging from contagion could be stopped at an early stage at the individual bank level through emergency liquidity assistance if identified in a timely manner, whereas macro problems would normally be addressed through more standard stabilization policies, such as open market operations"*(see [18], p.6). Not least for this reason, bank contagion as a substantial part of systemic risk is an important issue in our research and is discussed extensively in the next section.

1.1.2 Contagion

The focus of this research is on the financial contagion in terms of the process described by the failure of a financial institution which triggers at least one further failure within the financial system.

The importance of the contagion risk for financial stability has been raised on more than once in the discussion above and in the broad spectrum of the relevant literature. For instance, Upper (2011) underlines that "*if contagion takes place, then it could lead to the breakdown of a substantial fraction of the banking system, thus imposing high costs to society. [. . .] Knowing whether the failure of a particular institution could trigger the failure of others is important not only for crisis management but also for crisis prevention."* (see [63]).

Contagion in the sense of the (financial) systemic risk component can stem from various sources and exists in a variety of dynamics and intensities. Domino effects through settlement and payment systems or interbank markets, assets with similar or correlated risks and also uncertainty about possible market developments because of absent or ambiguous data and information or even a lack of precedent shall be mentioned as the most important types of financial contagion.

However, the contagion from one financial institution to another originates from the existence of a network of financial contracts primarily created in three types of systems: the settlement and payment systems, the interbank market which is used by banks for short term financing as well as the 'off-exchange-trading' market (OTC) for derivatives, as described by Freixas et al. (2000) in [28]. Nevertheless, the role of direct and indirect medium-to long-term interbank exposures must not be underestimated. Not only a bankruptcy but even a decline in the credit rating of the debtor bank and associated interruptions in payment or potential insolvency could force the lender bank to increase loan loss provisions substantially. Thus worsening the return on regulatory capital, defined as the ratio between operating profit after risk provisions and average employed equity capital. Which in turn would cause more restrictive lending policies due to the capital requirements or even a sale of liquid assets at fire-sale prices.

While the contagion effects have been an important aspect in other scientific disciplines for several decades, this issue is relatively young in economic and financial sciences. As pioneering works, the studies by Allen and Gale (2000) in [4] and Freixas, Parigi, and Rochet (2000) in [28], shall be mentioned here, their research analyzed the financial contagion in banking systems and the resilience of the system to the insolvency of any individual bank depending on the degree of interconnectivity. Furfine (2003) in [31] and Müller (2006) analyzed in [52] the role of liquidity in the contagion process. Thereby, Furfine (2003) considered the federal funds market, focusing on the case that the largest lender withdraws from the market, forcing then its counterparties to seek a new lender or to reduce their own lending. Müller (2006), considered the effect on solvency and liquidity of a complete unwinding of all interbank lending.

Nier, Yang, Yorulmazer and Alentorn (2007) in [53] modeled the contagion mechanisms as a simulation model and analyzed the risk of knock-on defaults triggered by the initial bank default depending on various bank properties and the financial network structure.

Haldane and May (2011) summarized in [35] three important contagion mechanisms, which are often applied in financial network models, and the impact of connectivity on system stability when such particular processes occur. According to Haldane and May (2011), the first and one of the mostly applied contagion processes is a propagation of shocks within the financial system via knock-on effects of a single bank failure. The second mechanism of the shock propagation which arises from losses in the value of a banks external assets is denoted by Haldane and May (2011) as an "almost surely more important source of shock propagation". The devaluation of assets may be caused by a fall in market prices, a rise in credit default risks or by the fire sale actions of troubled banks. Thereby, Haldane and May proposed to distinguish between strong liquidity shocks, associated with depreciation of specific asset classes, and weak liquidity shocks, resulting from the expectation of further defaults or a more general loss of confidence. The third mechanism of shock propagation, described by Haldane and May, is the diminished availability of interbank liquidity on the financial markets called funding liquidity shocks and is the kind associated with the interbank market collapse of 2007 - 08. This has often taken the form of liquidity hoarding in interbank funding markets as long as one bank calls in or shortens the term of its interbank loans and affected banks tend, in turn, to do the same. In this way the funding contagion may spread widely through interbank linkages.

A considerable number of theoretical studies over the last couple of years have now directly addressed the issue of bank contagion. However, empirical literature on bank contagion mechanisms remain scarce due to the poor availability of data and the rarity of systemic events from a statistical perspective. For instance bank equity returns, debt risk premiums, deposit flows or physical interbank and further credit risk exposures for emerging market countries as well as for a high number of developed countries cannot be collected in full or are virtually non-existent. Moreover, the substantial differences in country-specific features of banking systems and safety nets make the available information less transparent and difficult to interpret.

Because of the importance of contagion, more research about the formation and development as well as about the impact of bank contagion is needed, which can be underlined by the following statements formulated by C. Upper (2011) in [63]: *" . . . vast majority of banking crises followed shocks that hit several banks simultaneously rather than domino effects from idiosyncratic failures. Common shocks may weaken the resiliency of the remaining banks and thus increase the risk of contagion. Perhaps surprisingly, the number of papers analyzing such common shocks is much lower than those considering single bank defaults. There is also a small set of papers focusing on contagion due to illiquidity"*.

Thus, even though research activities and models in the field of (financial) contagion risks and processes have moved forward significantly during the last couple of years, there are still considerable gaps in them. Moreover, the current state of uncertainty about the formation and dynamics of contagion and thus of systemic risk is reflected in particularly conflicting views in the relative literature, especially in terms of the relationship between the structure of the financial network and the contagion processes and their impact on the stability of the financial systems.

The contagion processes is one of the important issues in the network analysis and modeling of financial systems and has also a prominent role in the present work.

1.2 Financial system and network

There is no distinct definition of the term 'financial system'. According to Franklin Allen and Douglas Gale (2001) in [3]: *"Financial systems channel household savings to the corporate sector and allocate investment funds among firms; they allow intertemporal smoothing of consumption by households and expenditures by firms; and they enable* *households and firms to share risks."*

By the External Relations Department of International Monetary Fond: *"A country's financial system includes its banks, securities markets, pension and mutual funds, insurers, market infrastructures, central bank, as well as regulatory and supervisory authorities. These institutions and markets provide a framework for carrying out economic transactions and monetary policy, and help to efficiently channel savings into investment, thereby supporting economic growth. "* (IMF, External Relations Department, Fact Sheet "Financial System Soundness")

Jean-Claude Trichet clarified in his lecture in Cambridge (December 2009): *"The financial system is composed of intermediaries, markets and the infrastructure of payment, settlement and trading mechanisms that support them."* This description is in accordance with European Central Bank (ECB), that defined the financial system on its web site, http://www.ecb.europa.eu/pub/fsr/html/index.en.html (accessed 10/1/2017) (Research & Publications/Financial Stability Review), by its three parts as follows. The first part is represented by the financial intermediaries, consolidating funds and transforming them into loans. The second part is constituted by financial markets, where lenders and borrowers meet, like money markets and stock exchanges. Financial market infrastructures, like payment systems and security settlement systems, which are used to settle financial transactions through the transfer of money and financial assets between buyers and sellers, represent the third part of a financial system.

We provide the following definition for the purpose of this work:

Definition 1.2.1 *The financial system is a set of complex and closely interconnected financial institutions, markets, settlement and payment systems and trading mechanisms and other market infrastructures supporting the trading and liquidity providing activities, as well as central bank, regulatory and supervisory authorities.*

The individual components of the financial systems are connected with each other through direct transactions, as in interbank markets, as well as indirect - through strongly correlated credit and investment contracts with third parties. Thus they form a complex and multidimensional financial network. Such financial networks are not independent of each other. They are connected with each other by trading activities of financial intermediaries and investors. Financial networks are extended through the savings and financing needs of all sectors of the real economy, households and the government. Thus by financial intermediation the financial system is crucial to the allocation of resources in the entire economy.

The general characteristics described above are common to most financial systems, yet the financial systems even in the developed countries reveal a varied picture.

1.3 Systemic risk in financial systems

Financial systems seem to be more vulnerable to systemic risk than other sectors of the economy. O. DeBandt and P.Hartmann (2000) identify three interrelated characteristics that explain this high susceptibility of the financial systems: the structure of bank balance sheets, the complex network of exposures among financial institutions and the intertemporal character of financial contracts and related credibility problems, see [18]. Moreover, systemic risk in the financial system relates to the risk that direct and indirect interconnections increase instability within the financial system. In a broader sense, systemic risk relates to the risk that propagated instabilities within the financial system evolve towards adverse effects on growth and welfare in the entire economy. This is because troubles within financial systems could not only disrupt financial intermediation and thus reallocation of funds, but the collapse of the financial system could plunge the real economy into a severe recession, exacerbating economic downturns and destroying the effectiveness of monetary policy. Moreover, the capital flight, the exchange rate pressures as well as the high costs linked to salvaging the troubled financial institutions have to be mentioned in this context. Furthermore, with increasing connectivity among financial systems, disruptions in one system can rapidly spill over across many financial systems and national borders.

Chapter 2

Financial network modeling

This chapter presents the asset-based approach and its implementation as a simulation based network model. The first section presents the motivation and premise that led to its development. It especially draws attention to the differences from other tools and highlights the special features of the model. The second section focuses on the basic structure of the model and deals with the design of the financial system, the network structure, characteristics of the initial shock, its absorption, and the loss transmission mechanism. The construction of the model and its implementation as a simulation engine will be discussed. Section three presents the transformation from the basic to advanced model by including the central bank as a further node in the economy, adding cash reserves according to the minimum reserve requirements and other central bank positions, inserting risk adjusted capital requirements and diversification of the initial shock, as well as the mechanism of deposit withdrawals and the subsequent dynamic processes. At the end, the implementation of the core-periphery network structure will be explained.

2.1 Asset-based approach

The studies of the determinants of systemic failures and of the structures and interdependencies within financial networks have made great progress in recent years. But because of the complexity and great diversity of the causes of failures, it can be said in the main that scientific research in this field has only just begun, and there is still a long way to go. Despite encouraging development in the financial and economical research areas with respect to systemic risk issues, *"... much work remains to be done understanding and controlling systemic risk and the effect it has on financial stability and the real economy - network analysis has a significant role to play in this"*, as Franklin Allen highlighted in his speech at the INQUIRE Conference (4 November, 2014).

The interdependence within a financial system exhibits a complex structure and is created via multiple channels. Interbank markets, where financial institutions are directly connected via mutual exposure, are the most commonly considered area. Such links represent a big part of direct connectivity between banks. The interbank markets play a crucial role, primarily for the short-term liquidity management of banks, allowing for an efficient liquidity allocation. Insolvency of one bank can propagate through credit links from borrower to lender banks leading to insolvency of other banks and to market failures, which can cause a liquidity shortage for many banks. Furthermore, financial institutions are also indirectly interconnected by holding similar assets sharing the pool of depositors, as well as holding assets which include credit risks from other banks.

The focus of the present research is on simulation based financial network models with the objective of reproduction and improving understanding of interactions between banks and other areas of the economy and their impacts on the stability of the financial system. In the related work and network models, the shocks result mostly from the failure of one or more randomly chosen financial institutions as in Nier et al. [53].

In contrast, we develop the dynamic asset based network model, the distinctive character of which lies in the dependency between the degree of affectedness of the individual banks through the initial shock and their asset structures.

Given that the main task of the financial system is to channel household savings to the corporate sector and allocate investment funds among firms, this intermediation function is in the core of the financial network modeling according to the asset-based approach. The foundation of the network is based on the borrower-lender relations between banks and the real-economy segments characterized by the different risks and other properties. Furthermore, the financial intermediaries in the model manage their risks by diversification and securitization of debts. Therefore, the asset based approach relates to building up and managing credit assets. However, the initial shocks are triggered by disruptions in the real economy with various levels of affectedness of the real sector. Furthermore, the initial affectedness of financial intermediaries depends on the direct and indirect relations between them and the troubled part of the real economy sectors as well as on their own risk appetite.

The work of Nier et al. [53] had a major impact on the development of the presented network model. However, we have completely redesigned and substantially developed the original model. Central to our conceptual approach has been the focus on the diversified financing of non-financial (external) segments, which we have distinguished by such properties as diversification of sector-bank relationships, risk-distribution, credit volume and credit securitization ratio. We have inserted in the model the securitization of debts, not least because of the large increase of such finance shortly before the financial crisis, in particular in the real estate finance between 2000-2006. Furthermore, we have taken into account risk adjusted capital requirements, minimum reserve, possible withdrawals of deposits as well as support by the central bank and further model supplements, detailed in section 2.3.

2.2 Basic asset based network model

Because of the complexity of the final model we present the 'basic' model here and then the extended 'advanced' model in the next section. We begin with the basic structure of the model and look at it from a theoretical perspective, initially. Then, we go into details and present the model more formally.

2.2.1 Financial system

The basic model consists of two groups of nodes: banks and other segments of the economy (externals), which are interconnected via credit and investment links. We distinguish between several external segments, which are characterized by the individual parameters (see 2.2.5).

The model is designed for any asset class. These classes are different in order to connect the credit default risk with the subordination of debts. With respect to the subordination, we distinguish between secured, normal, subordinated debts and equity. As secured we consider such assets as Pfandbrief (German covered bonds). For ease of presentation, we will simply call them 'covered bonds'. Covered bonds (CB) are debt securities backed by cash flows normally from mortgages or public sector loans, but also from other sectors like shipping or aircraft. For an investor, one major advantage of covered bonds is that the underlying asset pool remains on the issuer's balance sheet, and the issuer must ensure that the pool consistently backs the covered bond. Non-performing loans or prematurely paid debt must be replaced in the pool. In the event of default, the investor has recourse to both the pool and the issuer. This property typically results in very good credit ratings of covered bonds. Hence, the origination of covered bonds is often a very good opportunity for the bank to fund liquidity on easy terms. Subordinated debt is debt which ranks after other debts, in our case after secured and normal (senior) debts. Subordinated debts, such as asset-backed securities, collateralized mortgage obligations or collateralized debt obligations, are usually issued in tranches connected with seniority of payments. We consider three different tranches in our model: Tranche A (Senior) is typically rated higher as it is ranked first in the priority of payments of the tranches; Tranche B (Mezzanine) is lower in priority to the Senior Tranche, and Tranche C (Equity) which generally remains after paying the liabilities such as miscellaneous expenses and interest of the Senior and Mezzanine Tranches.

The basic idea in the model is that different external segments finance their projects or even consumption using financial intermediation of banks. Additionally, banks can invest in liquid (risk-free) assets. We distinguish external segments by their credit weight, diversification of bank-connections, credit securitization degree and, last but not least, by the creditworthiness structure. The number of segments and segment properties can vary in the model in order to design different scenarios for further analyses. Banks securitize one part of external debts and channel them by true sale in the financial system in form of tranched securities as for example the collateralized debt obligations (CDO). The remaining non securitized part of loans should be refinanced. We implement the following liquidity funding channels. External credit assets of higher quality build the asset pool for covered bonds, which are used to provide the liquidity from other banks or external segments. The rest of the externals debts must be refinanced by external and interbank deposits and by the net worth of the bank.

However, in designing the financial network with the properties mentioned above, it must be ensured that all banks balances are accurately composed and the predefined ratios like the equity ratio or the percentage of external loans refinanced through the interbank deposits stay in compliance with the predefined model parameter. The construction of such network is not a simple task and will be demonstrated below in more detail.

2.2.2 Network structure

The financial system model is a network of nodes, where each node represents one subject like a bank or an external segment. The nodes are linked by risky assets like debts or securities. At each link we have two nodes. We look on one node as on a "risk taker" and on the other as a "risk causer". For example, in the case of the credit relationship we consider the borrower as the causer of risk and the lender as the risk taker.

It should be mentioned here with regard to the securitization process that, traditionally, banks physically sell the assets which build the collateral pool to a special purpose vehicle (SPV). The SPV in turn issues several classes of securities against the collateral pool and markets them to investors in form of tranched securities. For simplicity, we dispense with the view of the SPV as a further network node, and assume that banks originate and market their securities to investors directly.

To design the basic model we have to define the possible relationships between banks and externals and banks among each another.

External lending and investment:

- Externals lend to banks in form of normal debt.
- Externals invest in secured assets like CB and true sale CDO with different subordinated tranches.

External financing:

- Externals borrow money from bank.
- Another part of external financing are bank investments in assets, originated by externals.

Bank lending and investment:

- Banks lend to externals in form of normal debt.

- Banks invest in assets originated by externals.
- Banks lend to other banks in form of subordinated debt.
- Along with externals, banks also invest in CB originated by other banks and CDO.

Bank financing:

- One part of bank activities should be financed by equity.[1]
- Banks borrow money from externals in form of normal debt.
- Banks borrow money from other banks in form of subordinated debt.
- Banks originate secured assets like CB.
- Banks securitize one part of external loans and sale them "true" to other financial market agents.

It may be helpful to look at the bank balance sheet structure (see Table 2.1).

Table 2.1 demonstrates the structure of assets in the order of their safety or subordination according to the contagion rules. Investments in external assets (external investments), assumed as risk-free and very liquid, can be considered as liquidity buffer of banks. Bank investments mean investments in CBs and CDOs originated by other banks. The latter consist of various subordinated classes (tranches A, B, C). The latest two positions are represented by loans to externals (external claims) and interbank loans (bank claims). While the left-hand side of the balance sheet shows the assets belonging to the bank, the right-hand side demonstrates how these are financed. The first and the second positions are built from capital of (CB) bondholder which belongs to other banks and externals (secured debt). The third position consists of external deposits (senior debt). The other banks' deposits build the next subordinated position (subordinated debt). However, the last and most risky position is the net worth or equity.

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[1] We assume, for simplicity, that no bank and no external holds the bank-shares and hence nobody in the financial system would be affected through the reduction of bank equity.

Assets		**Liability**	
external investments	i_i^e	bondholder capital (externals)	b_i^e
bank investments	i_i^b	bondholder capital (banks)	b_i^b
external claims	c_i^e	external deposits	d_i^e
bank claims	c_i^b	bank deposits	d_i^b
		net worth	e_i

Table 2.1: Balance sheet structure for any bank i.

2.2.3 Initial shock

We identify external loans as the source of the initial shock. In the basic model a certain percentage of external debts of some given sector is allowed to default. This initial default (idiosyncratic event) impacts on one hand the loans to the affected sector in the balance sheet of banks. On the other hand it affects the CDOs which include defaulted loans in their collateral pool. Because of the different risk classes of these securities, not all CDO tranches will be affected at the same time. At first tranche C will absorb the shock, then tranche B and finally tranche A. Because CDOs can be held by externals and by banks, both may be affected by the initial default.

2.2.4 Shock absorption and contagion

Subordination of assets is important to the construction of the shock absorption and the contagion processes. Losses arisen through the initial shock could lead one or more banks to initially default if the net worth is not sufficient to absorb this initial shock. In this case the rest of default will be transmitted to creditor banks through interbank liabilities. In the case that these liabilities are not large enough, some of the losses could be absorbed by external depositors. Only in the case that this loss exceeds the amount of the external deposits would the holder of CB be affected. Because the bondholders are at least partially represented by other banks, we would see the next step of default transmission in the bank system. This contagion process is an iterative process and will continue until no further shock transmission is possible.

2.2.5 Modeling and implementation

Determination of the network structure

In the construction of our model we were inspired by the network model of Nier et al.[53]. However our model deviates from it in many respects. As far as possible and appropriate we try to maintain the notation of [53] for the purpose of comparability. To construct a coherent financial network with the help of the simulation engine by using random matrices, it is necessary to define some rules and give some specifications.

At first we define the parameters that should be given and then describe the rules to compute the remaining parameters with help of the specified exogenous parameters and random graphs constructed by the simulation engine.

Exogenous parameters: N denotes the number of banks building the financial system and S the number of external sectors. The interbank relationship structure is built by random graphs with prescribed interbank network densities. The exogenous parameter p^c gives us the probability that any bank i has lent money to another bank; p^i is defined as the probability that any bank i has invested in covered bonds and CDOs originated by another bank. To construct the random graphs we assume in general[2] that the interbank lending probability p^c and the interbank investment probability p^i, respectively, are equal for all ordered pairs (i, j): $P(c^b_{i,j} > 0) = p^c$ and $P(i^b_{i,j} > 0) = p^i$, $\forall i \neq j$ and $i, j \in 1, ..., N$, with $c^b_{i,j}$ as interbank credit exposure of (lender) bank i given to (borrower) bank j, and $i^b_{i,j}$ as interbank investments of (investor) bank i into the assets originated by (originator) bank j, Further, we construct our model and the simulation engine so that all debt

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[2] However, in specific cases, as by the implementation of the core periphery network structure, this assumption will be modified through specific probabilities for different bank groups.

and investment contracts between any two banks are initially netted, which means that $c^b_{i,j} = 0$ if $c^b_{j,i} > 0$. Furthermore, the investment relationship between any two banks is unidirectional too: $i^b_{i,j} = 0$ if $i^b_{j,i} > 0$. Hence, the following restrictions must be applied: $0 < p^c \leq \frac{1}{2}$ and $0 < p^i \leq \frac{1}{2}$.

The next exogenous parameter C^e give us the total external credit exposure. To construct the credit matrix which describes the external-bank credit relationships, we need to define for each external segment $s \in \{1, ..., S\}$ the following properties. The probability of bank credit connections $p_s \in [0, 1]$ determines the probability that an external segment s is connected to the bank $i \in \{1, ..., N\}$ via credit relationship. The credit weight w^c_s denotes the percentage of loans to sector s from all external loans, and the securitization ratio q_s is the percentage of debts securitized as covered bonds or CDO.

The allocation of securitized credit volume to CB and CDO tranches relate to the individual risk degree distributions of the underlying credit exposure for each sector. These individual distributions are determined by beta distributions defined on the interval $[0, 1]$ and parameterized by two positive shape parameters α^s and β^s for each $s \in \{1, ..., S\}$.

Furthermore, we define the upper borders for the maximum permissible risk degree for the underlying assets of CB and collateral pools for each CDO tranche, denoted by u^{CB} and u^{CDO}_t with $t \in \{A, B, C\}$, which are unique for all segments.

To calculate the interbank loans we determine the percentage of (non securitized) external loans which must be refinanced through interbank loans for any bank i denoted by $\eta_i \in [0, 1]$. We assume that η_i is equal for any bank connecting other banks via credit links, $\eta_i = \eta$ with $\eta \in (0, 1]$. $\eta_i = 0$ if no interbank credit links exist, which is in fact unusual but possible for quite small networks, in particular, because of the usage of random matrices.

To fix the total sum of interbank investments we determine $\beta^{CDO}_t \in [0, 1]$ as percentage of interbank investments to the total volume of CDO for any CDO tranche $t \in \{A, B, C\}$ and analogously the $\beta^{CB} \in [0, 1]$ for bank investments in covered bonds.

The volume of external investments i_i^e, i.e liquid assets, is determined by the exogenous parameter ζ as a percentage of the external loans for any bank i.

The last exogenous parameter is $\gamma \in [0,1]$, which denotes the equity ratio of banks. We assume that all banks initially have the same equity ratio measured as percentage of individual bank capital from total credit volume, that the bank has loaned out to other banks or externals, $\gamma_i = \gamma \ \forall i \in \{1, ..., N\}$.

To build the financial network and construct balance sheets for individual banks we run the simulation engine to set up the initial random graphs for credit and investment relationships according to the given parameters and calculate all the remaining initial quantities as follows below.

Basic network structure via random matrices: The simulation engine delivers two $N \times N$ random matrices R_b^c and R_b^i for interbank credit and investment relationships respectively, and one $N \times S$ matrix R_s for the sector-bank connections with realizations 0 and 1 according to probabilities $0 < p^c \leq 0.5$, $0 < p^i \leq 0.5$ and $0 < p_s \leq 1$. Formally, $R_b^c, R_b^i \in \{0,1\}^{N \times N}$ and $R_s \in \{0,1\}^{N \times S}$ with $R_b^c[i,i] = R_b^i[i,i] = 0$. Thereby, the following equalities for number of realized interbank links Z_b^c for loans and Z_b^i for investments and sector-bank links Z_s hold.

$$Z_b^c \equiv \sum_{j=1}^{N}\sum_{i=1}^{N} R_b^c[i,j] \approx (N^2 - N)p^c, \qquad E[Z_b^c] = (N^2 - N)p^c \tag{2.1}$$

$$Z_b^i \equiv \sum_{j=1}^{N}\sum_{i=1}^{N} R_b^i[i,j] \approx (N^2 - N)p^i, \qquad E[Z_b^i] = (N^2 - N)p^i \tag{2.2}$$

$$Z_s \equiv \sum_{i=1}^{N} R_s[i,s] \approx Np_s, \qquad E[Z_s] = Np_s \qquad \forall s \in \{1, ..., S\} \tag{2.3}$$

External credit structure before securitization: Now we construct the credit matrix of sector-bank credit relationships. We calculate the credit volume for each sector by

$$\widetilde{C^e_s} = C^e w^c_s, \tag{2.4}$$

where w^c_s is the percentage of loans to sector s from the total external credit C^e. We assume, that $\widetilde{C^e_s}$ is equally distributed between the lender banks of sector s. Hence, for each lender i we can compute the external credit volume before securitization by

$$\widetilde{c^e_{i,s}} = \widetilde{C^e_s}/Z_s \tag{2.5}$$

Securitization of external loans: We distinguish between two different classes of debt securitization: covered bonds (CB) and collateralized debt obligations (CDO). The latter are a type of structured asset-backed securities (ABS). Even though CB tend also to be associated with ABS, there are fundamental differences. Firstly, whereas the underlying cover assets for CB remain on the bank's balance sheet, ABS are typically off-balance-sheet transactions. Secondly, cover pools of covered bonds are dynamic. Their composition, by definition, usually change in time, depending on the maturities and on the newly registered cover assets. An independent cover pool contains cover assets and asset replacements. In the event of the issuer's insolvency, CB investors have a preferential claim on the cover assets in the cover register, given that cover pool assets are not included in insolvency proceedings. CDO securities are split into different risk classes, or tranches, whereby 'senior' tranches are considered as the safest securities, as described in 2.2.1.

The total credit volume in our model and its securitization ratio for each segment are known for each segment. Because of the differences described above, we have to build different underlying pools for CBs and CDOs. Now we get the volume of securitized loans for each segment by $\widehat{C^e_s} = \widetilde{C^e_s} q_s$, where q_s denotes the segment specific securitization degree. We distribute this volume between the covered bonds pool and CDO-Tranches A, B and C using the cumulative risk distribution functions of credit assets and thresholds (upper boarders) for the collateral pools, respectively. We compute now the following collateral pools: P_s^{CB} for the CBs and P_s^t for each tranche of the CDOs $\forall t \in T$ with $T = \{A, B, C\}$.

We assume that all lenders consider the same segment-specific risk distributions of the external claims. Moreover, all lenders securitize assets with the same properties in the same way. For example,

$$\frac{P_s^{CB}}{\widetilde{C_s^e}} = \frac{p_{i,s}^{CB}}{\widetilde{c_{i,s}^e}}, \tag{2.6}$$

where P_s^{CB} are total credit to sector s securitized as covered bonds, and $p_{i,s}^{CB}$ only bank's i loans to sector s securitized as covered bonds by this bank. We calculate the collateral pools for each originator bank and external segment as follows:

$$p_{i,s}^{CB} = \frac{P_s^{CB}}{\widetilde{C_s^e}} \widetilde{c_{i,s}^e} \tag{2.7}$$

$$p_{i,s}^{t} = \frac{P_s^{t}}{\widetilde{C_s^e}} \widetilde{c_{i,s}^e} \quad \forall t \in T \tag{2.8}$$

Interbank investments: We use the random matrices R_b^i and R_s and the given quota of interbank investments $\beta_t^{CDO} \in [0,1] \quad \forall t \in T$ and β^{CB} for covered bonds to distribute the securities between external investors and other banks. This allows us to calculate the balance positions for each bank: bank investments in covered bonds and CDO i_i^b, bondholder capital of banks b_i^b and external bondholder capital b_i^e.

External credit structure after securitization: Because of true sale of loans building

CDO collateral pools, we reduce the external credit volume balanced by banks accordingly, while the CB underlying assets still stay in the banks balances and don't reduce the external loans:

$$c_i^e = \widetilde{c_i^e} - \sum_{t \in T} p_i^t, \tag{2.9}$$

where $\widetilde{c_i^e} = \sum_{s=1}^{S} \widetilde{c_{i,s}^e}$ and $p_i^t = \sum_{s=1}^{S} p_{i,s}^t$. Nevertheless we have to change the bonds originators balances by bondholder capital at the liability side. The bondholder balances must be adjusted by bank investments, which are equal to covered bonds, held now by this bank.

Interbank credit structure: We compute for each bank the volume of external debts which should be financed by other banks' deposits. We distribute it equally between all depositor banks of the bank i. Thus, the amount of money one bank j lends to the bank i , if $R_b^c[j,i] = 1$, is given by:

$$w_{j,i}^c = \frac{\eta(c_i^e - p_i^{CB})}{z_i^c}, \tag{2.10}$$

where $z_i^c = \sum_{k=1}^{N} R_b^c[k,i]$ is the number of banks giving money to bank i.

All these (weighted) interbank credit links can be represented in a matrix $W^c \in \mathbb{R}^{N \times N}$, and namely $W^c = (w_{i,j}^c)_{1 \leq i \leq N}$, determining the total interbank loans and deposits for each bank:

$$c_i^b = \sum_{j=1}^{N} w_{i,j}^c \quad \text{(row sum)} \tag{2.11}$$

$$d_i^b = \sum_{j=1}^{N} w_{j,i}^c \quad \text{(column sum)} \tag{2.12}$$

Bank net worth, investments into external assets and external deposits: Now we can calculate the initial net worth for each bank i as its total (credit) risk assets RA_i multiplied by the equity rate γ.

$$e_i = \gamma RA_i = \gamma(0.5c_i^b + c_i^e + i_i^b - i_i^{b(CB)}) \tag{2.13}$$

with equity ratio γ, (inter)bank claims c_i^b, external loans c_i^e and CDO-investments $i_i^b - i_i^{b(CB)}$, where $i_i^{b(CB)}$ denotes CB-investments. For bank claims a risk weight of 50% is applied, while other claims are weighted by 100%. [3] The latter are excluded being assumed to be risk free. Note that the underlying credit assets are included in the external credit amount of the originator bank and will be backed up by its equity capital. We calculate the bank investments into 'liquid' and free of 'credit risk' external assets like special corporate or sovereign bonds, stocks etc. as percentage of the external credit exposure by

$$i_i^e = \zeta c_i^e \tag{2.14}$$

The volume of external (liquid) assets is thus proportional to the external debts by assumption.

External deposits take up the remainder to meet the bank's balance sheet identity

$$d_i^e = c_i^b + c_i^e + i_i^b + i_i^e - b_i^b - b_i^e - d_i^b - e_i \tag{2.15}$$

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[3] The idea that investments into external assets are free from credit risk implies that such investments are irrelevant for the calculation of bank capital. Note, that market price risks are not contained in the model.

Thus, we get the balance sheet structure. Thereby, the assets a_i include external claims c_i^e, bank claims c_i^b, external investments i_i^e and bank investments i_i^b:

$$a_i = c_i^e + c_i^b + i_i^e + i_i^b \tag{2.16}$$

Bank liabilities, denoted by l_i, are composed of net worth (capital) e_i, external deposits d_i^e, bank deposits d_i^b, capital from external bondholder b_i^e and bonds holden by other banks b_i^b

$$l_i = e_i + d_i^e + d_i^b + b_i^e + b_i^b \tag{2.17}$$

for each of $i = 1, ..., N$. As a balance sheet identity, we get $a_i = l_i$ for $i = 1, ..., N$ due to (2.13).

Modeling of the initial shock and contagion

Shock and shock transmission: We construct the initial default by wiping out a percentage λ of loans to any given sector s. The total initial default $D_{credit}^{initial}$ includes the losses of assets in CDO collateral pools and of external loans, held by banks. Thus we have the following definition:

$$D^{initial} = \lambda \widetilde{C_s^e} = D_{credit}^{initial} + D_{CDO}^{initial}, \tag{2.18}$$

where $D_{credit}^{initial} = \lambda(C_s^e)$ and $D_{CDO}^{initial} = \lambda \sum_{t \in T} P_s^t$.

We assume that the losses are distributed proportionally to the volume for all assetholders.

Hence, we have to reduce the credit assets by $\lambda c^e_{i,s}$ for each bank. Regarding CDO collateral pools, the assets are not equally reduced because of different risk classes. We implement the following mechanism for losses in the different subordination classes of CDO:

$$\begin{aligned} L^C &= \min\{P^C_s, D^{initial}_{CDO}\} && (2.19)\\ L^B &= \min\{P^B_s, D^{initial}_{CDO} - L^C\} && (2.20)\\ L^A &= \min\{P^A_s, D^{initial}_{CDO} - L^C - L^B\}. && (2.21) \end{aligned}$$

Collateral pool losses lead to the changes in the investments of CDO holders, accordingly.

Reduction at the asset side of bank balances affects the bank net worth. If the net worth of any bank is not sufficient to absorb the initial losses $e_i < D^{initial}_i$, the bank will go bankrupt and contagion may take place: the rest of the loss will be transmitted via lending channels in the financial market.

Contagion: We model a contagion as an iterative process. In each iteration we identify banks which get into financial troubles and trigger the knock-on effects as described below.

The rest of the default $D^{rest}_i = D^{initial}_i - e_i$ would be transmitted at first to creditor banks through interbank liabilities.[4]

Let i be the bank getting into trouble because of the wiping out of external loans. Hence, if $e_i < D^{initial}_i$, creditor banks receive the loss $L^b_i = \min\{D^{rest}_i, d^b_i\}$, where the sum of bank's deposits by the bank i is d^b_i, initially given by (2.12). Let j be a lender bank of bank i. Bank j receives a loss $l^b_{i,j} = (d^b_{i,j}/d^b_i)L^b_i$, where $d^b_{i,j} = c^b_{j,i}$ is money that bank i has borrowed from bank j.

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[4] Remember, that because of subordination assumptions in this paper, we require priority of external deposits and (covered) bond holder capital over bank deposits which in turn take priority over equity.

In the case that all bank liabilities are not enough to cover the losses, some of the losses should be absorbed by external depositors. Formally, if $D_i^{rest} > d_i^b$ then external depositors receives the loss, limited by their deposit amount. Thereby, the external loss will be given by $L_i^e = min\{D_i^{rest} - d_i^b, d_i^e\}$.

If the external deposits of the defaulted bank are not sufficient, the losses become absorbed by bondholders (banks and externals), analogous to bank liabilities. Formally, if $L_i^e < D_i^{rest} - d_i^b$, then $L_i^{bondholder} = D_i^{rest} - d_i^b - d_i^e$. If bank j is one of the bondholders of bank i. Then bank j would receive the partial loss $\triangle\ l_{i,j}^b = (b_{i,j}^b/(b_i^b + b_i^e))L_i^{bondholder}$, where $b_{i,j}^b$ is money that bank j has invested in bonds, originated by bank i, b_i^b bond amount of bank i held by all banks, and b_i^e amount of bank's i bonds held by externals. External losses are given by $\triangle\ L_i^e = b_i^e/(b_i^b + b_i^e)L_i^{bondholder}$.

This process will continue until no further transmission is necessary or possible.

2.3 Advanced asset based network model (ABN-Model)

The financial system in the advanced model includes the central bank as well as the bank sector with N banks and the external sector. All these objects are nodes of the financial network, which are interconnected via credit and investment links.[5]

Similar to the basic model, the advanced model is designed for any number of external segments and several asset classes. The latter have to be different in the order of subordination of debts. The model includes the credit default risk as before and is extended by the liquidity risk in the form of withdrawal of deposits. Furthermore, the advanced model includes extra liquidity reserve (minimum reserve) m_i and two central bank positions: central bank deposits d_i^{cb} and central bank claims c_i^{cb} . The latter two

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[5] Because of the integration of the central bank in the model, the transmission of bank losses via lending links to the central bank is now also possible. We determine loans of the central bank being the safest.

balance sheet items contains deposits with or loans from the central bank, respectively. These positions are created throughout dynamics of deposits described in section 2.3.4.

The items trade result and liquidity gap are ancillary balance sheet items and are used for the dynamic processes during the simulations. A (temporary) liquidity gap Δl_i is created when deposits are being withdrawn. The item trade result r_i^t contains profits or losses resulting from the purchase or sale of assets at fire sale prices. Both balance sheet items are equal to zero at the beginning of simulations.

Moreover, in contrast to the basic model, we implement now the risk adjusted capital requirements using more differentiated risk-weighted assets (RWA) for the calculation of the initial and the required regulatory bank capital. The latter will be used for some new dynamics in the model like withdrawal of deposits and fire-sale processes. In addition, we adjust the definition of the initial shock, so that many of the external segments can cause credit defaults simultaneously and to a varying degree. In the following subsections we describe these modifications in more detail.

However, the initialisation process of the simulation engine will be adjusted according to the new specification to ensure that all bank balances are accurately composed and the ratios like the equity ratio or the percentage of external loans, refinanced through the interbank deposits, stay in compliance with the predefined model parameter. The new balance sheet structure is pictured in Tab. 2.2.

Assets	a_i	**Liability**	l_i
external investments	i_i^e	bondholder capital (externals)	b_i^e
bank investments	i_i^b	bondholder capital (banks)	b_i^b
external claims	c_i^e	external deposits	d_i^e
bank claims	c_i^b	bank deposits	d_i^b
central bank claims	c_i^{cb}	central bank deposits	d_i^{cb}
trade result	r_i^t	liquidy gap	Δl_i
minimum reserve	m_i	net worth	e_i

Table 2.2: New bank balance sheet structure.

2.3.1 Minimum reserve

Minimum reserve is a minimum value of cash that a commercial bank must hold in relation to customer deposits and notes (reserve base). In order to determine an institution's reserve requirement, the reserve base is multiplied by the reserve ratio. The minimum reserve is generally stored physically in a bank vault in the form of cash or deposits on account with the central bank. This reserve requirement is an instrument of central bank regulation and can be used for monetary policy. The higher the required liquidity ratio is set, the less credit money can be created by depository institutions. The absence of a minimum reserve requirement means that banks could loan out their funds retaining zero reserves and create an infinite amount of credit, theoretically.

Not all financial systems require a minimum reserve. The Bank of England for example uses a voluntary reserve ratio system. But also countries requiring the minimum reserve ratio use such an instrument in a number of different ways. In some countries like China, India, Russia and Brazil the reserve requirements are frequently altered. The People's Bank of China, for example, uses changes in reserve requirements as a tool to keep inflation under control and is ready to alter reserve requirements quite frequently to implement a certain monetary policy. But others, especially the western central banks prefer open market operations as a tool of monetary policy. The reserve requirements do not change frequently, in order to avoid liquidity problems for banks and associated short-time disruptions in financial markets. The key functions of the minimum reserve system, in the Eurozone for example, are to stabilize money market interest rates and to enlarge the structural liquidity shortage of the banking system, see [25]. The reserve ratio required by the ECB is 1% from 18 January 2012.

We extend the model by including liquidity reserve m_i in each bank balance so that $m_i/(d_i^b + d_i^e) = \nu$, where ν is the required reserve ratio and d_i^b, d_i^e are deposits of other banks and externals, respectively, represented in sum the reserve base.

2.3.2 Risk adjusted capital requirements

Capital requirement is the required amount of capital a bank or other financial institution has to hold to limit credit risks or leverage. Capital requirements govern the ratio of equity to debt, in other words the structure of the liabilities and equity side, while minimum reserve requirements govern the assets side, as described in the previous section.

Capital requirements are mostly determined by a capital adequacy ratio of equity (CAR) that must be held to cover credit risk usually expressed as risk-weighted assets (RWA).

RWA are bank's assets, weighted according to their credit risk, which entail different allocations of risk-bearing capital for different claims and investments.

Thus, in the context of the current model, CAR must be viewed for any bank i by $CAR_i = \frac{e_i}{RWA_i}$, where e_i is the equity capital of the bank. The level of capital requirements is given by the regulatory capital ratio γ^r:

$$CAR = \frac{e_i}{RWA_i} \geq \gamma^r$$

The specifics of CAR and RWA calculation, respectively, vary from country to country. For countries that apply the Basel Accords, the general approaches tend to be similar. Our intention is to implement principal ideas of Basel Accords very generally and be able to vary the key parameters in the simulation engine.

We calculate RWA as

$$RWA_i = \tilde{c_i^b} + \tilde{c_i^e} + \tilde{i_i^b},$$

with risk-weighted interbank claims $\tilde{c_i^b}$, risk-weighted claims to externals $\tilde{c_i^e}$ and risk-weighted CDO-investments $\tilde{i}_i^b$.

Moreover, for the initial capital we assume instead of (2.13)

$$e_i = \gamma RWA_i = \gamma(\tilde{c}_i^b + \tilde{c}_i^e + \tilde{i}_i^b)$$

Interbank credit risk: The calculation of RWA for interbank claims is very simple:

$$\tilde{c}_i^b = \omega^b c_i^b,$$

where ω^b is a risk weight for interbank claims which is equal for all banks and exogenous given.

Thereby we assume that interbank credit must be backed up by less equity capital than the average assets which are based on external debts. To argue this assumption, we have followed the idea of the standardized approach. It is the simplest of the three broad approaches to credit risk according to the Basel Capital Accord (II and III). The risk weighted assets in the standardized approach are calculated as the product of the amount of exposures and discrete risk weights (0, 10, 20, 50, 100, 150 %), determined by the category of the borrower such as sovereign, bank, or corporate and ratings from External Credit Rating Agencies. Even if the risk weights for claims on banks in the standardized approach are not lower than for claims on corporates in general, the required capital for interbank credit risk portfolios tends to be substantially lower than for loans to corporates because of the better creditworthiness of banks in terms of the rating distribution. Moreover, claims on an unrated bank may receive a risk weight of 50 %, while those on an unrated corporate will be assigned a 100 % risk weight. In addition, banks face essentially lower risk weights for bank claims with an original maturity of three months or less, which are very typical for the interbank market.

Because ratings from External Credit Rating Agencies have not been incorporated into the model, we will simply assume the 50 % risk weight for claims on banks ($\omega^b = 0,5$) and 100% risk weight for external claims in general ($\omega^e = 1$), which is also in line with Principle I of the Deutsche Bundesbank, which covered equity of institutions before the Basel Capital Accord II.

External credit risk: We implement the following calculation of risk weighted external credit assets:

$$\tilde{c_i^e} = c_i^e - p_i^{CB}(1 - \omega^{CB}),$$

where p_i^{CB} is the credit portfolio securized by bank i as covered bonds and ω^c is the average credit risk weight. Note that the average risk weight for external claims is equal to 1 by assumption. Because the underlying credit assets of CB stay in the bank balance of the originator bank and have lower risk than the average of the external credit portfolio, we will reduce the external credit amount by the CB underlying value, firstly, and add the risk adjusted CB-underlying afterwards. The calculation of the CB specific risk weight ω^{CB} is presented below.

Risk of credit investments: We determine risk weights for CB and for each CDO tranche based on each sub-portfolio and use these weights for the calculation of RWA for each bank i in accordance to their portfolio. The calculation of RWA which relate to the investments in CB and CDO $\tilde{i_i^b}$ is somewhat tedious as the investment portfolios of banks are heterogeneous. Thereby, the risk of investments mainly depends on the risk content of the underlying debts and the risk appetite of banks. At first we determine the risk weights for the underlying assets for CB and each CDO tranche, simultaneously. Eventually, we use these weights for the calculation of the individual RWA for each bank.

Remember that we used the assumption that the risk factor X_s, which is not further specified here, in each segment credit portfolio $\widetilde{C_s^e}$ is distributed according to sector specific beta distributions. We implement the process for credit securitization using maximum risk factor thresholds (*upper boundaries*) for covered bonds u^{CB} and each tranche of the CDO u_t^{CDO} with $t \in \{A, B, C\}$, see section 2.2.5. Using these properties we calculate the relative risk weights for each tranche and apply them for the calculation of RWA. First, we determine segment specific expected risk factors for each tranche applying the following algorithm. The conditional expectation of $X_s \in [a, b]$ is

$$E(X_s | X_s \in [a, b]) = \frac{\int_a^b \varphi_s(x) x \, dx}{\int_a^b \varphi_s(x) \, dx}, \tag{2.22}$$

given a segment specific beta probability function $\varphi_s(x)$ and a and b - boundaries of a tranche. For example, for the tranche A we will calculate $E_s(X | X \in [u^{CB} + \varepsilon, u_A^{CDO}])$ with the lower boundary for tranche A derived from the upper boundary for covered bonds $u^{CB} + \varepsilon$, where $\varepsilon \to 0$, and the upper boundary for tranche A, denoted by u_A^{CDO}. Since no analytical form of the primitive of the β-function φ exists, the integral can not be solved by an explicit expression and has to be treated numerically.

Therefore, we apply for the integrals in (2.22) quadrature formulas as an approximation

$$\int_a^b f(t) \, dt \;=\; \sum_{i=0}^{M-1} \int_0^h f(x_i + t) \, dt \;\approx\; \sum_{i=0}^{M-1} h \sum_{k=1}^{K} \omega_k f(x_i + \xi_k)$$

with $x_i = a + ih$, $h = (b - a)/M$ and integration weights $\omega_1, \ldots, \omega_K > 0$, $\sum_{k=1}^K \omega_k = 1$. The corresponding integration weights ω_i and integration nodes ξ_i can be obtained from a numerical database according to the specific quadrature rule. In order to reduce the quadrature error as much as possible, one should chose a large enough value of M and quadrature rules of high order. Therefore, we we chose in our simulations always he Gauss rule with $K = 8$ and $M = 100$.

Hence, knowing the expected risk factors $\bar{x}_s^{CB} = E_s(X|X \in [0, u^{CB}])$, $\bar{x}_s^A = E_s(X|X \in [u^{CB}, u_A^{CDO}])$ and by analogy for tranches B and C for each sector $s \in S$, we can determine the relative risk weights by

$$\begin{aligned} \tilde{\omega}^t &= \frac{\sum_{s\in S} \bar{x}_s^t P_s^t}{P^t}, \quad \forall t \in T & (2.23) \\ \tilde{\omega}^{CB} &= \frac{\sum_{s\in S} \bar{x}_s^{CB} P_s^{CB}}{P^{CB}} & (2.24) \end{aligned}$$

Note that $P^{CB} = \sum_{s\in S} P_s^{CB}$ and $P^t = \sum_{s\in S} P_s^t \quad \forall t \in T$ are the cover (underlying) asset pools for CBs and each tranche of CDOs, respectively.

Now, we have to normalize the risk weights so that with respect to regulatory capital it would be equivalent for each credit portfolio whether it is securitized or not [6], because of the credit risk of the entire (external) credit portfolio still remaining the same.

Remember the assumption regarding the risk distribution of credit pools. We assumed the same risk distribution for securitized loans as for the total credit pool.
Therefore, we correct the risk weights $\tilde{\omega}^t$ and $\tilde{\omega}^{CB}$, determined above, by an adjustment factor ω^*, so that total RWA of the secured portfolio would be equal to the RWA of the underlying credit pool, calculated by the average risk weight of external claims ω^e:

$$\omega^e P = \omega^{CB} P^{CB} + \sum_{t\in T} \omega^t P^t, \tag{2.25}$$

with total securized credit portfolio $P = P^{CB} + \sum_{t\in T} P^t$.

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[6] provided that banks are the only asset holder, no purchase of investments by externals exist

We calculate the final risk weights by adjusting the weights $\tilde{\omega}^t$ and $\tilde{\omega}^{CB}$ satisfying the condition 2.25.

$$\begin{aligned} \omega^{CB} &= \tilde{\omega}^{CB}\omega^* \\ \omega^t &= \tilde{\omega}^t\omega^* \quad \forall\, t \in T, \end{aligned}$$

where

$$\omega^* = \frac{\omega^e(P^{CB} + \sum_{t\in T} P^t)}{\tilde{\omega}^{CB}P^{CB} + \sum_{t\in T}\tilde{\omega}^t P^t}.$$

Determining the risk weights in this way we ensure that total RWA of the secured portfolio would be equal to the RWA of the underlying credit pool. Remember that the average risk weight of external loans $\omega^e = 1$ corresponds to the risk weight of 100%.

To determine the bank specific investment RWA $\tilde{i}_i^b$ we summarize all risk weighted CDO bank investments. Because of the low risk specification of CBs, we suppose that no equity is necessary to cover the CBs for the investment bank. But the credit risk of the underlying pool should be considered in the capital requirement by the originator bank as described above.

$$\tilde{i}_i^b = \sum_{t\in T} \omega^t P_i^t$$

2.3.3 Diversification of defaults

Until now we always considered the case in which only one sector can be the source of the initial shock. Now, we expand the initial shocks across the real sector in a variable manner. Thus, several external segments can induce credit defaults at the same time and at various levels. To make simulation results for multiple segment defaults comparable to the case with an idiosyncratic shock as before, we change the definition of the variable λ. Now it gives the percentage of the total credit default with respect to the total external credit exposure. To specify the defaults for each sector we introduce further segment specific parameters $\delta_s \; \forall s \in \{1, \ldots, S\}$ defining the individual part on the total credit default for each external segment. Hence, the initial default for each segment s is calculated by $\delta_s \lambda C^e$ and $\lambda C^e = \sum_s \delta_s \lambda C^e$. Note that in the case of $\delta_s = 1$ for only one segment while other parts are equal to zero, we would deal with an idyosyncratic shock analogous to the basic model.

2.3.4 Dynamic of deposits and liquidity risk

In this section we will extend the network by modeling the capital movements like withdrawal of external and interbank deposits. We determine withdrawal of interbank deposits as a reaction of depositors to the deterioration in the capital base of banks in relation to the credit risks involved. The starting point of the dynamic is the identification of such "weak" banks which become objects of withdrawal. So we introduce an auxiliary attribute $\tau \in \{0, 1\}$ denoting the tolerance limit for the deviation of the capital ratio of banks from the required capitalization level permitted by depositors. We identify "weak" banks by the following condition

$$\gamma_i < \tau \gamma^r \tag{2.26}$$

with regulatory equity ratio γ^r and current equity ratio γ_i.

Firstly, we introduce the regulatory requirements for the minimum risk adjusted bank capital. Thereby we assume the possibility that a bank equity rate falls under the regulatory level in the short term without the need of the bank being liquidated. It is an appropriate assumption because of the short term consideration of the dynamics in the model. Even in the real world it is possible that there are capital shortfalls below the regulatory requirements. Banks have to report such a circumstance to the supervisor immediately. It would take time to meet the appropriate measures to stabilize or to liquidate the bank. We assume that depositors can react immediately withdrawing their deposits. To trigger such event we suppose that depositors would tolerate a capital gap up to a certain threshold value. This threshold is determined through the tolerance level of depositors $\tau \in [0,1]$. The next step is to calculate the volume of deposits d_i^w for each "weak" bank i that will be withdrawn at once. We define this volume as the difference between the current risk assets of the bank RA_i and the maximum risk assets that conform to the regulatory framework: $d_i^w = RA_i - e_i\gamma^r$. We assume that external depositors and other banks will get their money back from the weak bank in proportion to their respective deposits at this bank so that $d_i^w = d_i^{wb} + d_i^{we}$, where d_i^{wb} and d_i^{we} denote the withdrawal of deposits of banks and externals, respectively, with $d_i^{wb} = \sum_{j=1}^{N} d_{i,j}^{wb}\Delta^w$ and $d_i^{we} = d_i^e\Delta^w$. Thereby, Δ^w denotes the withdrawal ratio, calculated in the way that the withdrawal deposits are equal to the amount of excessive risk assets in each iteration.

Any change of balance items requires updating the network because of the balance constraints for each bank, so that all banks are well balanced. Hence, withdrawals of deposits may produce two kinds of problems: refinancing problem (liquidity gap) of the weak banks subjected to the withdrawals, and liquidity surplus of the banks withdrawing their deposits. Therefore, the liquidity chain reaction may be triggered. Furthermore, the withdrawal of deposits may have led to bank losses because of the possible need of fire-sales of assets below their purchase value. This effect may lead to further solvency chain reactions such as the case of losses of external loans.

Refinancing problem: Reduction of interbank deposits will open the refinancing gap, which has to be closed by funding of fresh liquidity or by reduction of assets. We assume very limited opportunities for refinancing in the short term. First of all, the minimum reserve and liquidity surplus will be used. Which means that a weak bank, with funds parked in a central bank account, will try to bridge the liquidity gap by recovering this money. If the central bank is prepared to support banks with liquidity, one part of the liquidity gap $0 \leq \delta \leq 1$ will be covered by (new) central bank loans. In further steps assets will be reduced:

1. external assets whose eligibility as high-quality liquid assets are assumed in the model,
2. bank loans because of their short term nature,
3. covered bonds and CDO, which are easier and faster to be placed on the market than (external) loans,
4. external loans.

Further, we assume that the external assets will be acquired by externals. So, the balances of other banks in the network may not be affected. Other assets will be generally bought up by well capitalized banks. Only if the bank system is no more able to do this because of the capital restrictions, the central bank may be forced to acquire remaining assets.

The reaction of weak banks in terms of withdrawing their own funds to cover the liquidity gap has an impact on the liquidity situation of their borrower banks now facing the refinancing problem. Such (new) refinancing problems will be treated analogously as above. Furthermore, we consider the price decrease as an important effect of 'fire sales' of assets. It can be considered as a purchaser gain, while the seller suffers a loss. We assume that the price of assets depends on the equity base of the banking system. Hence, if banks have sufficient equity to buy all excess assets, the price for unit of asset value $p_a = 1$. If the equity base is not enough to cover the excess assets, the price will be reduced according to the available equity base. In order to prevent the total (or very high) price crash for excess assets in the case of the banking system not being able to absorb them entirely, the central bank will intervene. We assume that if the price of assets deteriorates below a certain threshold $0 < \beta < 1$ the central bank buys the excess assets at the threshold-price β. Hence, for fire-sale prices there is a following convention:

$$\beta \leq p_a \leq 1 \tag{2.27}$$

The refinancing of buying banks is achieved through excess liquidity if available, otherwise through loans of the central bank for simplicity.

Liquidity surplus: Banks build excess liquidity by withdrawing their money from weak banks. This liquidity will be used to repay the central bank money at first. The rest of the excess liquidity will be parked in the central bank accounts and can be used for buying assets in the next step or to close the liquidity gaps as they occur.

Linkage between solvency and liquidity: We model the solvency chain reaction as an iterative process. In each iteration we identify banks which get into financial troubles and trigger the solvency chain reaction, as described above. Furthermore, withdrawal of deposits disturbs the bank balances. Liquidity problems will be iteratively solved. We call this process liquidity chain reaction which may cause additional bank losses because of fire-sales of assets. This effect may lead to further solvency chain reaction like in the case of losses of external loans. Thereafter, new withdrawals may be possible again. This process continues until all bank losses are covered by equity or transmitted, and no more withdrawals happen.

2.3.5 Core-periphery network structure

For the analyses of the network structure effects, the asset-based model has been extended in the following way: The network structure has been modified by the division of banks into three groups: core, periphery and semi-periphery, which are different in the average bank size and the interbank linkage structure. The core includes banks with larger balance sheet totals on average, while the periphery contains much smaller banks on average. Semi-periphery comprises banks which are smaller than the banks of the core, but larger than the periphery banks on average. With regard to the interbank relations the core-periphery formation is characterized by restrictions of the out-degree and in-degree links for banks of the same group. More formal definitions of the discussed bank groups can be expressed as follows.

Definition 2.3.1 *Core banks are characterized by the higher external exposure than periphery and semi-periphery banks. Core banks possess also higher interbank exposure because of the higher in- and out-degrees and higher external exposure. They are extremely interconnected, highly connected with periphery and also linked to the semi-periphery banks.*

Definition 2.3.2 *Periphery banks have the smallest external exposure on average. They are nearly disconnected within the periphery, but highly connected with core banks. Furthermore, they are moderately linked to the semi-periphery banks.*

Definition 2.3.3 *Semi-periphery banks are connected with banks of the network with equal frequency and are medium-sized with respect to the external exposure.*

Core-periphery formation procedure

To keep the core formation simple but flexible, we implement the following concept. After a random initialization of network links we intervene in the network structure. Firstly, we redistribute the external credit assets between the banks in the network to get bank groups with different average sizes. The linkages between banks and external segments stay unchanged in terms of their structure and so the number of links Z_s for each segment s. However, the weight of links will be adjusted. This is a suitable method here because of the random distribution of the assets between banks in the model initially. Secondly, to determinate the relationships between the banks, we adjust the initial random matrices for credit and investment linkages, R_b^c and R_b^i, according to the new requirements (see definitions above). To adopt this procedure further exogenous parameters will be used here: percentages of the banking system ψ_1 and ψ_2 included in the core and the periphery respectively, and the percentage of the external assets ξ to be reallocated from banks of the periphery to the core.

Note the following notation will be used here. Bank i is included in the core $i \in N_C$, if $i < \underline{i}$ with $\underline{i} = \psi_1 N$. Bank i is included in the periphery $i \in N_P$, if $i > \bar{i}$ with $\bar{i} = N - \psi_2 N$. Bank i belongs to the semi-periphery $i \in N_{SP}$, if $i \in [\underline{i}, \bar{i}]$.

Reallocating external loans: The aim of this procedure is to implement three bank groups with different average sizes, especially with regard to the external assets.

Remember the credit volume for each sector given by $\widetilde{C_s^e} = C^e w_s^c$, where w_s^c is a percentage of loans to sector s from total external debts. We assumed until now, that $\widetilde{C_s^e}$ is equally distributed between the lender banks of sector s. Hence, for each lender i we compute the credit volume before securitization given by $\widetilde{c_{i,s}^e} = \widetilde{C_s^e}/Z_s$, where Z_s is the number of banks connected to sector s, see 2.2.5. Now, we have to redistribute the external credit volume without changing the basic network structure $R_s \in \{0,1\}^{N \times S}$, so that $Z_s = \sum_{i=1}^{N} R_s[i,s] \approx N p_s, \forall s \in \{1,,S\}$. Using the exogenous parameter ξ the external credit volume to be reallocated to core banks from the periphery is given by $\xi \sum_{i \in N_{C2}} \tilde{c}^e_{i,s}$ for each s. We recalculate the new external debts by scaling the loans to each sector according to

$$\tilde{c}^e_{i,s(new)} = \begin{cases} \tilde{c}^e_{i,s}(1 + \frac{\xi \sum_{i \in N_P} \tilde{c}^e_{i,s}}{\sum_{i \in N_C} \tilde{c}^e_{i,s}}), & \forall i \in N_C \\ \tilde{c}^e_{i,s}(1-\xi), & \forall i \in N_P \\ \tilde{c}^e_{i,s}, & \forall i \in N_{SP} \end{cases}$$

Note that the semi-periphery remains unchanged. Furthermore the presented redistribution ensures $\sum_{i \in N} \tilde{c}^e_{i,s(new)} = \sum_{i \in N} \tilde{c}^e_{i,s}$

Updating the relationship between cores: Remember, we determine the existence of the interbank links via the simulation engine delivering two $N \times N$ random matrices R^c_b and R^i_b for interbank credit and investment relationships with realizations 0 and 1 accordingly to probabilities p^c and p^i, respectively. Formally, $R^c_b, R^i_b \in \{0,1\}^{N \times N}$ with $R^c_b[i,i] = R^i_b[i,i] = 0$.

Our aim is to ensure the validity of the following equations for a sufficiently large number of banks N as in the original model (see 2.2.5):

$$Z^c_b = \sum_{j=1}^{N} \sum_{i=1}^{N} R^c_b[i,j] \approx (N^2 - N)p^c, \tag{2.28}$$

$$Z^i_b = \sum_{j=1}^{N} \sum_{i=1}^{N} R^i_b[i,j] \approx (N^2 - N)p^i, \tag{2.29}$$

with the number of realized interbank credit and investment links Z^c_b and Z^i_b, respectively.

For this purpose we implement a network structure adjustment procedure applying a two-stage iteration process, where $\underline{i}$ is a maximum bank index of the core and $\overline{i}$ is a minimum bank index of the periphery as defined above.

Firstly, for each pair of core banks it should be checked whether they are interconnected. Otherwise, we have to search for an existing connection within non-core banks, beginning with a periphery bank with highest index and a semi-periphery bank with a lowest index. If the connection has been found, it will be transferred to the pair of core banks, which has not been interlinked until now. The procedure has to be done until the core is completely interconnected or the transfer of links is no longer possible.

Secondly, it should be examined, for each of the periphery banks, whether a core bank exists which is not linked to this periphery bank. In such case, we seek for an existing connection between the examined periphery bank and another bank of the periphery and to transfer the detected connection to the unlinked core bank. This loop has to be followed until the described link transfer is no longer necessary or possible for each pair of the core and the periphery banks.

1. **Complete the interconnectedness within the core:** For each pair of core banks which are not interconnected an exchange connection has to be found and transferred:

   For each pair of core banks $i < \underline{i}$ and $j < \underline{i}$: If $R^c_b[i,j]$ =0, then search for the $max\{k\}$ and $max\{l\}$, with $k > \underline{i}$, $l > \underline{i}$ and $R^c_b[k,l] = 1$ or $R^c_b[l,k] = 1$. If such a pair (k,l) exists, modify the matrix R^c_b by $R^c_b[i,j] = 1$ and $R^c_b[k,l] = 0$, respectively $R^c_b[j,i] = 1$ and $R^c_b[l,k] = 0$. The same procedure will be applied for the investment links matrix R^i_b.

2. **Complete the interconnectedness between the periphery and the core:** For each pair of core and periphery banks which are not interconnected an exchange connection has to be found and transferred:

   For each pair of banks (core and periphery) $i < \underline{i}$ and $j < \bar{i}$: If $R^c_b[i,j]$ =0, then search for the $max\{k\}$ and $max\{l\}$, with $k > \bar{i}$, $l > \bar{i}$ and $R^c_b[k,l] = 1$ or $R^c_b[l,k] = 1$.

> If such pair k, l exists, modify the matrix R^c_b by $R^c_b[i, j] = 1$ and $R^c_b[k, l] = 0$, respectively $R^c_b[j, i] = 1$ and $R^c_b[l, k] = 0$. The same procedure will be applied for the investment links matrix R^i_b.

Because the described iteration process is primarily based on the reallocation of links interconnected the periphery banks from periphery to core banks, no further adjustment process is generally required to disconnect the periphery within itself. [7]

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[7] Only if the core is very small with respect to the connectivity degree of the network, which should be sufficiently high, the interconnected periphery banks will still remain after the described procedure. We will ignore this possibility.

Chapter 3

Methodology of simulation analyses

The complexity of banking systems and a lack of availability of complete bank credit risk data explain why the most commonly chosen methods of analyzing their stability involves high levels of simplification. However, we believe that a deep understanding of financial products and of actual developments in the financial markets, transparency of bank books to the greatest possible extent, and a continuous developing of the most sophisticated models using this knowledge and data are essential for monitoring and regulating the banking systems.

According to the ECB the following conditions should apply to characterize the financial system as stable: Firstly, the financial system should be able to efficiently and smoothly transfer resources from savers to investors. Secondly, financial risks have to be assessed and priced reasonably accurately and should be relatively well managed. Thirdly, the financial system must be able to comfortably absorb financial and real economic surprises and shocks. As that ECB underlines on their official website,*"... the safeguarding of financial stability requires identifying the main sources of risk and vulnerability such as inefficiencies in the allocation of financial resources from savers to investors and the mis-pricing or mis-management of financial risks. This identification of risks and vulner-*

abilities is necessary because the monitoring of financial stability must be forward looking: inefficiencies in the allocation of capital or shortcomings in the pricing and management of risk can, if they lay the foundations for vulnerabilities, compromise future financial system stability and therefore economic stability."

It is obvious, that the mentioned macro- and micro-prudential considerations are essential to safeguard the stability of the financial system. Nevertheless, a constant search for fresh approaches and further characteristics of the financial system, its components and environments which are relevant for the financial stability is also crucial due to the fact that the world is constantly changing. Furthermore, the manner in which these further potential factors could affect the systemic stability must be continually examined, particularly from the systemic risk perspective.

We try to contribute to more clarity and understanding of these complex matters by using the ABN-model described in the previous chapter. In this context we consider the individual banks' properties, network characteristics, as well as the environment of the financial network. We study the impact of them depending on the initial shock properties like intensity and concentration, as well as on the dynamic processes including or excluding liquidity risk in connection with an unexpected withdrawal of bank deposits.

From the characteristics of the financial system stability given by the ECB as above it follows that banks may be considered as the most important financial intermediaries. Banks are crucial for the economic systems because of their role of allocating financial resources and transforming risks and maturities, as already mentioned by Diamond and Dybvig (1983) in [20]. The ability of the individual banks and of the banking system as a whole to assess, price and manage the financial risks and take appropriate precautions at all times determines the capability of the financial system to absorb and withstand shocks. Hence, we will consider the resilience of the banking system defined by the default rate of banks as the first important measure for systemic risk in the following analysis. Furthermore, the costs of the systemic events, such as absorption of shocks by the banking system and transmission of losses to the external segments, will be examined. Thereby, we are in line with the definition of financial stability, provided by the European Central Bank (ECB) on their official website, as *"...a condition in which the financial system - intermediaries, markets and market infrastructures can withstand shocks without major disruption in financial intermediation and in the effective allocation of savings to productive investment."*

This chapter deals with the methodology of the simulations which we use for several analyses presented in the next chapters. In particular, the simulation engine and the general construction of the applied scenarios and the initial events will be set out in section 3.1. Subsequently, the simulation analyses in general form will be presented in section 3.2.

3.1 Simulation engine

The heart of the model application is the simulation engine which is used to create numerous scenarios, execute the developed (advanced) ABN-model for these scenarios and collect results in terms of preprocessing, aggregation, and storage of simulated data in a local file system. The methodology and implementation of the ABN-Model has been already described in the previous chapter, particularly in section 2.2.5. One or any two of the existent exogenous parameters can be simultaneously stressed in the engine. The stress scenarios can be repeated several times for a number of networks defined in a random way. The results, based on the initial and final states of the stressed networks will be calculated and stored as the 25% quantile, 50% quantile (median), 75% quantile and the mean value for each parameter setting.

The simulation engine is programmed completely in the open ISO-standardized language

`C++`. For statistical computation and some graphics, the free software environment `R` has been used. For visualization of the data the free data plotting program `Gnuplot` has been preferred.

The focus of the simulation analysis presented in the following chapters is the systemic risk as described in section 0.2, implying the failures of financial institutions caused by strong idiosyncratic or limited systematic shocks, accompanied by the subsequent shock transmission processes and further dynamics within the network.

3.2 Simulation analyses

In the following chapters we will present and discuss the results of simulation experiments designed with regard to the particular problems. To be able to compare the results, we generally use four baseline simulation scenarios, which will be appropriately adjusted depending on the question to be answered. However, the baseline scenarios seek to capture very different constellations with respect to the concentration of the initial shock and existence of the liquidity risk.

The majority of the simulation experiments presented here are based on the baseline scenarios and work as follows: Initially, 100 different networks will be simulated by a random generator and stressed then by the initial shock (100 runs), varying one (two-dimensional analysis) or two (three-dimensional analysis) parameters simultaneously in each simulation iteration. All other parameters remain at the same value. The default parameter settings (baseline scenarios) and the intervals for the variation of the parameters are stated in the appendix (A.1.1) in Tables A.1 to A.3. Table 3.1 pictures the general differences between the baseline scenarios [1], which will be described in the following.

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[1] The letters NW denote a **n**et**w**ork (scenario) and the numbers refer to the identifier of the baseline parameter setting.

Scenario	**Withdrawal of deposits**	**Concentration of the initial shock**
NW 01	yes	high
NW 02	no	high
NW 03	yes	low
NW 04	no	low

Table 3.1: Parameter settings characterizing the main kinds of simulation experiments.

Withdrawal of deposits in the table means the existence of deposit withdrawals or liquidity risk, which is connected to intolerance of depositors for the undercapitalization of banks. Hence, scenarios 01 and 03 presuppose the existence of liquidity risk, while in the two remaining scenarios no withdrawal of deposits is feasible, i.e. the intolerance for undercapitalization is set to 0 and, thus, no liquidity risk exists. For details we refer to chapter 2.3.4.

Concentration of the initial shock determines how the initial shock is distributed across the external segments. We assume for high concentration that all initial loan losses are caused by only one external segment (idiosyncratic shock). In contrast, the low concentration implies that all segments will be affected, even though individual intensities of the shock for particular segments will be presupposed (limited systematic shock). Thereby, we will consider the same affected segment for all scenarios with the high shock concentration, and the same relative distribution of the initial shock across external segments for all scenarios with the low concentration of the initial event, respectively, which is important for the comparability of results, see A.2.

As described in this section, banks do not keep all external loans on their balance sheets. One part of debts may be securitized as covered bonds and collateralized debt obligations and be marketed to other banks and externals thereafter. The claims issued against the CDO collateral pool are prioritized by creating different tranches of securities. We distinguish between three tranches A, B and C. Thereby tranche C is the equity or the first loss tranche, which bears the highest default risk. We suppose for the baseline scenarios that banks prefer high risk assets (*high risk appetite of banks*) with respect to their initial investments: They invest only in the two riskiest CDO-tranches B and C, while the CBs and the CDO-tranche A will be purchased by externals. We determine the risk appetite of banks with the help of parameters β_t^{CDO} with $t \in \{A, B, C\}$ and β^{CB}, which describe the percentage of bank investments to the total volume of CDO and covered bonds, see A.3.

We support the analyses by several figures, using the average results of a number of random networks for each parameter setting. When illustrating the results, mean values of simulation experiments are displayed in general.

To explain an example in more detail we refer to Fig. 4.5, which pictures the development of the bank default rate in relation to the intensity of the initial shock for four baseline scenarios. For each of them we see the results of the following procedure:

1. initialize parameters
2. generate random matrices
3. create network
4. stress the network by the initial shock with the lowest magnitude, calculate and save results (here default rate of banks)
5. repeat step 4 stepwise increasing the intensity of the initial shock (20 times)
6. repeat steps 2-5, creating new matrices for each iteration (100 iterations)
7. aggregate results (here calculating averages) for each value of the intensity of the initial shock

Note, that in some experiments parameters will be varied which affect the random matrices (number of banks or probability of interbank lending links, for example). In this case the generation of random matrices is needed for each iteration and each value of the varied parameter(s). In such cases steps 2-4 will be repeated in step 5. Moreover, the number of iterations and steps may vary.

Chapter 4

Systemic events

Here, we focus on two main properties of the initial shock - intensity and concentration, which are able to characterize the type of the systemic risk according to the concept proposed by O. De Bandt and P. Hartmann (2000), see 1.1.1.

The research of Gai and Kapadia (2010) published in [33] needs to be mentioned here, being the most relevant previous work, where the effects of initial shocks of various magnitudes have been examined by using a financial network model. Thereby, contagion in financial systems has been modeled with the primary focus on how losses may potentially spread via a complex network of direct counterparty exposures following an initial default. Further, the knock-on effects of distress at some financial institutions, which trigger further rounds of default has been considered analytically and numerically. The authors assumed that the network of interbank linkages forms randomly and exogenously. They recognized, that similar shocks could have very different consequences for a financial system depending on whether or not the shock hits at a particular pressure point in the network structure. Moreover, they noted that when capital buffers were eroded to critical levels, the level of contagion risk could very rapidly increase.

We study the impact of the initial shock dependent on how strong and concentrated it is. We define the initial shock as default of external loans and vary the total default rate λ to examine the impact of the initial shock magnitude. Thereby we distinguish between two extreme cases with respect to the concentration of the initial shock: the first one with only one real sector involved (idiosyncratic shock), and the second one with a widely distributed (systematic) shock. Note that we only change the shock distribution between both cases without changing the total volume of defaulted credit assets, which in turn depends only of the intensity of the shock. The remaining parameters are chosen according to the baseline scenarios, see 3.2 and are displayed in Tab. A.1 - A.3). The relevant dynamics in the system include absorption and transmission of the initial shock, as well as the liquidity chain reactions caused by the deposit withdrawals, which are described in the previous chapters. To better understand the results of the simulation experiments in the following, it is worth looking first at the final states of the asset/liability structure of the entire financial system for two kinds of network dynamics: with and without liquidity risk. The asset/liability structure will be graphically displayed as the aggregate positions of the total balance sheet of the financial system and will be explained below.

Asset/liability structure: To illustrate the impact of network dynamics on asset/liability structure after the clearing processes are finished, the final averaged[1] total assets and liabilities of simulated financial systems are presented exemplary in Fig. 4.1 - 4.4 which are dependent on the on magnitude of the initial shock. The first two figures represent the total asset/liability structure in the case of an idiosyncratic shock with a high confidence in the banking system (zero intolerance against short time undercapitalization), making deposit withdrawals unlikely.[2] The further two figures represent results of similar

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[1] For each given percentage of initial default we performed 100 simulations with randomized network structures. These figures show averages of those simulations. This statistical procedure is also applied to almost all results presented in this thesis as mentioned in section 3.2.

[2] The figures picture the balance sheet positions as single lines or as areas (cumulative structure). Both kinds of graphics contain the same information, but allow a more differentiated analysis and control of the simulation engine.

experiments but with the difference that withdrawal of deposits is now probable.

The magnitude of the initial shock has different effects on final asset/liability structure for cases with and without withdrawals, which can be seen by a direct comparison of Fig. 4.1 and 4.3 or Fig. 4.2 and 4.4, respectively.

The final impact of the initial shock and according dynamics are straightforward if deposit withdrawals do not occur. The total assets are reduced due to the initial shock, reducing external exposures of banks as well as the cumulated value of the CDO investments[3]. The *asset side* of the entire banking system includes then reduced external loans and CDO-investments of banks and externals and liquidity reserves of banks (very small here). Covered bonds are not true-sale transactions with underlying credit assets which remain on the originator banks' balance sheets. Thus, covered bond investments are not considered explicitly as assets, but included in the position "external loans". Furthermore, for simplicity no liquid external assets exist in this example.

The *liability side* consists of banks' and external capital, of which the last is reflected in the financial statements of banks and in the financial system as a whole in two ways: external capital that is tied up in the investments (CB and CDO) and external deposits. Interbank loans and bank investments are financed by banks' equity or through the external deposits and represent a genuine transfer of capital rather than the real capital. That is why these positions have been considered neither on the asset nor on the liability side here.

In the example, reduction of assets is primarily accompanied by reduction of bank capital and particularly by reduction of external deposits via transmission of losses from banks to externals (here only a small effect at a very strong initial shock), as can be seen in Fig. 4.1.[4]

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[3] In the presented case only bank investments are affected, because of the high risk appetite of banks holding the riskiest CDO tranches.

[4] Remember, that bank losses will be covered by bank equity or be transmitted to depositors if bank capital is depleted. Thus, the value of the external deposits in the system can decline for two reasons: withdrawal and utilization to cover bank losses. This is the reason, why a decline of external deposits exist even though withdrawal of deposits does not take place.

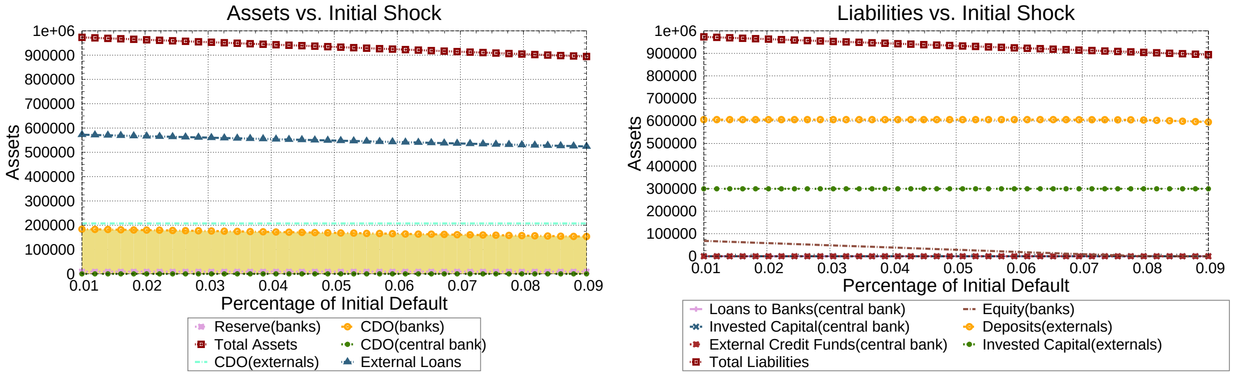

Figure 4.1: Asset/liability structure after the shock absorption in relation to the intensity of the initial shock λ with low shock concentration, high risk appetite of banks, and without liquidity risk (NW04).
Parameter setting: see Tables A.1 to A.3 in the appendix (A.1.1).

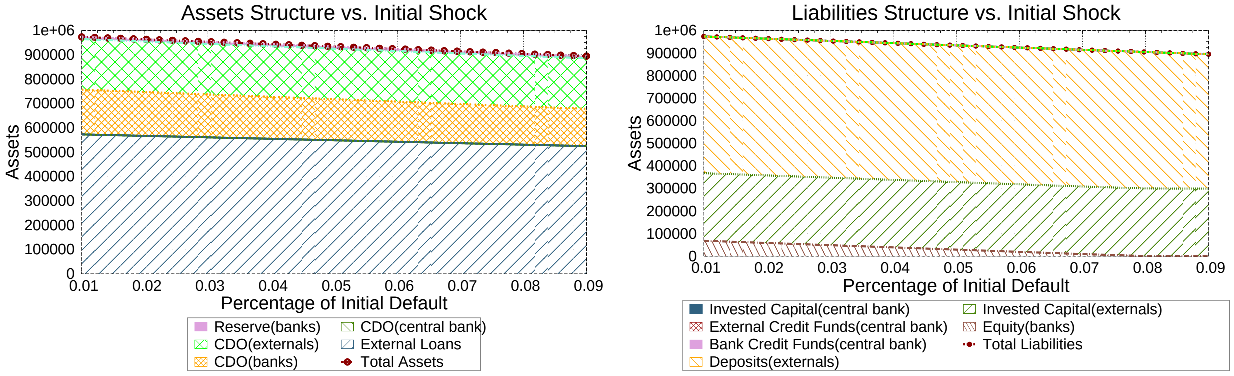

Figure 4.2: Cumulative asset/liability structure after the shock absorption in relation to the intensity of the initial shock with low shock concentration, high risk appetite of banks, and without liquidity risk (NW04).
Parameter setting: see Fig. 4.1.

If withdrawals are not possible, which corresponds to the high confidence in the banking system because of an efficient deposit protection for example, the intervention of the central bank is not required. Hence, the central bank does not play a role in the final cumulated balance sheet structure of the financial system, see Fig. 4.1.

The integration of liquidity risk into the contagion dynamics clearing processes leads to the final state of the system becoming more complex. As described in section 2.3.4 in

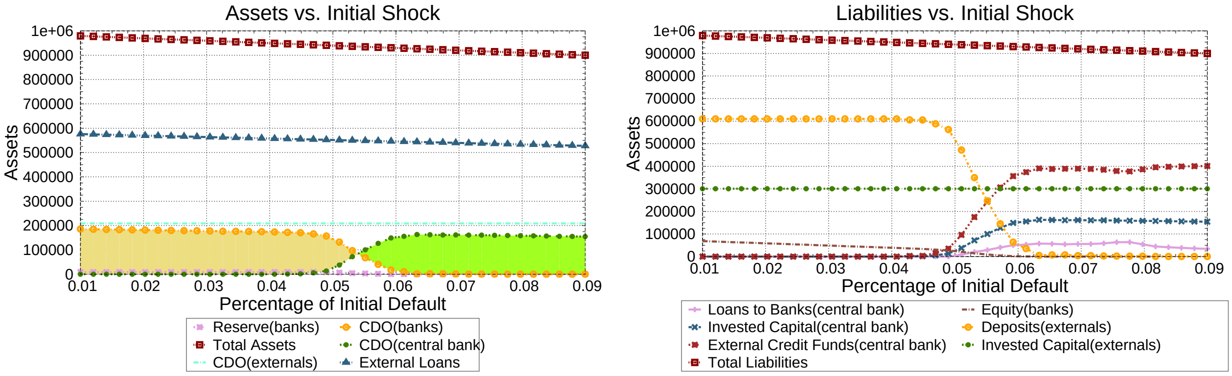

Figure 4.3: Asset/liability structure after the shock adsorption in relation to the intensity of the initial shock in the scenario with low shock concentration, high risk appetite of banks and the withdrawal risk (NW03).
Parameter setting: see Fig. 4.1.

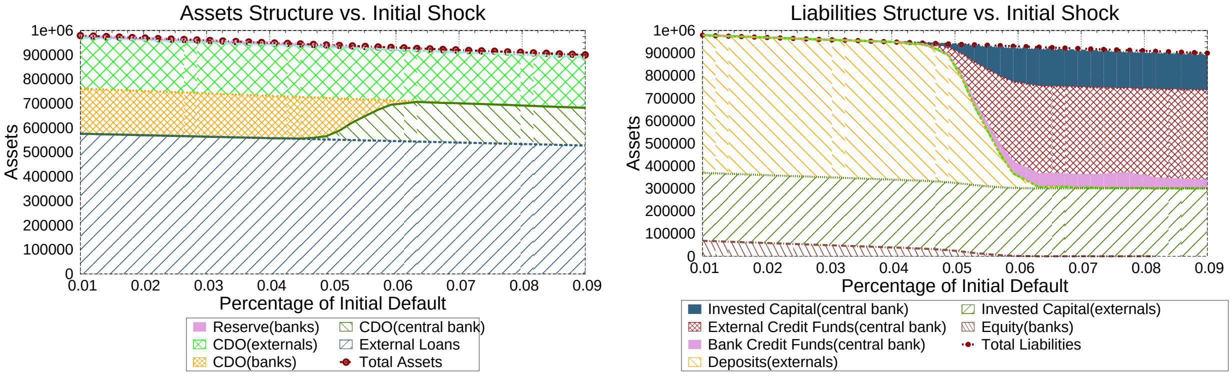

Figure 4.4: Cumulative assets/liabilities after the shock adsorption in relation to the intensity of the initial shock in the scenario with low shock concentration, high risk appetite of banks and the withdrawal risk (NW03).
Parameter setting: see Fig. 4.1.

more detail, withdrawal of deposits takes place as a reaction of depositors to the deterioration of a single bank's capital base in relation to credit risks that have been taken by the bank. Thus, the risk adjusted capital rate of the bank should fall below a certain threshold to trigger withdrawal of deposits. The threshold depends on the confidence in the banking system itself, which is related to the exogenous parameter τ that determines the lack of tolerance of depositors for the undercapitalization of banks. Withdrawal of deposits would force the affected banks to reduce their assets. However, the volume of offered assets and the capitalization level of the banking system affect the unit price of assets and thus the probable intervention of the central bank. The central bank's intervention would explain the financing capital provided by the central bank, which can be seen on the liabilities side. It is obvious then, that the final liabilities structure in the case of withdrawal of deposits may include some central bank positions, especially if the initial shock is strong enough for the intervention of the central bank in order to close the lack of liquidity in the banking system or to avoid a strong asset price decline from the fire-sale of assets. The total balance sheet of the system comprises the following central bank items. The asset side contains CDOs, CBs and external loans, purchased by the central bank through fire sales. The latter two are included in the external loan position in the figures. The liability side comprises the central bank funds for the refinancing of banks (bank credit funds) and the direct financing of external loans (external credit funds, which also include the invested capital in CBs) as well as the central bank capital invested in CDOs (invested capital).

A closer look at Fig. 4.3 or Fig. 4.4 reveals a remarkable aspect at a high level of the initial shock, concerning the decrease of the central bank money in terms of loans to banks after a phase of previous growth. This effect relates findings of the following analysis related to external losses and must be looked at closely in this regard.

Resilience of the bank system

Fig. 4.5 demonstrates the dependence of the stability of the banking system on the magnitude of the initial shock for the base line simulation scenarios described above.

It appears logical to assume an increase of bank defaults and bank losses with an increasing initial shock.[5] Moreover, the increase of defaults would be higher, in general, if deposit withdrawals take place.[6] Furthermore, in the case of diversified initial shocks bank defaults start to increase at a significantly higher value of the shock than if shocks

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[5] Note, that a positive correlation between bank defaults and bank losses is not always the case. In particular, increasing equity of banks can increase bank losses while decreasing defaults of banks.

[6] Compare scenarios NW01 and NW02 or NW03 and NW04, for example.

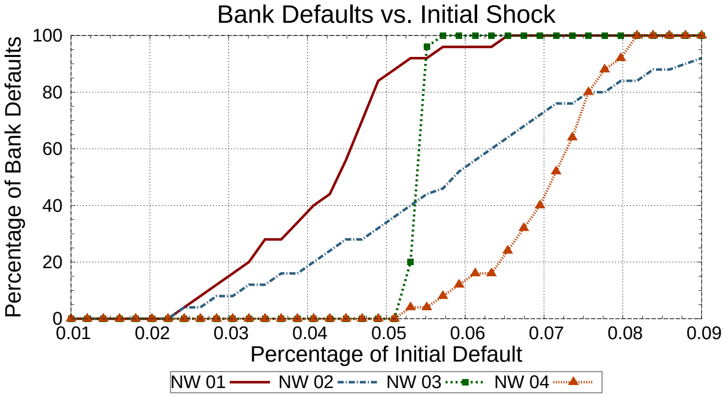

Figure 4.5: Resilience of the bank system in relation to the intensity of the initial shock. *Parameter setting*: see Tables A.1 to A.3 in the appendix (A.1.1).

are more concentrated. This means that if defaults are broadly distributed, we will observe higher stability of the banking sector than in the case of more concentrated shocks provided that the shocks are relatively low. With a further increase in the magnitude of the shock, the banking system may become more resistant against idiosyncratic events than against broader distributed shocks, even if it will transmit more losses to externals, particularly if banks are weakly interconnected. Subsequently, broadly distributed external credit defaults may rapidly lead to a complete collapse of the financial system when a certain level of the shock is reached. This finding discloses that the resistance of the banking system is connected to two opposite effects, which have been frequently discussed in the literature regarding the interconnectivity of the banking system, as for example in Nier et al. (2007): the positive effect of sharing losses across banks and the negative impact caused by the contagion effects. A broader distribution of the initial shock implies a lower affectedness of banks immediately after the shock. The following contagion is thus less likely than after an idiosyncratic shock with the same magnitude. But, if the intensity of the initial shock is high enough to trigger the contagion processes by widely distributed shocks, the effects of the shock transmission will be tremendous because of the greater number of banks, triggering the contagion within a very short time, and depleting capital base of the banking system. The whole effect will be more dramatic, than after an idiosyncratic initial shock with a similar magnitude. That can be observed by comparing NW01 and NW03 (with liquidity risk) or even NW02 and NW04 (without liquidity risk), for example, where default rates of banks are higher in the cases characterized by limited systematic shocks, NW03 and NW04, at percentage of external credit defaults $\lambda \approx 0.6$ and $\lambda \approx 0.8$, respectively. With this observation, we are in line with Gai and Kapaida (2010).

Bank losses

Cumulated bank losses increase with an increasing initial shock and stay constant at a maximum value, that corresponds to the total bank capital, see Fig. 4.6. Such complete loss of capital in the banking system arises at smaller values of the initial shock if deposit withdrawals happen. The straight line representing the initial loss, refers to the complete absorption of losses by bank capital in the case that no withdrawals have been triggered, which can be seen for sufficiently low magnitudes of the initial shock. The divergence from this line occurs at different levels of the shock for the analyzed scenarios. In the case of low concentration of the shock, only the restriction of the total banking capital forces the system to transmit the losses to the external sector. In this case, we obtain the highest absorption capacity by banks, while strong idiosyncratic shocks tend to affect externals to a higher degree (NW03-04). Further, the banking system is also better protected against withdrawals if shocks have been broadly distributed, as long as the intensity if the initial event is relatively low. However, at a high magnitude of the shock, withdrawals will create higher losses and thus transmission of them to externals after a strong systematic shock compared to an idiosyncratic shock with the same intensity, as demonstrated below.

External losses

Generally, external losses may increase with increasing initial shock. But, it is also possible that losses are zero or small if the risk appetite of banks [7] is high and the initial shock is

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[7] High risk appetite of banks implies low investment risk of the externals and probably no affectedness of them by the initial shock directly.

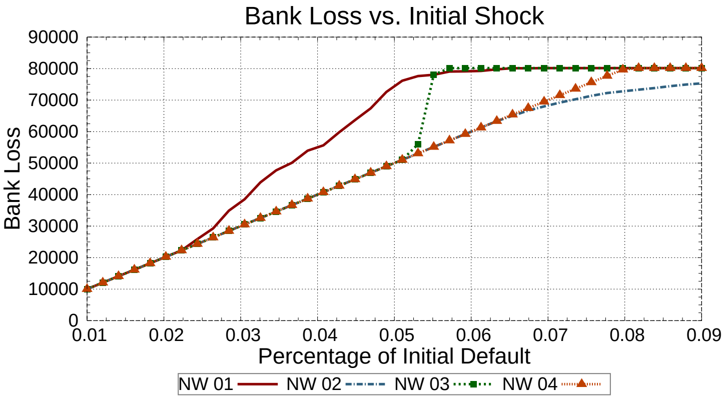

Figure 4.6: Cumulated bank losses in relation to the intensity of the initial shock. *Parameter setting*: see Fig. 4.5.

small enough compared to the equity base of banks, especially if the initial event is widely spread across banks or banks are highly interconnected. Furthermore, for relatively small shocks, external losses are smaller if the shock has a broader spread, which can be seen by comparing the scenarios NW 03 and NW 01 or NW 04 and NW 02 in Fig. 4.7. This effect is explained by better absorption of losses by the banking system. For higher widely spread shocks, we can see a very strong increase of the external losses, which can becomes higher than in the case of an idiosyncratic shock with a same intensity.

Moreover, if withdrawals are possible, the external losses curve sharply increases at a certain value of the shock and decreases again from a higher degree of intensity of the shock. This curve shape relates to the case with low concentrated initial shock (NW 03) in the example presented in Fig. 4.7. We use the term "overshooting" to designate the range of the shock characterized by extraordinary high losses, which can be obtained in Fig. 4.7 for values of shock intensity between $\lambda \approx 0.07$ and $\lambda \approx 0.08$.

However, low concentration of the initial shock is not a necessary condition for such overshooting but makes this phenomenon more likely, which can be seen in Fig. 4.8, that presents the results for idiosyncratic and systematic initial events for several levels of bank capitalization.

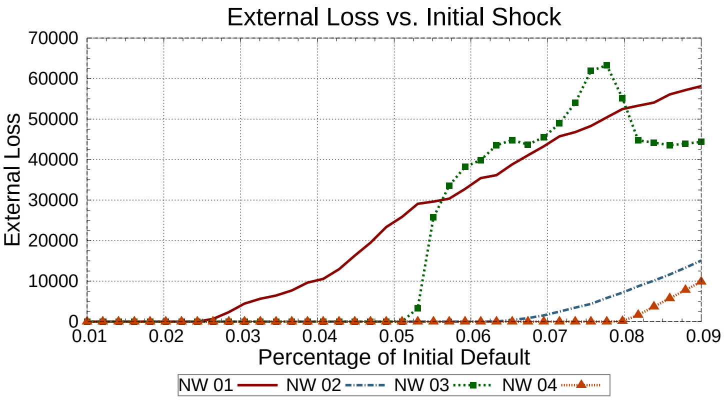

Figure 4.7: External losses in relation to the intensity of the initial shock. NW 03 shows an overshoot.
Parameter setting: see Fig. 4.5.

To understand the curve shape in the "overshooting range", we highlight the scenarios NW03 and NW04, which only differ with respect to liquidity risk reflected in withdrawal of deposits. Look at the development of the default rate in the banking system in the range between 0.07 and 0.08, presented in Fig. 4.5. The value $\lambda = 0.07$ means that 7% of loans to different external segments has been wiped out initially. As result, approximately 40% of banks go bankrupt if withdrawal risk does not exist (NW04), while $\lambda \approx 0.08$ corresponds

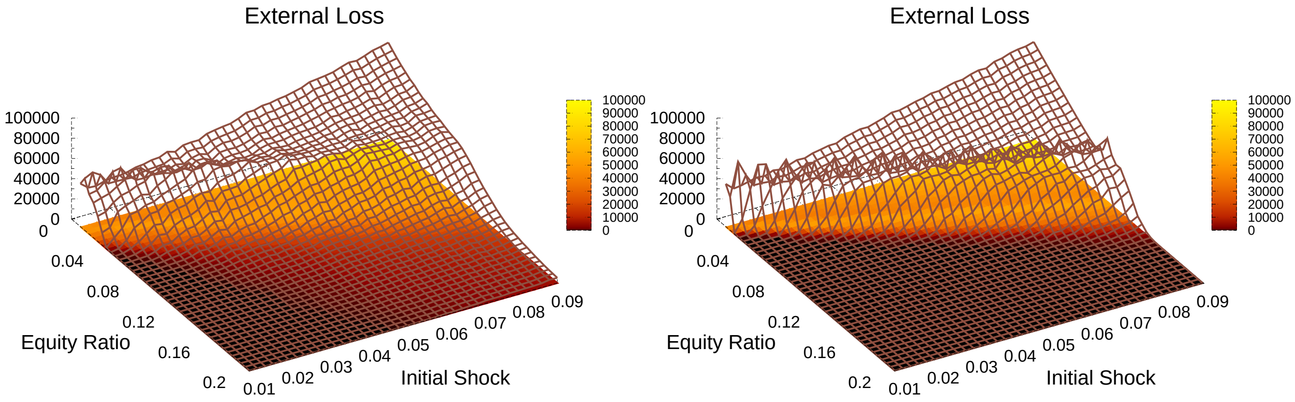

Figure 4.8: External losses in relation to the intensity of the initial shock in scenarios NW01 and NW03 with high (left) respectively low (right) concentration of the initial shock and deposit withdrawal risk.
Parameter setting: see Tables A.1 to A.3 in the appendix (A.1.1).

to the total collapse of the banking system even without withdrawals, meaning that all withdrawals in NW03 occur after the banking system collapsed due to the initial shock. This is because withdrawals start only after the (first) solvency chain reaction triggered by the initial shock has finished. The realized losses from the following fire sales will be transported to the remaining depositors. That is why the external losses are higher than in the case without liquidity risk.

The overshooting phase is then characterized by high degrees of affectedness of the banking system by the initial shock, which is, however, not high enough to trigger an immediate total collapse of the banking system. Two opposite effects play an essential role in the development of the external losses in this range. On the one hand, externals save parts of their capital withdrawing deposits. On the other hand, such actions generate further losses to banks and destabilize the entire system. External losses increase with an increasing amount of bank losses, which are transmitted to the external sector. With a further increase of the initial shock, withdrawals will be triggered earlier and on a larger scale, reducing the loss of deposits for their owner. The interplay of these effects leads to fluctuations or humps of the external losses, which can be clearly seen in Fig. 4.11 in the lower left part, that presents the results of an random simulation experiment.[8] Combination of two opposing effects (saving of external funds by withdrawal of deposits, and higher transfer of losses to externals due to the increase of bank losses) provides the alternate phases of upwards and downwards developments of external losses. Such fluctuations are irregular and depend on the network structure to a high degree. For sufficiently high shocks the curve shapes become more similar for all experiments showing a hump in the "overshooting range". The aggregated result of a number of simulation experiments shows then a moderate increase of the external losses at the beginning of

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[8] Fig. 4.10 show in an exemplary way the results for a single simulation run (with only one random network) NW03 for a better understanding of the network dynamics. The figures can be well used to consider single effects and the relationship between the losses to banks and externals and the development of withdrawals, for example. But, the results as whole depend significantly on the network structure. That is why a number of simulation scenarios will be used in general, and averaged results will be presented and analysed.

the range in which withdrawals occur, because of the compensating fluctuations (shifted humps) for different scenarios. At the end, the last hump is clearly visible even in the aggregated curve in Fig. 4.9 to the right, for example.

To the right of the overshooting range, all deposits will be withdrawn with a highest possible grade, after the total collapse of the system, minimizing the losses to externals. External losses increase then constantly with increase of the magnitude of the initial event, which is demonstrated in Fig. 4.10. Remember that the volume of the deposits which are withdrawn from a weak bank, with immediate effect, is determined as the difference between the current risk assets of the bank and the maximum risk assets that conform to the regulatory framework: $d_i^w = RA_i - e_i\gamma^r$, as presented in section 2.3.4. Furthermore, external depositors and other banks withdraw their deposits in proportion to their shares of the weak bank's refinancing. In this way the amount of withdrawn deposits is positively dependent on the remaining risk weighted assets of the weak bank and negatively dependent on the bank's equity. Both values are negatively dependent on the initial shock. If the initial shock is high enough, to the degree that the total equity of the financial system is exhausted even before withdrawals could happen, the amount of the withdrawn deposits depends only on the risk assets by formula. It decreases with an increasing intensity of the initial shock and relates to the increasing external losses in Fig. 4.10, lower right.

The pronounced growth of external losses at the beginning of the overshooting range can be explained as follows. The advantages for well capitalized banks, generated by profits from the purchase of assets at a price less than their face value, improve their own capital base reducing the deposit withdrawal risk and enabling these banks to purchase additional further assets.[9] Thereby, the necessary finance will be raised by central bank funding and not least by withdrawn deposits from seriously weakened banks. Thus, the better capitalized banks are able to use the freed up liquidity in this manner. However, at some point

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[9] A real devaluation of assets is not assumed in the model – losses to sellers will be considered as buyer revenue.

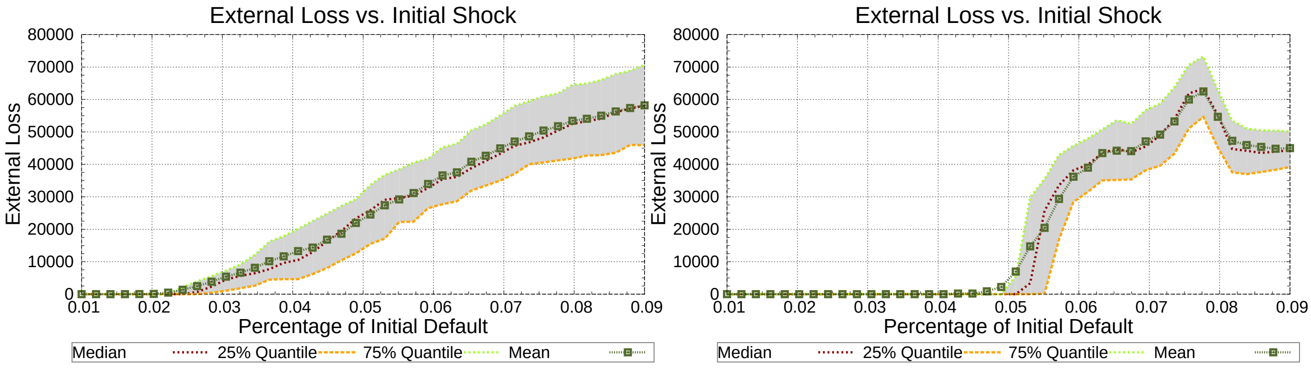

Figure 4.9: External losses in relation to the intensity of the initial shock in scenarios NW01 and NW03 with high (left) respectively low (right) concentration of the initial shock and deposit withdrawal risk.
Parameter setting: see Tables A.1 to A.3 in the appendix (A.1.1).

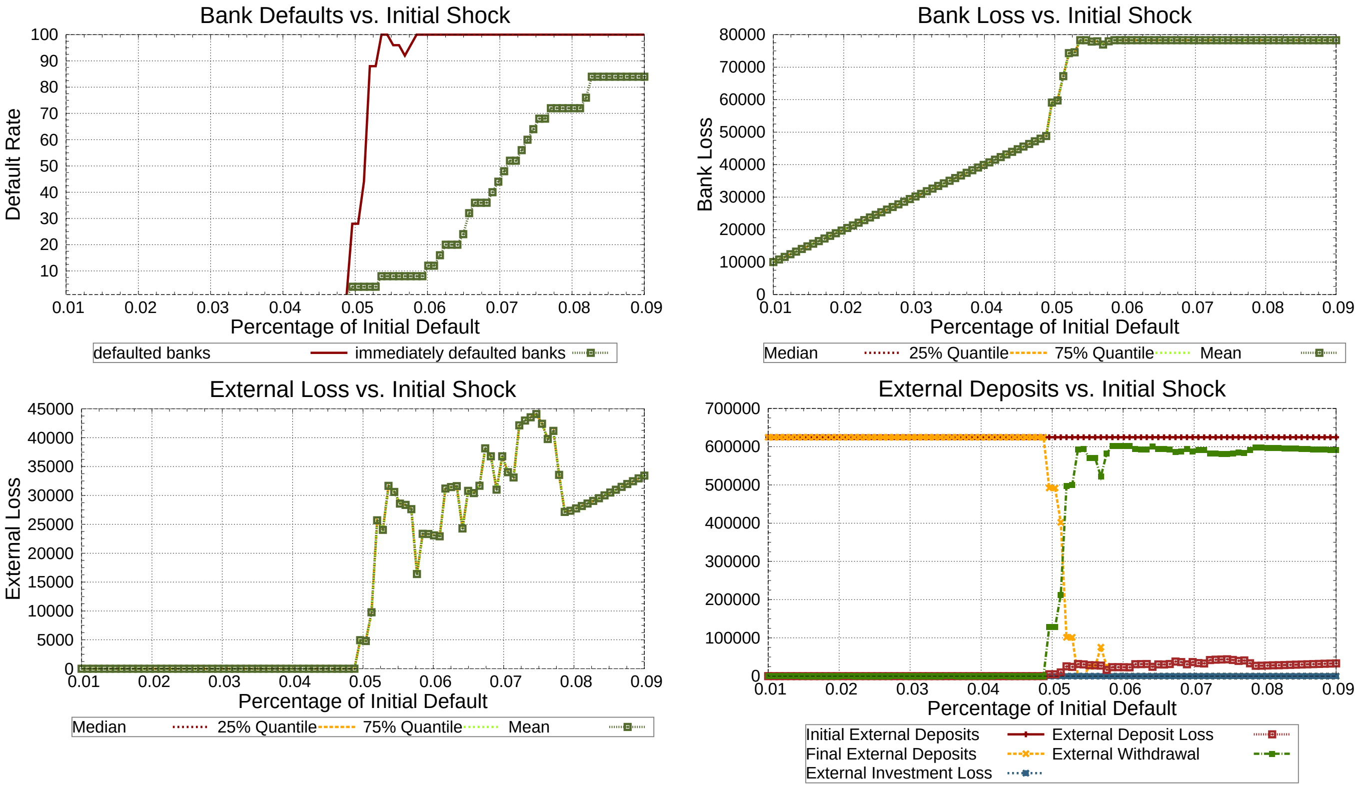

Figure 4.10: Development of losses and bank defaults in relation to the magnitude of the initial shock λ with low concentration of the shock and deposit withdrawal risk(NW03) - results at the end of a single simulation run for each value of λ.
Parameter setting: see Tables A.1 to A.3 in the appendix (A.1.1).

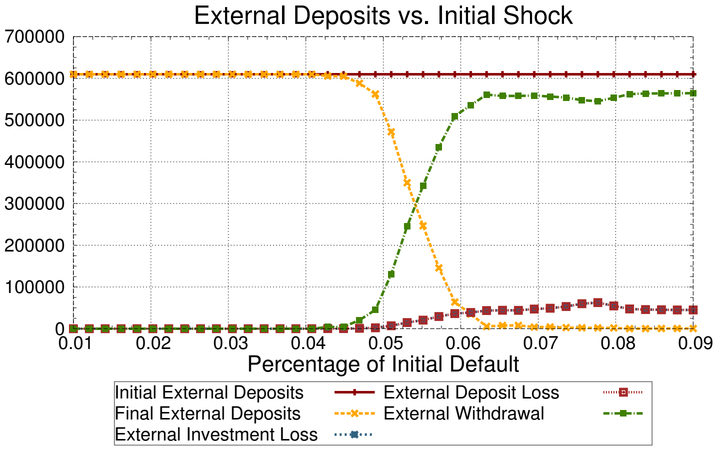

Figure 4.11: External deposits, losses and withdrawals in relation to the intensity of the initial shock in the scenario with low shock concentration and the withdrawal risk (NW03). *Parameter setting*: see Fig. 4.10.

of the dynamics, contagion in terms of solvency chain reactions will strongly affect even such initially lucky banks and trigger withdrawal of deposits from them. Because of the already severely weakened banking system and thus by absence of the absorption capacity for oversupplied assets due to capital requirements, the rapid drop in prices of the assets to be sold would consequently lead to losses to banks. Furthermore, because of the almost nonexistent or scarce interbank lending in the progress of the crisis, transmission of losses to externals may be very high and increasing with the growth of the initial shock. The effects responsible for the decrease or downward correction of the external losses in the right half of the overshooting range can be described as follows. The increasing initial shock deteriorates equity of banks, increasing external losses through transmission of bank losses, but forces the externals to rescue more deposits by withdrawal. In addition, the earlier intervention of the central bank becomes more likely, because of scarce banking resources available for oversupplied assets. External losses would decrease once again, when the positive effect (rescue of deposits) outweigh the negative impact (loss transmission). This decrease is substantially related to the increasing withdrawal of deposits in Fig. 4.10. From a certain degree of shock intensity, which is enough to completely destroy the banking system even without withdrawals, external losses increase again, but much more moderately than in the overshooting phase.

In order to underpin the argumentation above, the development of the (averaged) external losses and withdrawal of external deposits has been pictured in Fig. 4.11. It can be clearly seen, that withdrawal of deposits and external losses develop in opposite directions in the 'overshooting phase'. Moreover, the additional consideration of the final liability structure as in Fig. 4.4, reveals the following in the overshooting zone: the shape of the central bank lending curve is similar to the shape of the external loss curve. The mentioned slopes are in accordance with both effects described above: lower withdrawals correspond to the higher central bank funds due to the higher fire sale interbank trading. The correction zone of the overshooting phase is characterised by increasing withdrawals but decreasing external losses, accompanied by increasing purchase of external debts by the central bank.

Conclusion

We showed that a banking system is more resistant against systematic initial events than against the idiosyncratic shocks with the same magnitude in total, provided that the shocks are relatively low. With a further increase of the shock magnitude, a banking system may become more resistant against idiosyncratic events than against broader distributed shocks, transmitting more losses to externals, especially if banks are weakly interconnected. Resistance of a banking system is connected to two opposite effects: the positive one by sharing losses across banks, and the negative one that is connected to contagion. Liquidity risk aggravates the crisis and may rapidly crash the whole system, causing significantly higher costs. Moreover, in the case of a moderate shock and liquidity risk related to withdrawal of deposits, losses incurred by banks after an idiosyncratic initial event are generally significantly higher than after a systematic shock of the same magnitude. Furthermore, underestimation of systemic risk, particularly in the early stages of crises, may cause significantly higher losses for depositors. The fire-sale trading within the banking system is able to deepen a banking crisis and raise its costs.

Chapter 5

Risk-taking capability

In this chapter we focus on the initial equity level of banks and its impact on the ability of the banking system to withstand shocks. Further, we investigate the influence of the risk appetite of banks with regard to their risk preferences concerning credit risk investments.

5.1 Bank capitalization

Here we are assuming the same initial capitalization level for all banks, $\gamma_i = \gamma$. Further, we are using the risk adjusted calculation for the equity ratio as described in 2.3.2. From this point of view, capital ratios calculated as a percentage of bank capital to total credit risk assets of bank must be computed specifically for each bank in the presented model and depend on the individual asset structure. It should be pointed out here that the mentioned subjects will not only be discussed in this section but will continue to play a role in the following chapters. In particular, we will examine targeting capitalization for systemic important institutions and impact of risk adjusted capital in comparison with lump sum capital requirements.

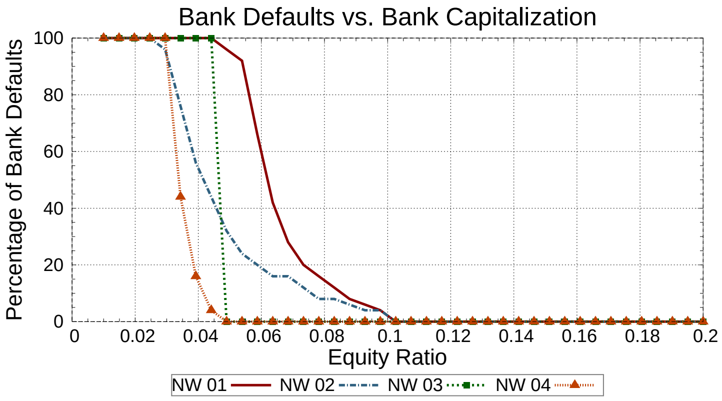

Figure 5.1: Resilience of the bank system in relation to the capitalization of banks γ. *Parameter setting*: see Tables A.1 to A.3 in the appendix (A.1.1).

The analysis here is based on the comparative experiments using the base line scenarios presented in Section 3.2 with variable initial equity rate of banks γ. Thereby, we quantify the equity ratio as a percentage of banks capital to its risk-weighted assets calculated as described in Section 2.2.1. We study the influence of bank capitalization when banks are affected by a more or less diversified initial shock, taking in consideration the risk of deposit withdrawals. We begin with the analysis of the impact on the banking system's stability by considering bank defaults.

Resilience of the banking system

Given that the number of bank defaults generally slows down with increasing equity rates. It is of little concern that bank capitalization is an important factor influencing the stability of banking systems. An interesting point here is that with decreasing equity, bank defaults occur much earlier but rise slower if the concentration of the initial shock is higher (see Fig. 5.1). The other aspect is that the increase in bank defaults is always higher if withdrawals of deposits happen. You can see this in Fig. 5.1 by comparing NW01 with NW02 or NW03 with NW04, for example.

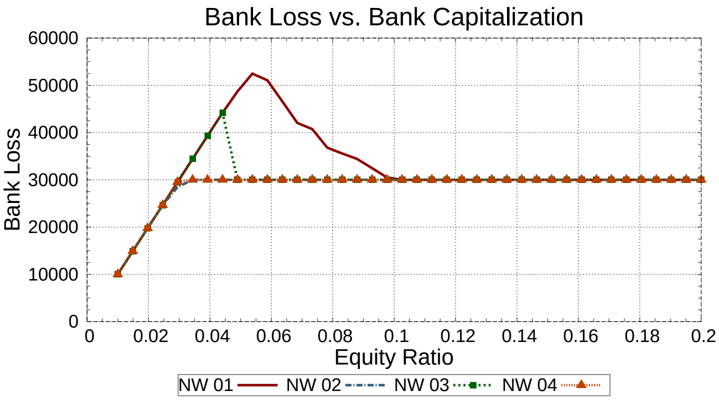

Figure 5.2: Cumulated bank losses in relation to the capitalization of banks. *Parameter setting*: see Fig. 5.1.

Bank losses

If the liquidity risk does not exist, the development of the cumulated bank loss is straightforward depending on the initial equity rate: the losses to banks increase with increasing equity rate until the initial shock can be totally absorbed by the banking capital. However, the dependence of bank losses on bank capitalization will be changed by withdrawal of deposits. So, bank losses increase above the value predetermined by the initial shock and begin to decrease after a certain level of equity (see Fig. 5.2). Cumulated bank losses decrease then until there are no deposit withdrawals, and remain constant at the level of the initial shock. The increasing slope corresponds to the increase of equity and presents therefore the loss restriction through the capital limit. The starting point for reversing the trend is given by the slowdown of deposit withdrawals corresponding to the increasing equity rate of banks. Further, without liquidity risk there is no visible impact of the shock properties on bank losses in total for the given parameter settings. But, if withdrawals happen the maximum of the losses incurred by banks in the case of an idiosyncratic initial event are significant higher than in the case of a systematic shock of the same magnitude.

The argumentation for this finding is based on the behavior of depositors, who begin to withdraw their deposits, when the capital level of any bank falls under a certain level. This occurs in the case of an idiosyncratic shock at a significantly higher level of the initial

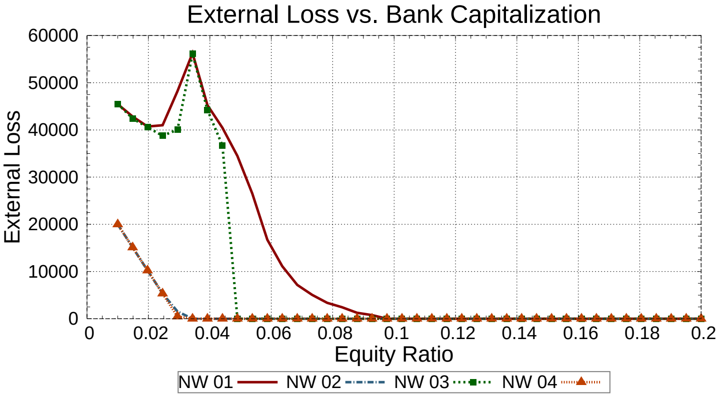

Figure 5.3: External losses in relation to the capitalization of banks. *Parameter setting*: see Fig. 5.1.

capital and with severe implications for banks as can be seen in Fig. 5.2) for NW 01.

External losses

The influence of bank equity in order to guarantee the security of deposits seems to be quite straightforward. A high equity ratio of banks should have a positive impact on externals, because more losses can be covered by banks and the likelihood of withdrawals is smaller. In the majority of cases, this presumption is likely to be true. However, when withdrawal risk exists, it can be seen that external losses depend on the (risk-adjusted) capital ratio of banks in a non-monotonous way. The downward trend of external losses with increasing capital will be interrupted at some relatively small equity ratio level by the phase of a sharp increase while the bank capitalization level continues to rise (see Fig. 5.3).

In the simulations presented here this phenomenon can be observed in scenarios NW01 and NW 03, where withdrawals are possible, that is, in the range where the shock with a given magnitude leads to an almost total collapse of the banking system. The argumentation here is very close to the description of the dynamics in chapter 4 with regard to the "overshooting range" and has to be only broadly outlined at this point. With increasing equity rate more and more banks may be spared from the total loss of their equity after

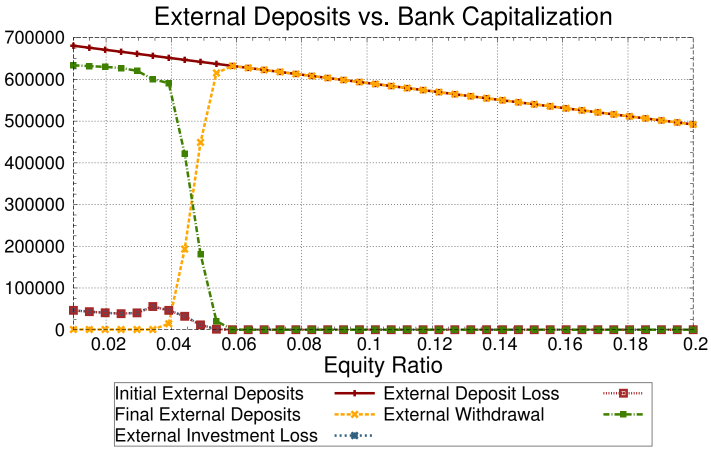

Figure 5.4: External deposits, losses and withdrawals in relation to the bank capitalization in the case of low concentration of the shock, high risk appetite of banks and deposit withdrawals (NW03).
Parameter setting: see Fig. 5.1.

the absorption of the initial shock, and some of them even remain well capitalized. More banks would avoid withdrawal of their deposits firstly and could be even able to purchase the fire-sale assets, gaining short-time profits from such acquisitions. At the same time, other banks on the sales side would consequently sustain losses, which would have to be transmitted because of the low or even absence of remaining equity. Eventually, the previously strong banks would be affected by the contagion, deposit withdrawal and massive equity losses.These losses arise from the fire-sale of recently acquired assets at very low prices due to the lack of demand.[1]

The final result of the described process deals with the massive transmission of losses to externals, which would be higher than at a lower initial bank capitalization. It is obvious, that this phenomenon is in line with the similar finding we analyzed in the previous section dealing with the initial shock magnitude. The initially hesitant reaction of depositors is responsible for their higher losses here.

The implications of the process just described here can also be seen in Fig. 5.4. In addi-

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[1] Remember, that the demand for assets depends on the bank capitalization because of the regulatory capital requirements.

tion, Fig. A.1 shows in an exemplary way the results for a single simulation scenario for each parameter setting using the same network. The phase of increasing external losses corresponds to decreasing deposit withdrawal. After a certain threshold, further increase of the equity rate weakens the deposit withdrawal rate, which first leads to increasing losses to externals. But then, lower withdrawals diminish the contagion. Further increase of capital improves the resistance of banks and reduces losses to externals. The inverse relationship between bank equity and external losses is then restored again. If the equity rate is high enough, further increase of initial bank capital does not have any influence on the losses to externals, because losses to banks can be fully covered by their equity and no loss transmission takes place.[2] The existence of such "overshooting range" is more likely, if the initial shock is more diversified, but also possible in other cases, which can be seen in Fig. 4.8. Moreover, the level of bank equity, where this phenomenon can be obtained, depends on the intensity of the initial shock: the higher the shock, the higher the bank capitalization level should be to see the described "overshooting".

Conclusion

It could be shown that bank equity normally has positive effects on resilience of the banking system and external losses. But if loan losses are able to trigger the nearly total default of the bank system, a moderate increase of the equity rate may lead to higher losses to external customers because of deposit withdrawals. Much more effective recapitalization of banks is necessary in this case to stabilize the banking system and to reduce the risk of further external losses happening.

5.2 Risk appetite of banks

Risk appetite of banks in the ABN-Model is determined by risk preferences of the bank-

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[2] Note, that the initial external deposits decrease with increasing equity, because of the consequently increasing bank capital together with a constant volume of assets, that needs to be financed.

ing sector with respect to their initial investments. As described above, banks do not keep all external credit assets. One part of debts may be securitized as covered bonds and collateralized debt obligations and marketed to other banks and externals thereafter. The claims issued against the CDO collateral pool are prioritized by creating different tranches of securities, see 2.2.5. As presented there, the risk appetite of banks is determined by exogenous parameters β_t^{CDO} with $t \in \{A, B, C\}$ and β^{CB}, as a percentage of bank investments to the total volume of the securities in the entire system. Hence, the increase of the risk appetite of banks can be simply permuted by increasing β_C^{CDO} and decreasing β^{CB}, for example. Because all generated assets must be initially purchased by only banks and externals, low risk appetite of banks would mean high risk appetite of externals and vice versa. The baseline scenarios assume relatively high risk preferences of banks: banks invest only in the two highest risk tranches of CDOs, whereas externals purchase CB and shares of the lowest risk CDO tranche (A), see table A.3.

However, by varying the mentioned β-parameters not only the risk content of banks investments will be changed in the model, but also the allocation of the amount of investments between banks and externals can be influenced. To avoid such unwelcome side-effects, we slightly adjust the model with regard to the initial allocation of the investments in order to neutralize the effect of the external deposits and to separate the pure risk appetite effect. We do not determine β_C^{CDO} and β^{CB} exogenously, but calculate them in dependence on the current risk preferences, which can be high or low, but also in dependence on the total volume of each tranche, and on the percentage of investments ϑ carried out by banks. In the case of low risk preferences, for example, banks will initially hold a ϑ %- stake in total CB and CDO, optimizing their portfolio to be as low-risk as possible. As a consequence, we modify the base-line examples NW01-NW04 for high and low risk appetite of banks, so that the amount of investments remains at the predefined level for both, banks and externals, regardless of the risk allocation between them. In the example to be analyzed now, the allocation of the investments is given by equal amounts of investment for both sectors, $\vartheta = 0.5$, with the difference that banks prefer the most risky tranches in the case of them having a high risk appetite (HR) and CB and CDOs with a risk as low as possible in the opposite "low risk"- case (LR). For the given parameter setting, the following values have been calculated and used in discussed examples:

Bank shares	**CB** β^{CB}	**Tranche A** β_A^{CDO}	**Tranche B** β_B^{CDO}	**Tranche C** β_C^{CDO}
LR (low risk)	1	0.74	0	0
HR (high risk)	0	0.26	1	1

Table 5.1: Investment risk parameters: β_t^{CDO} as percentage of interbank investments to the total volume of investments for each tranche of CDO $\forall t = \{A, B, C\}$ and β^{CB} for investments in covered bonds (CB).

The results of these experiments are shown in Figures 5.5 to Fig. 5.11 for increasing magnitude of the initial shock represented by an increasing external credit default rate, and in Figures 5.6 to Fig. 5.12 for an increasing equity rate of banks. The differences between the scenarios with a focus on risk appetite of banks will be discussed in the following section. For an explanation of the curve shapes we would like to refer to chapter 4 and section 5.1, where the impacts of initial shocks and capitalization of banks are discussed.

Resilience of the bank system

Figures 5.5 and 5.6 present results for eight simulation experiments based on the base line scenarios for the two opposite risk preferences of banks as described above. With respect to the risk appetite of banks, its negative influence on the stability of the banking systems might be generally expected. Therefore, it is of little relevance that bank defaults are generally higher for higher risk appetite banks. Nevertheless, a remarkable reverse of this impact in the presence of withdrawals should be noticed here, especially when banks are differently affected by the initial shock. In such a case the bank default rate can be higher at lower risk appetite, as can be seen using the scenarios NW01 LR with NW01 HR

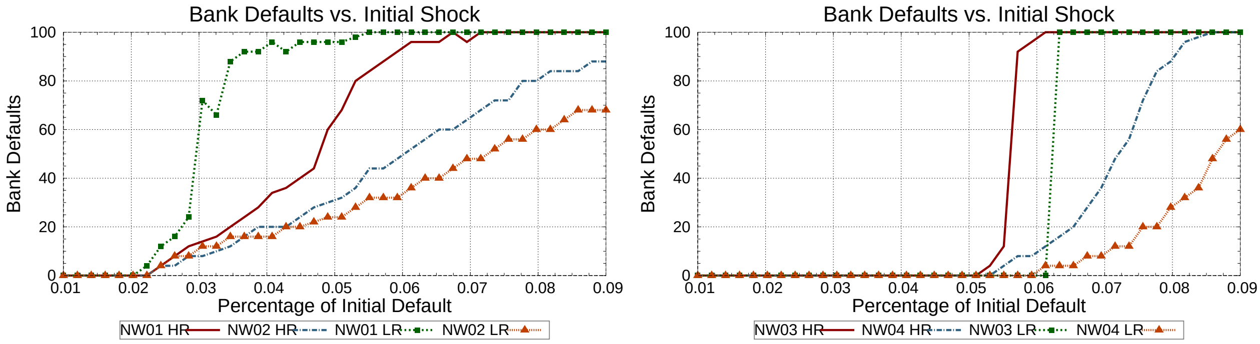

Figure 5.5: Bank defaults in relation to the intensity of the initial shock λ in scenarios with high (left) and low (right) concentration of shocks.
Parameter setting is similar to the base-line scenarios with the exception of the investment risk parameters. The later are specified in Tab. 5.1 for high (HR) and low risk (LR) of banks, respectively. For the remaining parameters please refer to the appendix (A.1.1).

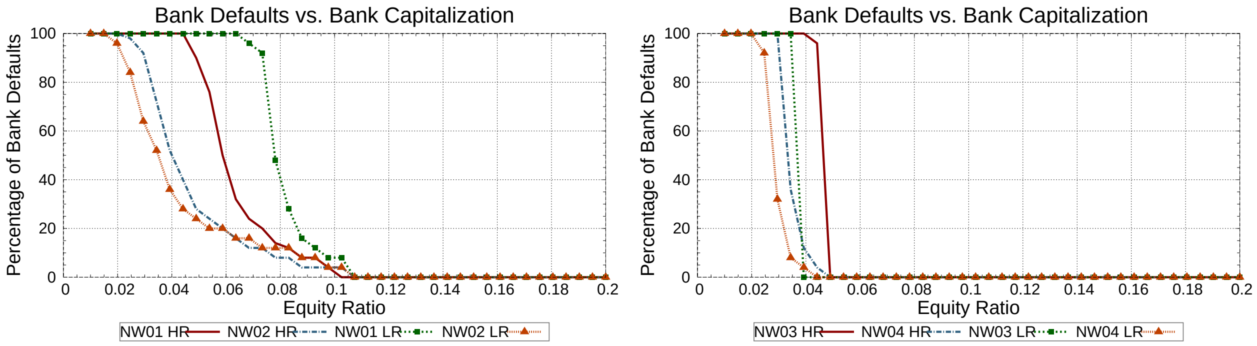

Figure 5.6: Bank defaults in relation to the capitalization of banks γ in scenarios with high (left) and low (right) shock concentration.
Parameter setting: see Fig. 5.5.

by comparing the full red line, representing the higher risk appetite, against the dashed green line with dots for the lower risk appetite of banks, see Fig.5.5 and Fig.5.6 on the left. We will intensively discuss this phenomenon with regard to the bank losses.

Bank losses

Generally, the cumulated bank loss is higher for higher risk appetite banks, which can be explained by two effects. Higher risk appetite of banks implies their stronger affectedness by the initial shock, firstly, and corresponds to the higher shock absorption due to the risk adjusted capital, secondly.

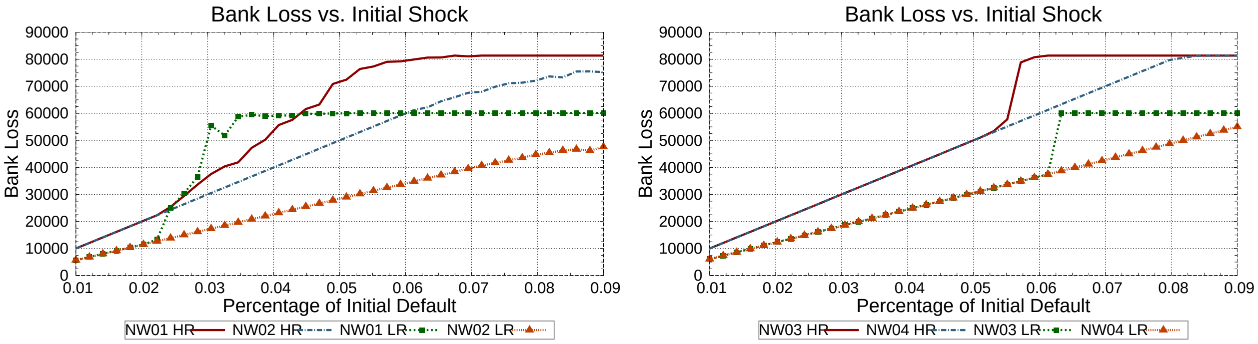

Figure 5.7: Cumulated bank losses in relation to the intensity of the initial shock in scenarios with high (left) and low (right) concentration of shocks.
Parameter setting: see Fig. 5.5.

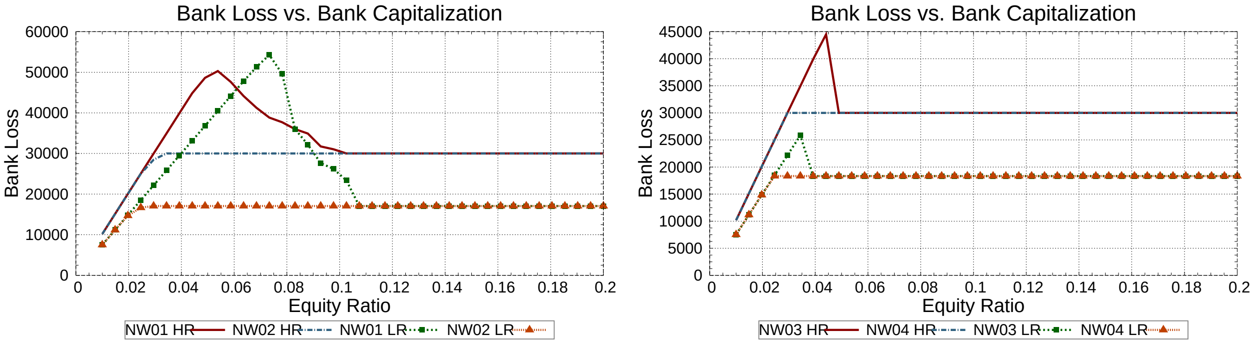

Figure 5.8: Cumulated bank losses in relation to the capitalization of banks in scenarios with high (left) and low (right) concentration of shocks.
Parameter setting: see Fig. 5.6.

Nevertheless, for moderate [3] idiosyncratic shocks, higher bank losses can be obtained for lower risk appetite of banks if withdrawal risk exists, as can be seen in Fig. 5.7 and Fig. 5.8 on the left. This phenomenon can be explained by a faster collapse of the banking system caused by withdrawal of deposits in the example NW01 LR because of the lower absolute capital level. Now let's look at this impact in greater detail. For the small shock values which are not strong enough to trigger withdrawals, higher losses for riskier banks are obvious, because of high risk assets, which are affected by the initial shock firstly. For higher magnitudes of the idiosyncratic initial shock, the higher capital buffer of riskier

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[3] with respect to the bank capitalization level

banks could mitigate the negative effect of withdrawal of deposits. Note, that if the shock is idiosyncratic, only part of high-risk assets will be affected by the shock. Thus, riskier banks could possess a higher capital buffer even after the shock absorption, especially when banks are well capitalized initially (above the regulatory requirements). By this, (absolutely) better capitalized and initially less affected banks are more likely to remain more stable in the case of higher risk initially, on condition that the initial shock has been highly concentrated. In this case we see, that some a-priori more risky tranches of CDO no longer cause the losses to banks if their underlying assets are not affected initially.[4] However, because of the relatively high capital requirements for all a-priori high risk assets, the corresponding banks would have much more equity buffer to withstand the shocks and losses from contagion and even to buy the fire-sale assets. Some banks could even make profits out of the fire-sales, buying assets at reduced prices from badly affected banks if withdrawals take place. Thus, the negative impact of deposit withdrawal could be smaller if banks were more inclined to high risk activity, a-priori.

Intensity of deposit withdrawals in both cases can be observed in Fig. 5.9, where the decrease of external deposits and the increase of withdrawals with increasing initial shock are steeper for lower risk appetite of banks. Furthermore, the higher external losses can be observed in this case, which are higher not only because of the riskier external investments, but also because of the higher loss transmission from the banking sector, due to the lower capitalization of the banking system and higher impact of the liquidity risk. Moreover, the higher capitalization of banks leads to higher prices for fire-sale assets due to the higher demand, in particular, as long as not too many banks are affected initially. As a consequence, lower losses to selling banks or even profits of better capitalized banks would be obtained by the favorable purchase of the assets. Furthermore, the idiosyncratic shock causes higher transmission of losses to externals, especially if banks are weakly

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[4] Loans to the real estate segment and accordingly CDO based on real estate credit risks, for example, could be strongly affected, while other investments remain relatively intact, even with respect to high risky tranches, if the crisis is confined to the only real estate segment. Banks which hold strongly affected credits and securities will be more shocked, than those that do not.

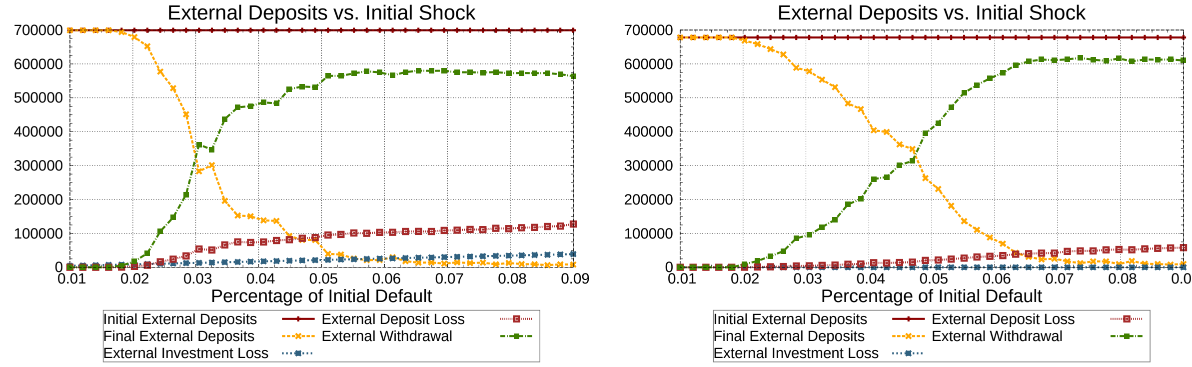

Figure 5.9: Development of external deposits and losses in relation to the intensity of the initial shock in the case of the high concentration of shocks and liquidity risk (NW01), modified by low (left) and high (right) risk appetite of banks.
Parameter setting: see Fig. 5.5.

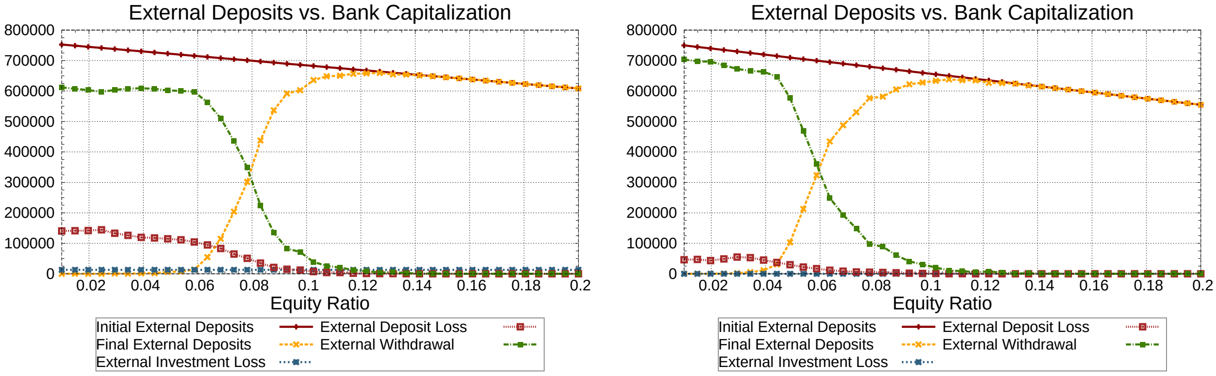

Figure 5.10: Development of external deposits and losses in relation to the capitalization of banks in the case of the high concentration of shocks and liquidity risk (NW01), modified by low (left) and high (right) risk appetite of banks.
Parameter setting: see Fig. 5.6.

interconnected. These effects would reduce the negative impact of withdrawals and the number of defaulted banks. This also explains why we obtain this phenomenon more clearly if withdrawals are possible as well as the concentration of shocks and the initial equity rate are relatively high. [5]

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[5] Lower external deposits in Figures 5.9 and 5.10 in the high risk scenarios correspond to the higher equity and thus the lower refinancing of banks via external deposits. This effect is too small to be considered here in greater detail.

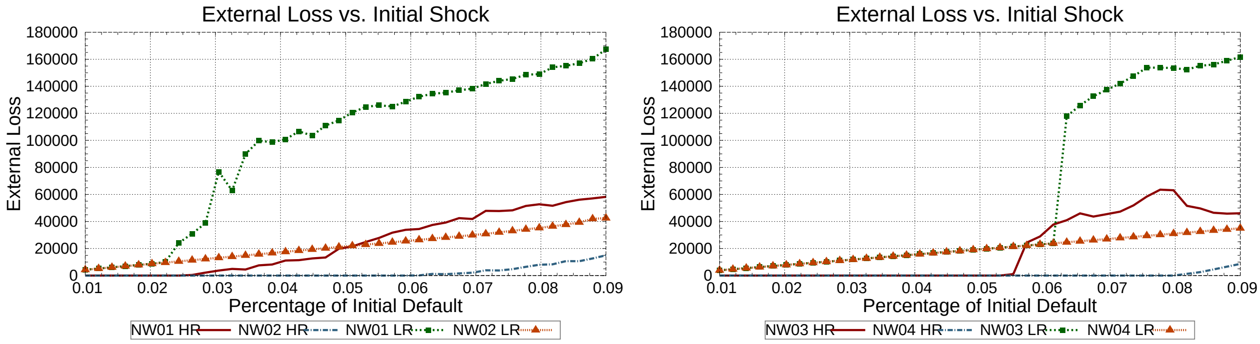

Figure 5.11: Cumulated external losses in relation to the intensity of the initial shock in scenarios with high (left) and low (right) concentration of shocks.
Parameter setting: see Fig. 5.5.

Note, that even if the banking system is less stable for values of the initial shock less than 7% in the case of NW01 LR compared to NW01 HR, cumulated bank losses are higher only in part of this range. On the left side, for small shocks, where neither withdrawals nor contagion play any role, the lower bank losses in the case of lower risk appetite are connected to the lower losses from investments. On the right side of the intervals, bank losses are limited by the total equity of banks, which is higher in the case of banks' higher risk appetite.

External losses

At this point, it is advisable to take a glance at the losses to externals for the same scenarios. Generally, the higher risk appetite of banks corresponds to lower losses to externals, because the predominantly lower-risk investments of the external segment, which can be seen in Fig. 5.11 and Fig. 5.12. [6] In the case without liquidity risk, the difference between low and high risk of banks increases with increasing capitalization of banks until no transmission of losses to them occur, while the external losses decrease. The impact of bank capitalization on externals is higher if banks face higher risks, which is at a trivial level. However, the existence of liquidity risk can change this claim: the increasing equity

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[6] Remember, that a higher risk appetite of banks corresponds, ceteris paribus, to a lower risk appetite of externals by model, because the asset structure remains unchanged.

rate scales down the impact of the risk appetite, which is significantly higher than in the case without withdrawal of deposits for low levels of bank capital. This can be seen by comparing results for scenarios NW03 LR with NW03 HR or NW01 LR with NW01 HR. In any case, the low risk appetite of banks could prevent losses to externals after a systemic initial shock. We can see that in Fig. 5.11 and Fig. 5.12 on the right hand side before and after the smooth red line crosses the green line. This finding is connected to the claim, that the banking system remains more stable for low risk appetite of banks until some magnitude of the systemic shock or bank capital ratio is reached. The explanation is the higher potential of contagion, which occurs earlier with decreasing equity rate when banks are higher risk takers and broadly affected by the shock: A lower magnitude of the initial shock is sufficient to trigger the withdrawal process in the case of higher risk banks if the initial shock is highly diversified. Hence, the banking system is collapsing faster than in the similar case with a lower bank risk. We can learn from this case, that even if banks assume the main risks arising from credit investments, externals may suffer higher losses than by taking more risks initially. This observation underlines the importance of the right mechanisms preventing the loss of trust in the banking system during the financial turmoil.

Conclusion

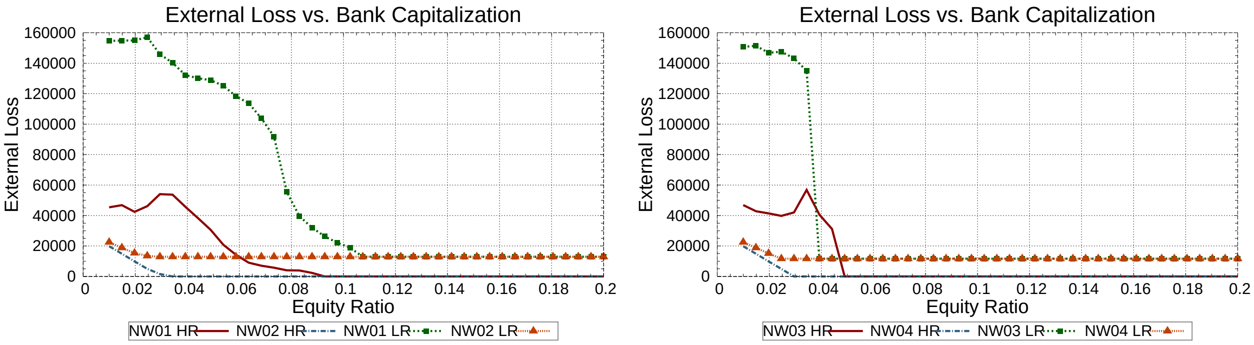

Figure 5.12: Cumulated external losses vs. capitalization of banks in scenarios with high (left) and low (right) concentration of shocks.
Parameter setting: see Fig. 5.6.

While the higher risk investment is connected to higher losses to banks, in general, we could show the inverse relationship for moderate idiosyncratic shocks if withdrawal risk exists: the higher absolute capitalization of riskier banks may be able to prevent defaults and partially losses to banks by reducing the deposit withdrawals.

The moderate intensity of the initial shock, compared to the bank capitalization, is an important condition for this phenomenon: If the banking system is affected too strongly initially, the advantage of less affected banks would rapidly become eroded by the following contagion dynamics and deposit withdrawal processes. Furthermore, the described benefit could also disappear if risk adjusted capital requirements are not differentiated enough.[7]

Generally, we observed lower losses to externals if banks hold more risky assets, especially if withdrawals can be prevented. But in the case that withdrawals occur, higher risk of banks may lead to higher losses to external deposits for a moderate magnitude of the initial shock, especially if it is widely distributed across the bank sector. We explained this finding by a stronger withdrawal effect in the case of more risky banks.

We should recognize, of course, that the described advantage of riskier banks is the property of an 'illusionary' system stability, which could be quickly destroyed by further dynamics or shocks in the system. This is one of the curious phenomena, which is important to remember and needs to be known before drawing any conclusions from empirical data. Otherwise, a distorted perception of stabilizing bank properties could be derived from empirical analysis of the financial crisis and lead to an incorrect assessment of the systemic risk and misguided political and economical decisions. The existence of more such phenomena together with problems of data quality and data completeness in the world of the complex financial systems should not be underestimated.

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[7] It would be interesting to see the effects of conditions that the underlying pools of asset backed securities are extremely mixed, banks are more homogeneous in terms of diversification of credit risk assets or extremely interconnected, which can be seen as a topic for further investigation.

The very nature of the banking business is to assume risks, which should be undertaken in a responsible manner. We have shown that contagion effects and especially withdrawal of deposits could lead to high losses to non-financial segments, even if banks are willing to accept greater risks, even if the granting of credit remains unchanged and only the reallocation of risks between bank and externals has been obtained. Thus, we all should have a natural interest in warning banks against taking on too much risk, especially because in the real world, the risk would not be exogenously given, but could be additionally created by banks through the irresponsible lending, for example. So not only the allocation of risk should be considered but also the incentives for high risk generation must be an issue of the management, limitation and monitoring of systemic risks.

Chapter 6

Network structure

The topic of this chapter is the impact of network properties on financial stability. The most prominent question in the related literature concerns the degree of connectivity and heterogeneity of the banking system. Although the issue has been analyzed several times, it is yet to be finally clarified. Instead, the contradictory statements raise further questions about the interplay of the connectivity and other network properties and their collective relevance and influence on dynamics and the resistance of the financial systems to shocks. Differences between the results of related studies exist due to the differences in network structures, contagion mechanisms and further dynamic processes or determination of shocks. These differences emphasize the importance of data collection in the financial sector, since the possibility and extent of contagion depend obviously not only on model specification but also on the precise structure of the network. Moreover, further efforts in the direction of empirical and theoretical studies are necessary, to understand and to explain the "financial contagion" processes.

In this chapter, firstly we provide a brief overview of previous findings from the most relevant literature related to this thesis. Thereafter, we will present and discuss our own research results. Thereby, analyzing the impact of various network properties and their interaction in terms of financial stability, contagion effects and distribution of losses in the system. Amongst others, we investigate to what extent the results discussed in the literature hold in the simulation experiments by using the asset based approach, presented in chapter 2.

Section 6.2 analyzes the impact of network interconnectivity. In section 6.3 we take a look at the bank size by varying the network size using the randomly distributed external credit exposures and interbank lending links. In section 6.4 more heterogeneous network structures such as core-periphery networks will be discussed.

6.1 Previous results

The connection between the structure of the financial system and systemic risk or contagion processes is one of the most interesting questions in modern financial network research. As earlier theoretical works Allen and Gale (2000) [4] and Freixas et al. (2000) [28] should be mentioned at this point as important contributions to the analysis of contagion in financial systems through credit interlinkages among banks. The aforementioned papers provide interesting insights analyzing very simple networks with a small number of banks. For example, they showed that network structures, in which all banks are completely interconnected, are much more stable than network structures, in which banks are partially interconnected. Further, the authors demonstrate that disconnected network structures with separate internal clusters are more vulnerable to contagion than perfectly interconnected networks, while at the same time such structures would avert a total collapse of the interbank network through their separation. One further insight of the mentioned work is that in some structures the possibility of contagion depends on the parameter settings in the models.

The evidence from the financial crisis that started in 2007 has amazingly shown that

the breakdown of a relatively small segment can not only spread to other segments but also push the system into great financial and economic distress. Moreover, this event may have a worldwide impact due to the integration of capital markets. Some of the post-crisis literature has tried to identify conditions under which an increase of network density is not beneficial, i.e. does not reduce systemic risk. In several works it has been pointed out that the relationship between connectivity and systemic risk is not monotone.
In the following sections we give the review of the post-financial crisis literature which addresses the issue of network structures and their impact on the systemic risk. We present the literature in a topically organized structure, according to the importance for the analyses in this dissertation.

We begin with the works focusing specifically on the degree of connectivity and its impact depending on the initial level of interconnectedness of banking systems and magnitude of the initial event.
Nier et al. (2007) in [53] and Battiston et al. (2009) in [6] showed that for different levels of connectivity systemic risk can increase or decrease with a further increase of connectivity, but they found the opposite results in terms of the pattern of the interdependence between the level of connectivity and the fragility of the banking system. Nier et al. (2007) simulated contagion from the initial shock caused by a single bank failure using an Erdös-Rényi random network and showed that, when the initial connectivity is low, an increase in connectivity increases the risk of contagion, but when connectivity is already high, a further increase in connectivity tends to help dissipate losses across the system which renders it more resilient to contagion. Furthermore, they pictured this nonlinear relationship between contagion and connectivity, showing the dependence between the number of interbank lending links and the number of bank defaults, as a non-monotonic M-shaped curve. The authors explained this result by the action of two opposing effects with the following interpretation: *"When the level of connectivity is low, an increase in the number of links increases the chance of contagious defaults. However, when connectivity is already high, a further increase in the number of links increases the capacity of*

the system to withstand shocks.", Nier et al. in [53].
Also Battiston et al. (2009) in [6] investigate the effect of the network connectivity on the probability of individual defaults of financial institutions and identified two competing effects of increasing connectivity. Contrary to Nier et al. the authors found that the relationship between connectivity and systemic risk decreases if the degree of connectivity is (relatively) low and increases when it becomes high.
Acemoglu et al. (2015) have arrived at the conclusion that only given a sufficiently low magnitude and a small number of negative shocks, a more equal distribution of interbank liabilities leads to a less fragile financial system. So the complete financial network, in which the liabilities of each institution are equally held by all other banks, seems to be the least susceptible to contagion defaults. The intuition provided in the literature is that a more equal distribution of interbank liabilities guarantees the sharing of losses among more counterparties. In the presence of relatively small shocks, the excess liquidity of the non-distressed banks can be utilized preventing further failures of banks, see [1]. Moreover, Acemoglu et al. (2015) suggested that, in the presence of large shocks, interbank liabilities facilitate financial contagion and create a more fragile system; more financial interconnections are no longer a guarantee for stability. Which means that, when the magnitude or the number of negative shocks crosses certain thresholds, the types of financial networks that are most prone to contagious failures change dramatically. The implication is that, with large negative shocks, the excess liquidity of the banking system may no longer be sufficient to absorb the losses. In such a case, less interbank connections protect the rest of the system, see [1].

Some papers are dedicated to the impact of connectivity on the banking system stability, depending on its capitalization level and the credit risk diversification of banks.
Nier et al. (2007) studied the interplay between connectivity and net worth in terms of banking system resilience and found "*a negative nonlinear relationship between contagion and the level of bank capitalization: in undercapitalized networks, increasing connectivity increases the risk of contagion whatever the initial level of connectivity is*". The authors

showed that these effects interact with the level of capital in the sense that *"...for less capitalized systems, an increase in connectivity tends to be associated with an increase in contagious defaults, while for better capitalized systems connectivity tends to work as a shock absorber, dissipating the effect of the shock across a larger number of banks, each able to withstand the shock"*, see [53].

Cont and Moussa (2010) in [13] studied a specific case of powerlaw network based on a scalefree simulation. The authors noted thereby a similar direction of the results to Nier et al. (2007): *"in well-capitalized networks, increasing connectivity is found to increase significantly contagion up to a certain threshold above which a further increase in connectivity leads to a decrease in the extent of contagion. However, in undercapitalized networks, increasing connectivity makes the network more prone to contagion whatever the initial level of connectivity is."* Further, Cont and Moussa (2010) have found in [13] that contagion is very sensitive to the network structure properties and especially to the level of connectivity and concentration. They observed a trade-off phenomenon in the network between increasing the potential channels for the propagation of financial distress and the stabilizing benefit of risk sharing when connectivity increases. Moreover, the authors underlined that more heterogeneous networks in terms of heterogeneity in degrees and exposures are more resilient to contagion.

Similar results were found by Hofmann de Quadros et al. (2014) in [37], who analyzed various types of interbank networks being considered in a differentiated manner according to the concentration of debts and credits for their resilience to contagion. Thereby they tested the effect of connectivity in conjunction with variation in concentration of links. The results suggested that more connected networks with high concentration of credits are more resilient to contagion than other types of networks analyzed.

In contrast, Gai, Haldane and Kapadia (2011) presented a network model of interbank lending in [32]. They illustrate how greater complexity and concentration in the financial network may amplify this fragility.

Battiston et al. (2012) in [7] explored the mechanisms that, following the default of an agent, may lead to an increase of systemic risk when connectivity increases. The authors construct a network of borrowing/lending relationships among financial institutions based on their balance sheets. They investigate how the size of the default cascade is affected by the initial distribution of robustness and by the level of risk diversification in the network. As a result of this study, the effect of diversification is not unique. The precise outcome depends crucially on the allocation of assets and liabilities across agents and the exposure structure. It could be shown that credit risk diversification has ambiguous results, especially in the presence of credit runs. The authors underlined that the benefit of sharing initial losses is counterbalanced by the fact that banks are more exposed to credit runs when the number of their counterparties increases.

In many works the authors show that the possibility for contagion depends on the precise structure of the analyzed network.
G. Iori et al. (2007) explored the network of interconnections among banks in the Italian overnight market by using data from the European electronic online market for interbank deposits (e-MID) and by applying several metrics derived from computer science and physics, uncovered a number of microstructure characteristics in [39]. The data set to be analyzed has been composed of banks operating in the Italian market for which the complete record of transactions was available. The authors characterized the banking system as highly heterogeneous with large banks borrowing from a high number of small creditors.

Bech and Atalay (2008) analyzed the structure of the federal funds market in [8] and represented it as a network, using a transaction-level data set (1997-2006). They also found out, that the considered network is sparse and disassortative. Moreover, the authors observed the small-bank large-bank dichotomy of the federal funds market, with small banks lending funds generally to larger banks. This phenomenon reflects that smaller banks, rather than transacting with each other, typically use a small set of money center banks as intermediaries, according to Craig and von Peter (2014) in [15].

Some of the related literature of the past few years addresses the question of core-periphery networks, which are able to fit the described properties of real networks in a very good way. For the references and descriptions of most related literature we refer to section 6.4.2.

One further question concerning the network properties is, whether the bank size is typically an important driver of systemic risk measures.
Lengnick et al. (2013) analyzed the impact of interbank lending on the stability of the financial sector via an agent-based computational economic (ACE) model that covers the monetary side of transactions among households, firms and banks. The authors showed that the banking sector is more stable if it is composed of equally sized banks. By contrast, the existence of large banks creates endogenous instability. As a consequence, the authors recommended that the regulatory policy should be more restrictive for large banks compared to the smaller institutions, see [44].
In [66] Varotto and Zhao (2014) analyzed systemic risk for US and European banks from 2004 to 2012. They recognized that common systemic risk indicators are primarily driven by bank size and draw attention to the fact that smaller banks may still pose considerable systemic threats. To confirm this statement, the authors mentioned the Northern Rock bank, which had been facing several liquidity problems as a result of the credit squeeze which started in 2007 and was finally put under state control. Furthermore, they showed that the ranking of most systemically important banks based on the 'too big- too fail' - approach enables them to identify, 9 months before the Lehman default, the most systemically important US banks that later either defaulted and/or were acquired by competitors or received the largest government sponsored rescue packages. Moreover, several studies show that different systemic risk indicators do not necessarily give consistent conclusions. It is particularly true concerning the different points in time that correspond to different phases of the same crisis or different types of crises. Furthermore, the results seem to be strongly dependent on characteristics of the financial network being studied. Varotto and Zhao (2014) showed for example in [66] that characteristics of a banks balance sheet can help to forecast its systemic importance. The authors noted that the systemic risk of the US and European banks appears to be driven by different factors.

However, it became the subject of a controversial debate, whether the bank size is suitable to identify the systemic important institutes and which systemic risk indicators fit better. The critical response to this is that large banks could create more systemic risk, even without being individually riskier. Laeven et al. (2014) try to provide an economic foundation for the debate on bank size, as well as on activities and complexity of large banks, using data from 52 countries in [42]. The authors focused on the question, whether there is evidence that large banks are riskier or create more systemic risk than small banks. Laeven et al. (2014) noted for example, that failures of large banks tend to be more disruptive to the financial system than failures of small banks. Anyway, large banks were in the epicenter of the current financial crisis, triggered by the collapse of the Lehman Brothers investment bank in September 2008. Their distress caused substantial damage to the real economy and continued to fuel the downward spiral. Empirical analysis by Laeven et al. (2014) showed that large banks may have a more fragile business model, with higher leverage and more market-based activities, than small banks. The authors summarized *"...large banks, on average, create more individual and systemic risk than smaller banks, especially when they have insufficient capital or unstable funding (fewer deposits), which are both common features of large banks. Additionally, large banks create more systemic risk (but, interestingly, not more individual risk) when they engage more in market based activities as measured by the share of noninterest income in total income or the share of loans in assets; or are more organizationally complex."* More specifically, Laeven et al. (2014) ask which characteristics of large banks, like size per se, lower capital, less-stable funding, more market-based activities, or higher complexity, determine more risk. Thereby, the authors focus on two dimensions of bank risk: individual bank risk, measured through the banks stock performance during the 2007 - 08 financial crisis; and the banks systemic risk contribution in the sense of how much the bank contributes to system-wide distress. The authors noted that *"...systemic risk contributions differ from individual bank risk, because they are driven also by correlations in returns between the bank and the financial system, and by bank size. It is the measure of bank risk most relevant to systemic risk (macro-prudential) concerns."* In the light of the empirical examinations made by Laeven et al. (2014) bank size per se seems to be substantial for the individual as well as for the systemic risk.

With respect to the individual risk, the economic effects of *size, capital, and funding* on bank risk are substantial due to the analysis mentioned. Systemic risk analyzed by Laeven et al. (2014) can be roughly described as the externalities of bank distress onto the rest of the financial system or the real economy. It can be narrowed down through an SRISK measure, provided by Brownlees and Engle (2012) in [11]. This systemic risk measure is defined as a bank's contribution to the deterioration of the capitalization of the financial system as a whole during a crisis. It captures the expected capital shortage of a firm given its degree of leverage and Marginal Expected Shortfall (MES), which is the expected loss an equity investor in a financial firm would experience if the overall market declined substantially. Using SRISK as systemic risk measure, the authors found that *bank size* and especially *organizational complexity* are significant for systemic risk of financial institutions, see [11].

In the following, the results of the analysis of different network properties will be presented and discussed. We begin with the investigation of network connectivity and bank capitalization.

6.2 Connectivity

6.2.1 Simple analytical approach

To illustrate the contagion mechanism and the interplay of the effects connected to the increasing connectivity, we develop a simple model, reflecting a shock propagation process in homogeneous networks, firstly. This simple way is helpful to understand the dynamics reflected in the M-curve, demonstrated by Nier et al. (2007) in [53].

Similar approaches already exist. One of the first and best known is the a simple model of May and Arinaminpathy (2010) in [49], which uses analytic approximations. This work is certainly an essential component contributing to the understanding of the earlier numerical work on the propagation of shocks in banking networks as by Nier et al. (2007). We are aiming at the same objectives, highlighting network interactions, but using an even simpler approximation. We derive the general conditions for propagation of shocks in the homogeneous networks without limitation on the parameters. Using such a simplified approach we analyze the interdependency between failures of banks and their interconnectivity. We compare the results with the findings made by Nier et al. (2007). In particular, we look at the existence of the M-curve in the analytical experiments.

The algorithm is based on the network, characterized by similar properties as the model of Nier et al.: number of homogenous nodes N, probability $p_{i,j} = p$ that bank i has lent to another bank j assumed to be equal across all (ordered) pairs (i, j), external credit exposure $c_i = c$ and external deposits $d_i = d$, equity rate $\gamma_i = \gamma$ and interbank loans $i_i = i = \beta c$ and interbank deposits $l_i = l$. Because of the homogeneous network structure $i = l$ holds for all banks. The number of direct (bank) lenders or depositors is given then by $m = (N - 1)p$ for any bank. Further, the initial equity e_i is equal for all banks and given by $e = \gamma(c + i)$.
The contagion process in the simple model is characterized by the assumption that each of the affected banks can be the only ones concerned. This would be for example the case if all branches of the contagion trees reflecting the shock propagation are disjunct, as shown in Fig. 6.1 for $m = 3$.

The initial shock is an idiosyncratic shock hitting one of the banks in the system. It is related to the banks external credit assets. The magnitude of the shock is given by an percentage of external loans, $s = \lambda c$.

Similar to the model of Nier et al., this initial loss is firstly absorbed by the banks net

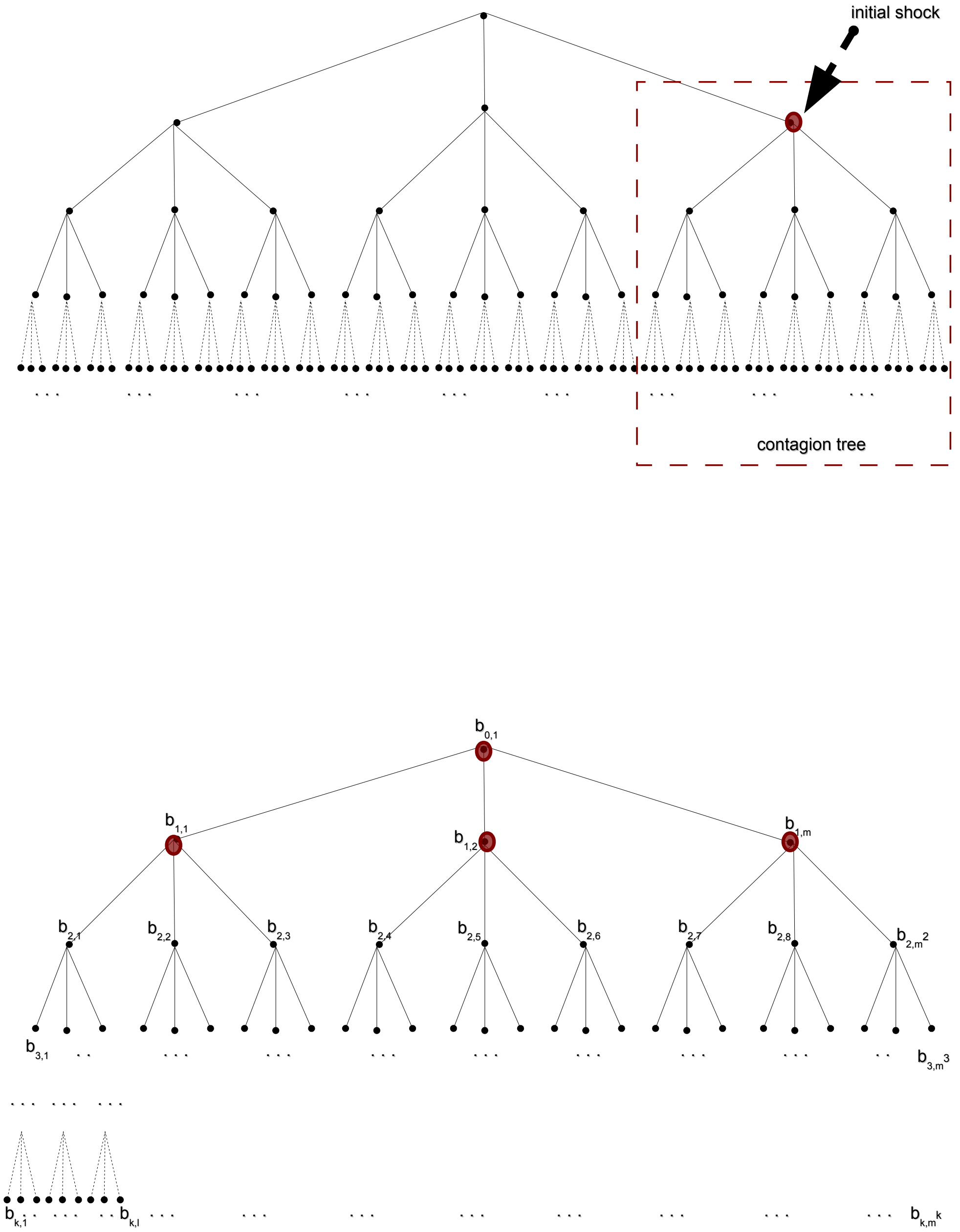


Figure 6.1: Propagation of defaults in the simple model (contagion tree).

worth e, then by its interbank liabilities l and last by its external deposits d. If the equity of the affected bank is not sufficient enough to absorb the initial shock, $s \geq e$, or $\lambda c \geq \gamma(c+i)$, the affected bank defaults and the remaining loss $(s-e)$ will be transmitted to its creditor banks through the interbank liabilities if $s-e \leq l$. And, in case these liabilities are not sufficient to absorb the shock, $s-e>l$, the residual loss $s-e-l$ will be born by external depositors. Hence the shock transmission to the lender banks is given by $s^r = min\{s-e, l\}$. Because of the perfect homogeneity by assumption, we will see that in each level of the shock transmission, all banks concerned by the propagation of the loss either default or survive, being able to cover the shock by equity.

Now, we can derive the necessary and sufficient conditions for the failure of banks for each level as follows.

The failure of the initially affected bank, or the **zero level default** $(D > 0)$ happens, if and only if $s \geq \gamma(c+i)$, where D is number of defaulted banks.

$$D > 0 \iff \lambda c \geq \gamma(c+\beta c) \Leftrightarrow \lambda \geq \gamma(1+\beta) \tag{6.1}$$

Contagion, or the first level default, means that the lender banks of the initially affected bank go bankrupt after the transmission of the residual loss to them. Hence, the necessary and sufficient condition for contagion depends not only of the shock s and the bank equity e, but also on the volume of the interbank liabilities determined by $l = \beta c$ for each bank, which restrict the loss transmission as mentioned above.

The total transmission of the residual loss to the lender banks is only possible, if the residual loss s^r does not exceed the interbank lending volume to the defaulted bank.

More formally,

$$\begin{aligned} s^r &= \begin{cases} s-\gamma(c+i), & \text{if } s-\gamma(c+i)\leq l \\ l, & \text{otherwise} \end{cases} \\ &= \begin{cases} \lambda c-\gamma(c+\beta c), & \text{if } \lambda c-\gamma(c+\beta c)\leq \beta c \\ \beta c, & \text{otherwise} \end{cases} \qquad \Rightarrow \end{aligned}$$

$$s^r = \begin{cases} (\lambda-\gamma(1+\beta))c, & \text{if } \lambda-\gamma(1+\beta)\leq \beta \\ \beta c, & \text{otherwise} \end{cases} \tag{6.2}$$

Hence, the condition that the contagion takes place or the **first level default ($D > 1$)** happens is defined as:

$$D > 1 \iff \begin{cases} \lambda \geq \gamma(1+\beta)(1+m), & \text{if } \lambda-\gamma(1+\beta)\leq \beta \\ \beta \geq \gamma(1+\beta)(m), & \text{otherwise} \end{cases}$$

where D is the number of defaulted banks and m gives the number of lender banks of the initially stressed bank.

In general, the necessary and sufficient condition for **(K+1) - level default** ($D > \sum_{k=0}^{K} m^k$) is given by

$$D > \sum_{k=0}^{K} m^k, \quad \text{if} \quad \begin{cases} \lambda \geq \gamma(1+\beta)\sum_{k=0}^{K} m^k, & \lambda \leq \beta+\gamma(1+\beta) \\ \beta \geq \gamma(1+\beta)\sum_{k=1}^{K} m^k, & \text{otherwise} \end{cases} \tag{6.3}$$

where D is the number of defaulted banks and m gives the number of lender banks of the initially stressed bank and K is the level of the shock transmission.

The derivation of 6.3 can be presented as follows:

Assume $\lambda - \gamma(1+\beta) \leq \beta.$

It follows from 6.2 that, the residual loss can be completely transmitted to the lender banks. The contagion of the direct lenders (first level contagion) occurs only if their capital is not enough to absorb the transmitted loss:

$$D > 1 \iff \underbrace{\lambda c}_{\substack{\textit{initial}\\ \textit{shock}}} - \underbrace{\gamma(c+\beta c)}_{\substack{\textit{absorbed}\\ \textit{shock}}} \geq \underbrace{\gamma(c+\beta c)m}_{\substack{\textit{absorption}\\ \textit{potential}}} \iff \lambda \geq \gamma(1+\beta)(1+m)$$

The contagion of the second level lenders occurs only if their capital is not enough to absorb the remaining transmitted loss:

$$D > 2 \iff \underbrace{\lambda c}_{\substack{\textit{initial}\\ \textit{shock}}} - \underbrace{(\gamma(c+\beta c)+\gamma(c+\beta c)m)}_{\substack{\textit{absorbed}\\ \textit{shock}}} \geq \underbrace{\gamma(c+\beta c)m^2}_{\substack{\textit{absorption}\\ \textit{potential}}} \iff \lambda \geq \gamma(1+\beta)\sum_{k=0}^{2} m^k$$

Generally, if $\lambda - \gamma(1+\beta) \leq \beta$ we have the equivalence:

$$D > K \iff \lambda \geq \gamma(1+\beta)\sum_{k=0}^{K} m^k, \quad \text{q.e.d.}$$

Assume $\lambda - \gamma(1+\beta) > \beta.$

It follows from 6.2 that, the residual loss transmitted to the lender banks is restricted by the amount of their deposits. The contagion of the 'second-level'-lenders occurs only if their capital is not enough to countervail this transmitted loss:

$$D > 1 \iff \underbrace{\beta c}_{\substack{restricted\\transmission\\of loss}} \geq \underbrace{\gamma(c+\beta c)m}_{\substack{absorption\\potential}} \iff \beta \geq \gamma(1+\beta)m$$

The contagion of the second level lenders occurs only if their capital is not enough to absorb the remaining transmitted loss:

$$D > 2 \iff \underbrace{\beta c}_{\substack{initial\\shock}} - \underbrace{\gamma(c+\beta c)m}_{\substack{absorbed\\shock}} \geq \underbrace{\gamma(c+\beta c)m^2}_{\substack{absorption\\potential}} \iff \beta \geq \gamma(1+\beta)\sum_{k=1}^{2} m^k$$

Generally, if $\lambda - \gamma(1+\beta) > \beta$ we have the equivalence:

$$D > K \iff \beta \geq \gamma(1+\beta)\sum_{k=1}^{K} m^k, \quad \text{q.e.d.}$$

6.2.2 Results in simple models

Nier et al. (2007) investigated the effect of connectivity and banking capital on the resilience of the banking system. The results from this experiment are illustrated in Fig. 6.2, see [53]. In the chart, the number of bank defaults resulting from simulations is pictured, where the Erdös-Rényi probability (ERP) p increases, banks become more connected on average. The blue line and the blue range represent networks with net worth equal to 1% of total assets, whereas, the red and yellow represent networks with net worth equal to 3% and 7% of total assets, respectively.

The authors obtained the dependence between the number of interbank lending links, determined by ERP, and the number of bank defaults as a non-monotonic M-shaped curve, described by the authors as "*First, for very low levels of connectivity (p close to zero), an* *increase in connectivity reduces system resilience, since connectivity increases the chance of shock transmission. For higher levels of connectivity, increases in connectivity may decrease or increase system resilience. But when connectivity is sufficiently high, further increases in connectivity unambiguously decrease contagion as the shock absorption effect starts to dominate and the initial shock is spread over more and more banks, each able to withstand the shock received*".

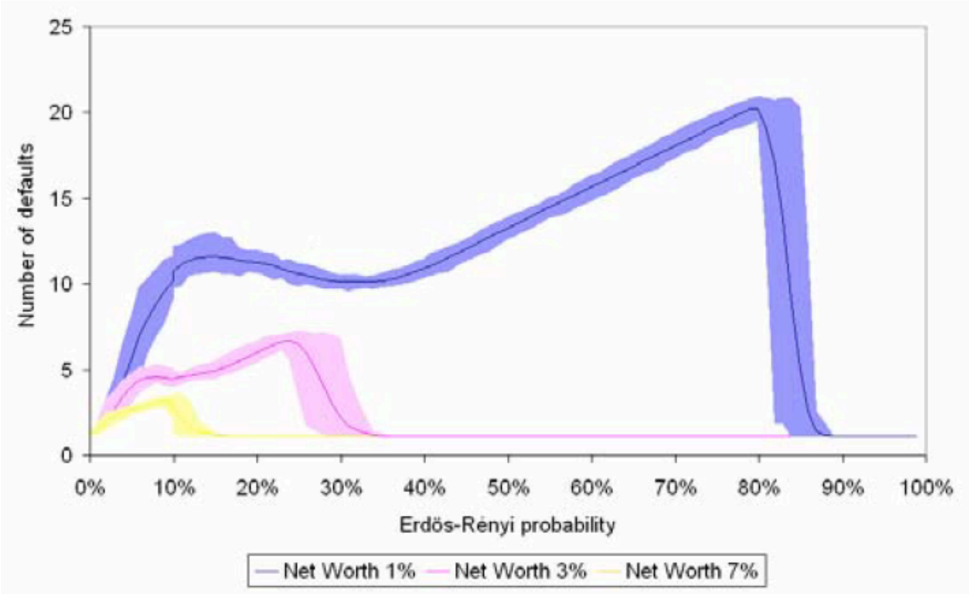


Figure 6.2: Interdependence between bank defaults and connectivity in the network model of Nier et.al.
Source: [53].

Now, we use the 'simple model', introduced above, putting the same parameters as in the experiment of Nier et. al in the model with 25 banks and 20% of interbank assets to total assets ($\beta = 25\%$ as percentage of interbank assets to external assets), where the initial shock applied to one of the banks is calibrated to wipe out all external assets of the bank. The according result is pictured in Fig. 6.3. Even if the amplitudes of the results of the simple model are higher, the curves match well the results of the mentioned simulation experiments of Nier et. al. The difference in the amplitude is not surprising according to the assumption of perfect homogeneity in the 'simple model', which does not hold in the

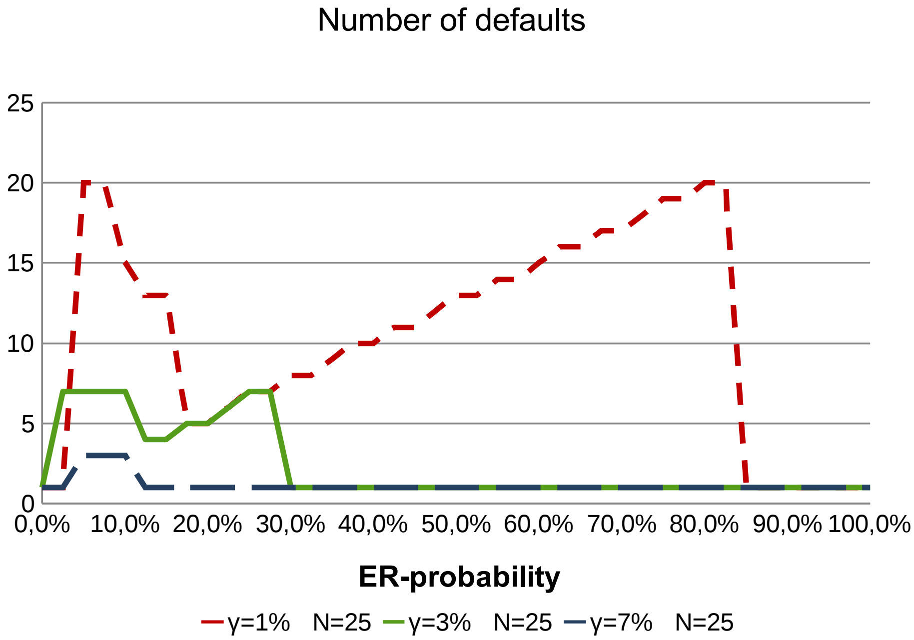


Figure 6.3: Interdependence between bank defaults and connectivity in the simple model with parameter setting similar to the experiment of Nier et. al.

same way in the referenced model.

Both graphs picture two opposing effects of increasing interbank connections: increasing propagation of the shocks and increasing potential of the shock-absorption, where each of these two mechanisms dominate over different ranges, generating an M-shaped graph.

However, from our point of view, the first increase of bank defaults for very low levels of connectivity has to be ignored, because p close to zero reflects for small N that the initially affected bank does not have any interbank lending links, which is a rather unrealistic assumption and is a contradiction to the terms of a perfect homogeneity in the simple model. More interesting is that the increases in connectivity would decrease or increase system resilience over different ranges. Variation of the number of banks and so of the magnitude of the initial shock in relation to the constant external assets in total discloses a further interesting point. The shape of the curves reflect the interdependence between connectivity and resilience of nearly homogenous banking systems does not necessarily have to be an M-shaped graph. We would called them rather 'irregular Sawtooth-waved graphs'. The number of waves, their amplitudes and periods are depending on the parameters of the network and the magnitude of the initial shock. The M-shaped graph pictures only one particular case. This can be seen in Fig. 6.4. Further, we found counterexamples to the claim that the increases in connectivity unambiguously decrease contagion when the connectivity is already sufficiently high, as the shock absorption effect starts to dominate and the initial shock is spread over more and more banks. Instead, we would argue that the decreasing contagion for higher levels of connectivity can be only obtained if the magnitude of the shock or shock transmission is sufficiently low, so that the shock absorption effect is able to dominate at least at the full interconnectedness of the system. Otherwise, even at very highly interconnected networks, further increases of interbank lending links would increase the vulnerability of the banking system and contagion can not be prevented by the further increase in connectivity.

Because of the restriction of the shock transmission by interbank lending, the condition for the prevention of the contagion by interconnectedness is dependent not only on the magnitude of the initial shock λ, but also on the intensity of interbank lending and the capitalization of banks, as can be seen below.

We derived the 'no-contagion'- condition for the simple model as follows, assuming that the remaining shock cannot by completely transmitted to the lender banks, $\lambda - \gamma(1+\beta) > \beta$. In this case we obtain the equivalence:

$$D = 1 \iff \beta < \gamma(1+\beta)m,$$

where $m = (N-1)p$.

Hence, the threshold (minimum) probability of interbank lending $\bar{p} < 1$, that is necessary to prevent contagion, is given by $\bar{p} = \frac{\beta}{\gamma(1+\beta)(N-1)}$ with the following properties for $N \geq 2$,

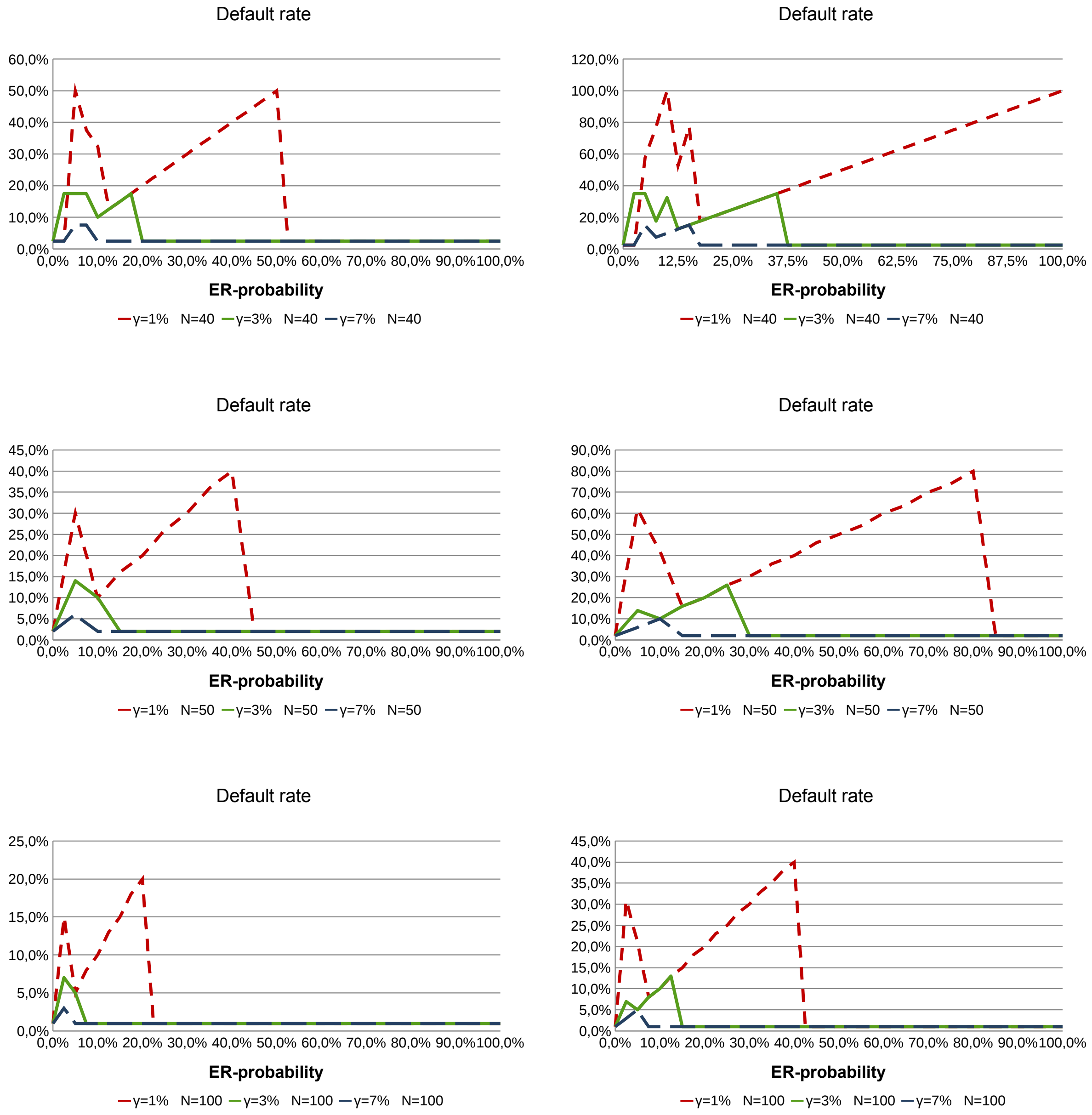


Figure 6.4: Interdependence between bank defaults and connectivity in the simple model for various numbers of banks and percentage of interbank lending of total assets: 20% (on the left) and 40% (on the right).

which increases in β and decreases in γ:

$$\frac{\partial \bar{p}}{\partial \beta} = \frac{1}{\gamma(1+\beta)^2(N-1)} > 0,$$

$$\frac{\partial \bar{p}}{\partial \gamma} = -\frac{\beta}{\gamma^2(1+\beta)(N-1)} < 0.$$

Furthermore, $\bar{p}$ does not make sense for $\beta \geq \gamma(1+\beta)(N-1)$ contradicting the assumption $\bar{p} < 1$, which follows from $\bar{p} = \frac{\beta}{\gamma(1+\beta)(N-1)}$.

6.2.3 Simulation results

Here we analyze the impact of network connectivity in more complex networks, using the ABN-model. Furthermore, we try to separate the impact of this network property from other possible effects. For this purpose we construct some examples based on a strong idiosyncratic shock, where only one external segment causes the initial event. Furthermore, the mentioned external segment is characterized by a relatively small circle of lender banks close to it via their active credit relations. Moreover, we assume that the loans affected by the shock are not securitized. In order to determine the contagion effect, we firstly assume that no withdrawal of deposits is possible. To investigate the impact of the connectivity level within the banking system, we vary the interbank lending probability p^c, described in 2.2.5, leaving the other parameters unchanged. Note that due to the initial credit netting in the model, $p^c \leq 0.5$, where $p^c = 0.5$ corresponds to the total interconnectedness of the banking system.

The way in which bank and external losses may be affected by the increasing connectivity for different levels of bank capitalization needs to be investigated, as well as the banking system resilience. We begin with the analysis of the vulnerability of the banking system in terms of the default rate of banks after the initial event and the contagion dynamics followed afterwards.

Resilience of the bank system

The results of the described simulation are pictured in Fig. 6.5. The default rate graphs provide no uniform conclusions for different levels of bank capitalization. It can rather be stated that the impact of an increasing connectivity depends not only on the initial level of the interbank lending probability, but also on the capital ratio and the magnitude of the initial shock, which can be seen in the graph on the left hand side. In undercapitalized banking systems (with regard to the initial shock), increasing connectivity makes the network more susceptible to contagion irrespective of the already existing connectivity degree. However, given a sufficiently high level of bank capitalization with respect to the power of the initial shock, an increase in the interbank lending connectivity has a negative impact on the resilience of the banking system only for low interbank lending connectivity and a positive effect if the connectivity is already sufficiently high. In the exercise presented in Fig. 6.5 this positive effect can be observed only if the capital ratio $\gamma = 8\%$.

These results are in accordance with results obtained by Cont and Moussa (2010) in [13]. They are also partially in line with considerations of Nier et al. in [53]. In particular, we have seen in the simulation analyses that the banking system can be stabilized by increasing interconnectedness of banks. But, even at various shock intensities and bank capitalization levels we have never seen such strong decreases of defaults as displayed via M-shaped graph by Nier et al. or by the simple model presented above. This reflects the fact that the networks constructed by the ABN-model are more heterogeneous and the initial events affect not only one but many banks simultaneously. The increase or decrease of the contagion does not start and end so abruptly with a further increase in connectivity as in the case of just one initially defaulting bank in a homogeneous system, where all lender banks connected to the insolvent bank usually fail or survive immediately. This would also explain that in more heterogenous systems no 'sawtooth pattern' would be observed.

Bank losses

In view of the impact of connectivity on bank losses a clear picture emerges: Bank losses

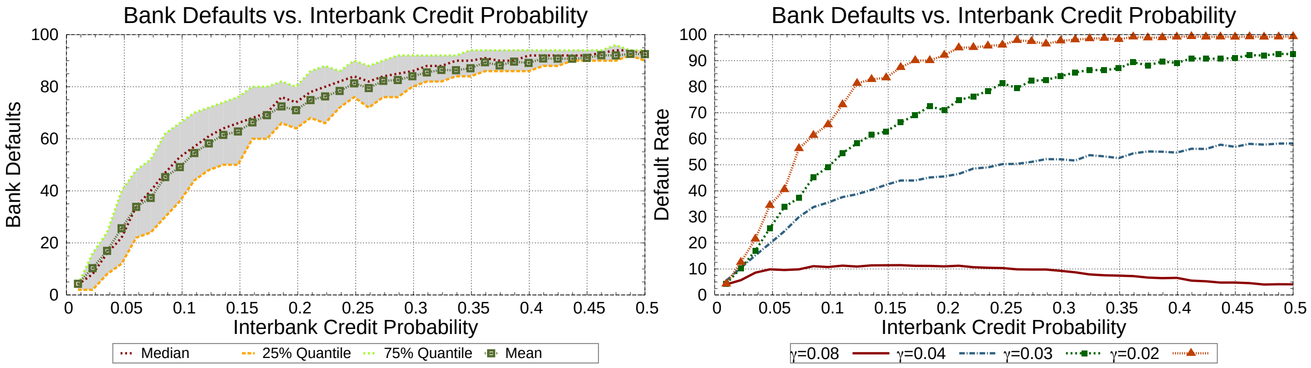


Figure 6.5: Impact of interbank credit probability p^c on bank defaults in the case of a strong idiosyncratic shock: with equity rate $\gamma = 3\%$ (left) and different bank capitalization levels γ (right).
Parameter setting: see Tables A.4 to A.6 in the appendix (A.1.2).

increase with increasing interbank lending linkage until the full absorption of losses by banks' equity has been reached or the maximum possible shock absorption by bank capital has been achieved. Thereafter, bank losses remain constant with further increase of the connectivity.

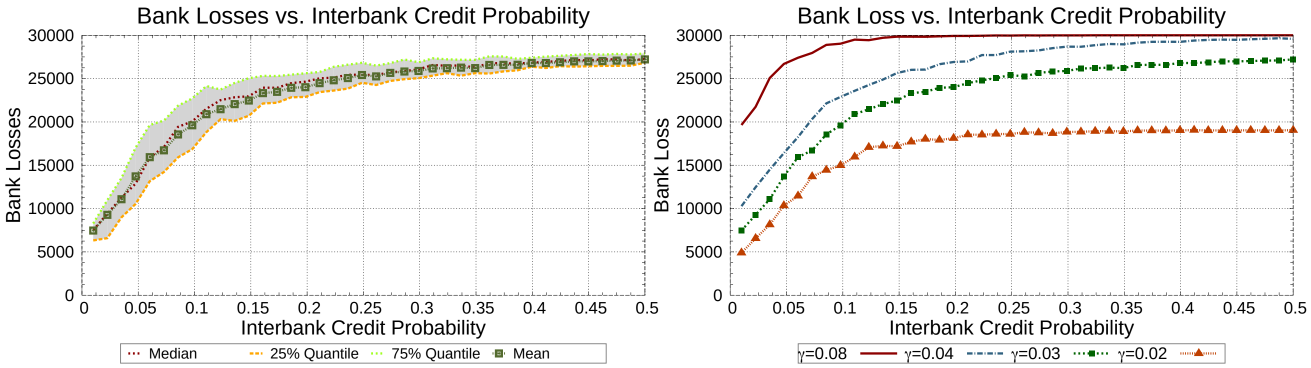


Figure 6.6: Impact of interbank credit probability on bank losses in the case of a strong idiosyncratic shock: with equity rate $\gamma = 3\%$ (left) and different bank capitalization levels (right).
Parameter setting: see Fig. 6.5.

External losses

As mentioned above, we assume in the simulation experiments presented here, that the loans affected by the shock are not securitized, meaning that the securitization ratio of the external segment caused the initial shock $q_s^s = 0$. In this case, the non-bank segments make a loss only if the initial shock is not fully absorbed by banks. Fig. 6.7 shows the results of the experiments. An increase in the interbank lending connectivity seems always to be beneficial for externals, in terms of the affectedness of the external segments through the transmission of bank losses to external depositors. That applies to all levels of bank capitalization and connectivity degrees: Losses to externals decrease monotonically until the point is reached where the full absorption by banks capital is possible or the total bank capital has been used up. These findings present an opposing picture to the view on bank losses, which is no surprise, as only the losses caused by the initial shock have to be completely split between these two sectors, and no further losses occur.

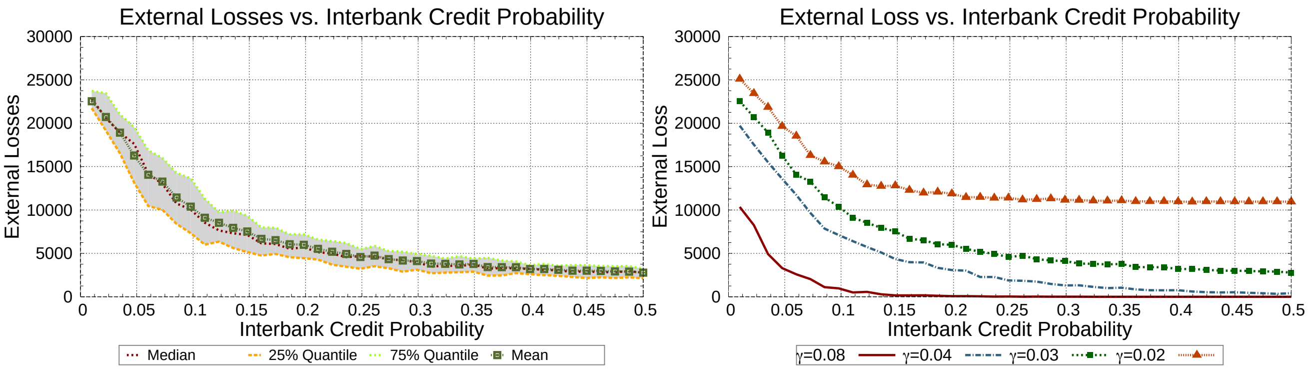


Figure 6.7: Impact of interbank credit probability on external losses in the case of a strong idiosyncratic shock: with equity rate $\gamma = 3\%$ (left) and different bank capitalization levels (right).
Parameter setting: see Fig. 6.5.

It is obvious, that the increasing interbank connectivity causes the distribution of losses among a larger number of nodes, mitigating the effects of the shock and reducing the contagion risk for external segments. The effect will be stronger the higher the banks are capitalized. Note that in the case of loan securitization, a certain portion of losses will still have to be borne by the external investors, especially if they had acquired high-risk positions (tranches). It is also obvious that banking system capitalization has a positive impact on external losses for each level of connectivity, at least if no withdrawals of deposits are allowed, which can be seen in Fig. 6.7 on the right.

We summarize the effects of interbank connectivity if liquidity risk does not exist:

- Increasing interconnectedness of the banking system increases the shock absorption provided adequate capitalization and thus implying a **higher systemic stability** of the system: Higher absorption means higher losses within the banking system and lower losses for the externals. This effect leads to higher resilience of the banking system with more equal allocation of losses across banks even if total bank losses are higher.
- Increasing interconnectedness may increase contagion causing a **lower systemic stability**: Higher contagion leads to more bank defaults. The extent of contagion depends on the bank capitalization level compared to the initial shock and of the system's ability to prevent bank runs.

As mentioned above, there are contradictory statements in previous studies about the context for interbank connectivity and systemic risk. Here we analyze the impact of interbank connectivity by using simulation experiments allowing withdrawals of deposits. The results are pictured in Fig. 6.8. As in the previous experiments, the example here includes a very strong idiosyncratic shock triggered by one external sector with a very small number of banks being stressed. The permitting of bank runs is the only difference here to the experiments discussed above.

In the same way as before we see the different results for banking systems with different capitalization levels: an increase in connectivity increases unfailingly the risk of contagion for low capitalized banking systems and could have a stabilizing effect for well capitalized systems above a certain magnitude. Moreover, the potential danger of a ”bank run” increases with further lending links for low levels of connectivity. For more highly interconnected systems, their vulnerability may decrease with increasing interconnectedness, but only for better capitalized, less leveraged banking systems in which losses triggered

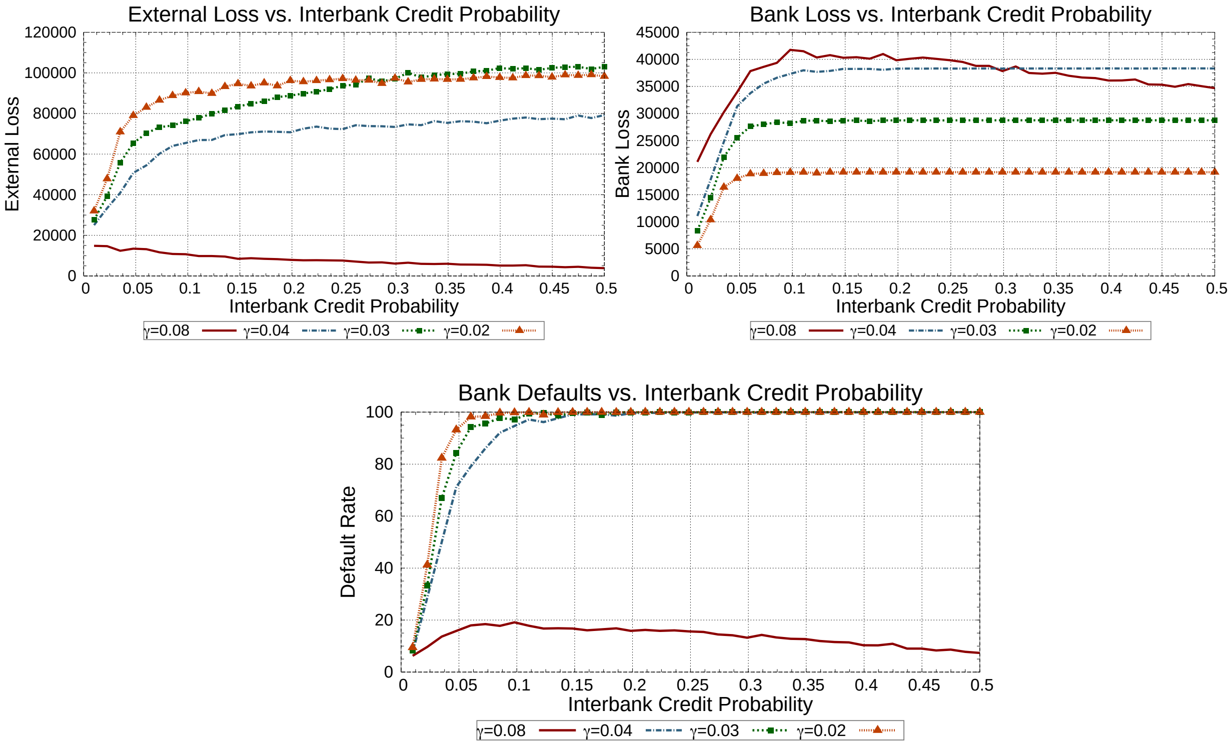


Figure 6.8: Impacts of interbank credit probability in the case of a strong idiosyncratic shock if withdrawals of deposits are possible for different bank capitalization levels γ.
Parameter setting: see Fig. 6.5.

by initial credit defaults and the following bank failure will be compensated by a broad spectrum of well capitalized banks, serving as a safety net. For low capitalized banking systems, the increasing interconnectedness poses a possible danger of reinforcing the contagion, especially if withdrawals of deposits can not be prevented. Similarly, the impact of connectivity on the aggregate losses within the banking system depends on the initial capitalization of banks. As in the previous experiment, we see in some cases, with relatively low capitalization, that the total loss to banks increases with increasing connectivity. Moreover, the higher the initial capital of banks, the higher the total loss, that can be covered by the equity.

In regard to losses to external (non-bank) depositors we can see, contrary to the exercise above, that only for high levels of bank equity, increasing connectivity has a positive impact, while in low capitalized systems external depositors face higher losses from bank failures if the connectivity increases. The reason for this is obvious: in low capitalized systems increasing connectivity increases the risk of bank defaults because of the higher risk of infection, generating greater uncertainty among investors in the banking system and, hence, a corresponding deduction of liquidity. This process triggers other dynamics, which generate more losses to banks, partly transmitted to the external segments.

The interplay between connectivity, capitalization and losses to banks is, then, more interesting, if liquidity runs are possible. In such cases the higher bank capitalization and high interbank connectivity could, together, prevent the runs and reduce the losses to both, banks and external depositors. Hence, for sufficiently high interconnectedness, banks' losses in the higher capitalized system can be lower, than in the less capitalized system for the same connectivity level, as it can be seen in Fig. 6.8.

Conclusion

We can conclude that, in general, higher connectivity can be positive or negative for the system resilience, depending on which of the two effects is dominant: In well-capitalized networks, increasing connectivity may intensify the financial instability up to a certain threshold above which a further increase in connectivity leads to an increase in the financial system resilience. For low capitalized systems increasing connectivity would have rather negative implications, in particular if the liquidity risk implied by bank runs exists. With this we rather agree with Cont and Moussa (2010) and Nier et al. (2007) and have shown that this statement holds regardless of the existence of liquidity risk. However, if withdrawals of deposits are not possible, higher connectivity seems to be positive for external depositors because more losses will be covered by bank equity. However, if a bank run cannot be prevented, higher connectivity would be advantageous for external depositors only if the capitalization of the banking system is strong enough.

6.3 Network size

In this subsection the effect of the size of interbank networks will be analyzed. Nier et al. (2007) studied the effect of concentration of the banking system on the resilience to contagion by varying the number of banks in the banking sector while keeping the aggregate size of banks' external assets constant. In their experiments, the authors applied shocks as different percentages of banks' external assets being wiped out. The authors showed that even for a given shock size a more concentrated banking system is more vulnerable to systemic risk. We will verify these results by using the ABN-model. The higher network size means here the higher number of banks which obviously corresponds to the lower bank size on average because total sum of assets in the financial system stay constant. This implies that a rising number of banks creates an higher granularity within the banking system. However, banks within the network may have significant differences in the size, especially at lower connectivity degrees between banks and externals or within the banking system. These differences will decrease with an increasing number of banks because of the increasing number of links if the probabilities of linkages between external and banks and within the financial system stay constant.

As in the previous section we will look at the impact on system stability as well as on levels of losses and sharing of losses between external depositors and banks. The following figures show the results of selected representative simulation experiments. The according scenarios include strong idiosyncratic shocks, but do not allow for withdrawal of deposits. For a given equity rate of banks or a given probability of the interbank credit links, only the size of the network will be varied in the following experiments. All other parameters are fixed. Note, that the overall initial capital will not changed if the equity rate of banks remains fixed.

Resilience of the banking system

Fig. 6.9 and 6.10 illustrate the dependence between the size and resilience of the banking

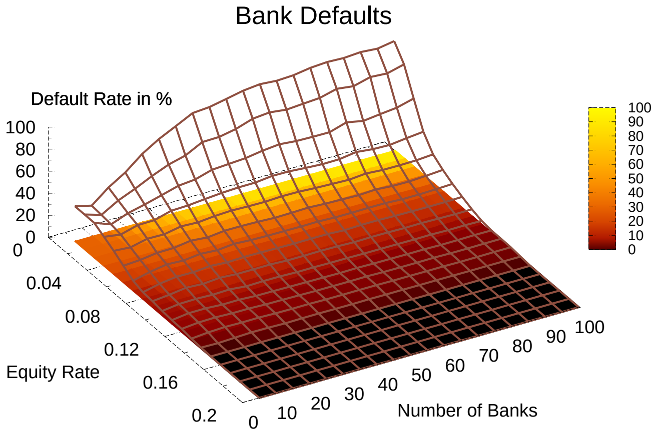


Figure 6.9: Banking system resilience in relation to the capitalization of banks γ and size of the banking segment N.
Parameter setting: see Tables A.4 to A.6 in the appendix (A.1.2).

system for different levels of initial capitalization or interbank connectivity. We obtain, that the impact of the increasing network size depends on its initial level and other network properties.

In general, a very low size of the banking system acts against the contagion. For low levels of bank capitalization we obtain the strong increase of bank defaults with a further growth of the network size, while for high levels of capital no impact exists, as can be seen in Fig. 6.9. Moreover, increasing connectivity would enhance the negative effect of network size if banks are characterized by low equity rates, as pictured in 6.10 on the left. A similar effect would be caused by the possibility of withdrawal of deposits (not illustrated here). But, for higher capitalized and highly interconnected systems the increasing granularity, related to the lower bank size on average, seems to have a stabilizing effect, as it can be seen in Fig. 6.10 on the right.

To clarify the impact of contagion the results can be compared with Fig. 6.11 - 6.12, which picture the corresponding direct default rates, defined as fractions of banks bankrupted after the initial shock but before the contagion processes. It is obvious that immediate default rate decrease on average with increasing size of the banking system, at least for

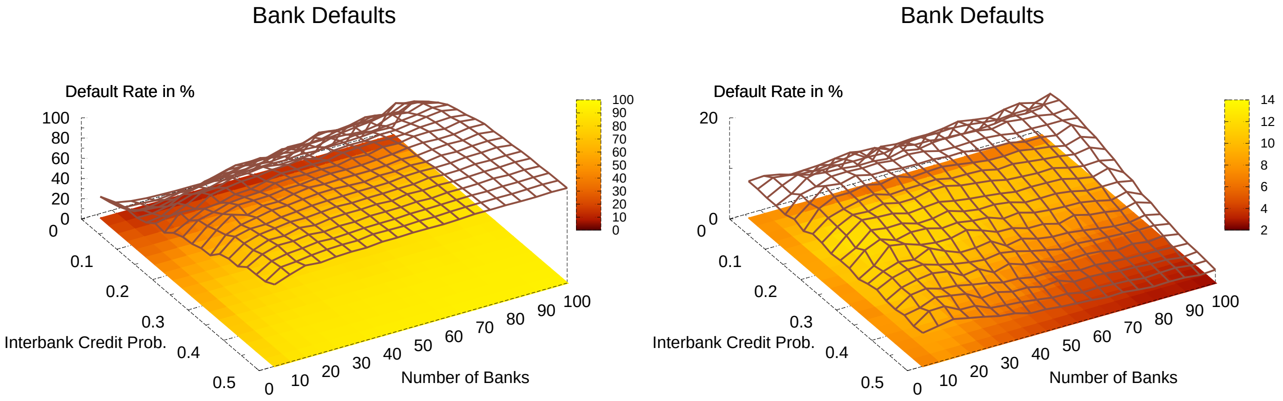


Figure 6.10: Banking system resilience in relation to the interbank connectivity p^c and size of the banking segment N for low and high bank capitalization levels $\gamma = 3\%$ (left) and $\gamma = 8\%$ (right).
Parameter setting: see Tables A.4 to A.6 in the appendix (A.1.2).

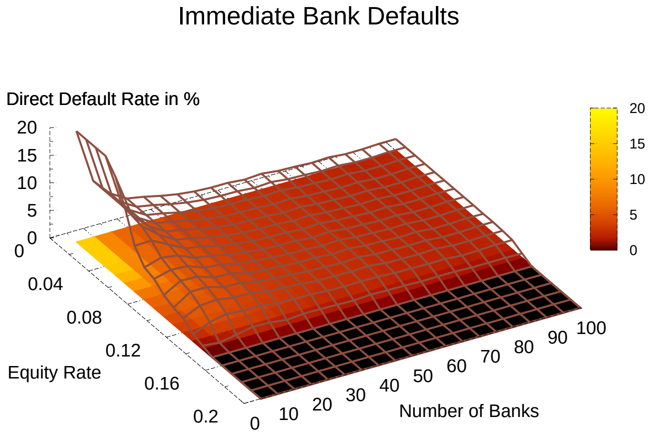


Figure 6.11: Immediate bunkruptcies of banks in relation to the capitalization of banks and size of the banking segment.
Parameter setting: see Fig. 6.9.

small numbers of banks, which is connected to the definition of the initial shock. This shock is triggered by only one external sector, which is connected via credit relation to only a small number of banks (2% in the example), but at least to one bank in the system. In the case of five banks, one bankrupted bank represents the direct default rate of 20%. In the case of 100 banks, two banks will be stressed by the initial shock, leading to the maximum direct default rate of 2%. Note, that the size of the total initial shock is equal,

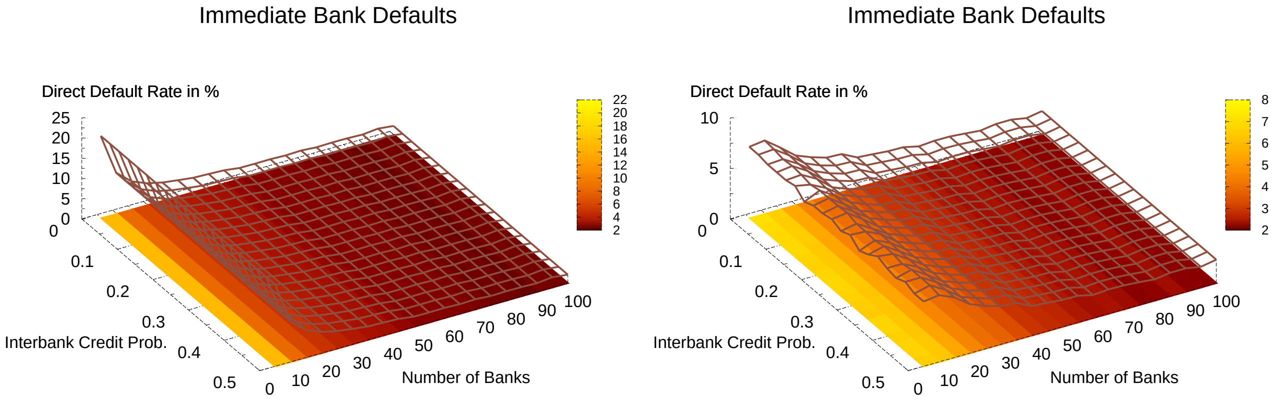


Figure 6.12: Immediate bankruptcies of banks in relation to the interbank connectivity and size of the banking segment for low and high bank capitalization levels ($\gamma = 3\%$ (left) and $\gamma = 8\%$ (right)).
Parameter setting: see Fig. 6.10.

irrespective of the number of the affected banks. In this light, the negative effect of the banking system's size on the stability of the system connected to the contagion processes seems to be more important, while the positive one seems to fit to the reported association between the number of banks and the initial default rate. So, the decreasing default rates with increasing number of banks for well capitalized and interconnected systems should be understood as the effect of a low risk of contamination due to the high capital buffer and loss sharing. The positive impact of the increasing number of banks is then only the technical effect as mentioned above.

However, increasing the number of banks corresponds to the raising granularity and the increase of the number of possible routes of contagion as the number of links increases. So, we can summarize that less concentrated banking systems with a higher number and, thus, with a lower size of banks would be more vulnerable against idiosyncratic shocks if banks have low capitalization and low interconnectivity. For well capitalized banks or highly interconnected systems the number of nodes does not play any significant role: if banks have sufficient capital buffer, further possible routes of infection remain without significance or, respectively, the highly interconnected systems suggest high contagion, that no

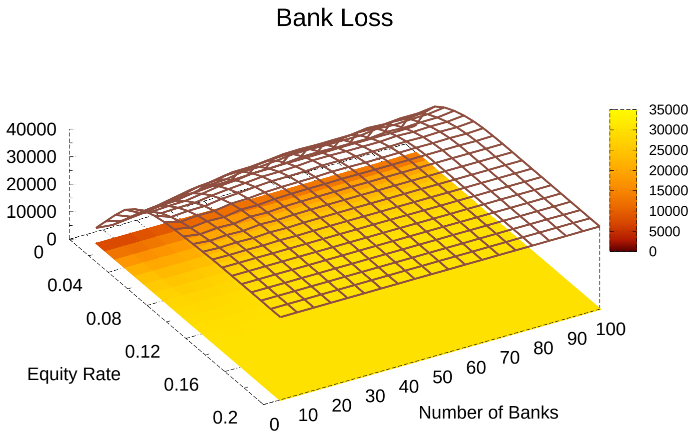


Figure 6.13: Cumulated bank losses in relation to the capitalization of banks and size of the banking segment.
Parameter setting: see Fig. 6.9.

significant effects will be additionally obtained by increasing the granularity of the system.

Bank losses

It can be seen in Fig. 6.13 - 6.14 that the impact of the network size depends on the interbank connectivity level for low as well for higher bank capitalization. Cumulated bank losses basically increase with increasing number of banks for relatively low connectivity degrees. In the highly connected banking networks, the number of banks plays hardly any notable role in terms of the amount of losses covered by banks' equity, as a result of a strong idiosyncratic shock. In very low connected networks with a small number of nodes, increase of the network size leads to a decrease of bank losses, because of the decline in the average size of banks and accordingly of the capital buffer of the affected bank, while the intensity of the shock remains equal for all simulation experiments. This is due to the technical effect described above and should be considered as a side effect.

External losses

As total bank losses, external losses can increase or decrease with increasing numbers of banks. We can see slightly decreasing losses to external depositors in the middle of the

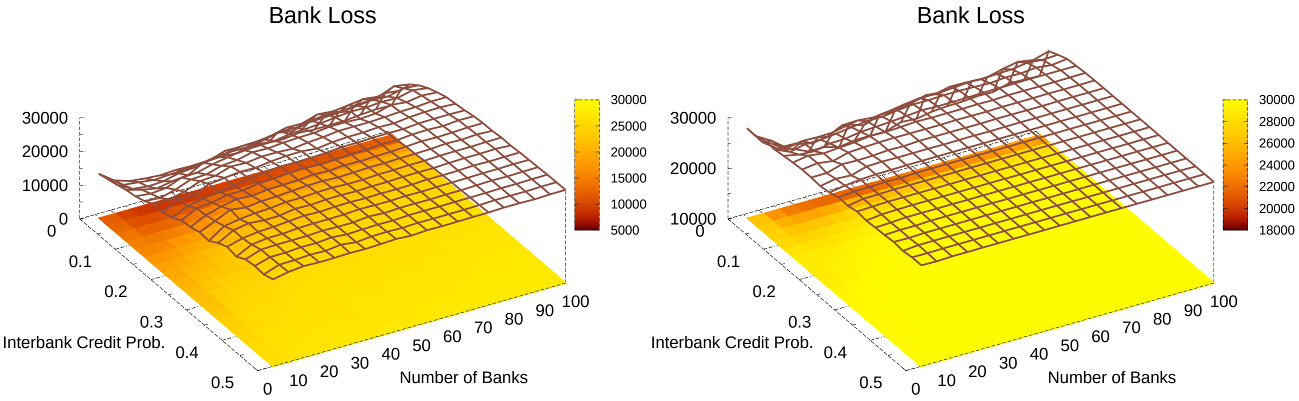


Figure 6.14: Cumulated bank losses in relation to the interbank connectivity and size of the banking segment for low and high bank capitalization levels $\gamma = 3\%$ (left) and $\gamma = 8\%$ (right). *Parameter setting*: see Fig. 6.10.

interval of bank capitalization looking at Fig. 6.15, when the size of the banking system grows in terms of the rising number of banks. For very low and sufficiently high levels of bank capital, the number of banks seems to have no significance on losses to be borne by externals. In such cases the losses would be transmitted to externals to the highest degree or, respectively, would be almost completely covered by banks' equity. Furthermore, external losses generally decrease with increasing number of banks for relatively low connectivity degrees, as can be seen in Fig. 6.16. This finding could be explained by higher number of links between banks, which increase the loss absorption capacity of the banking system. A relatively strong increase of external losses for low levels of connectivity and relatively small network size is connected to the side effect already obtained in connection with default rate and losses to banks.

Such a non-monotonic relationship between the number of banks and the impact on the entire system can be traced back to two opposing effects: a negative relationship between the size of the banking system and the average bank size, measured by the balance sheet totals of banks and accordingly the capital buffer of the affected bank, firstly, and a positive relationship between the size of the banking system and the absolute number of interbank lending links, secondly. Smaller banks exhibit lower absolute amounts of equity

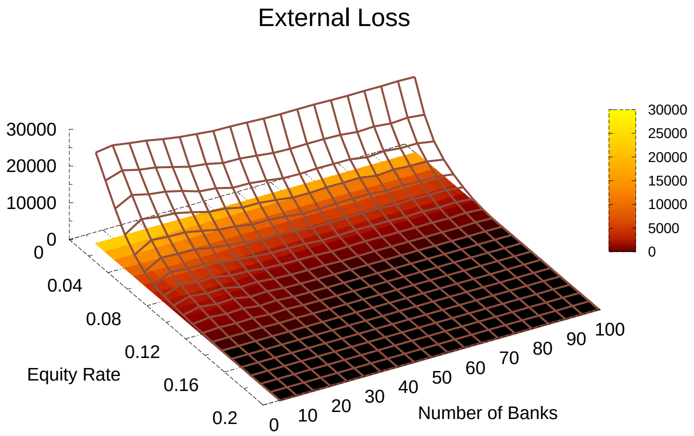


Figure 6.15: Cumulated external losses in relation to the capitalization of banks and size of the banking segment.
Parameter setting: see Fig. 6.9.

relative to the initial shock. Hence, the initially stressed bank would transmit more loss to the depositors and to the externals. By contrast, the increasing numbers of interbank credit links reinforces the transfer of losses to other banks, so that the externals would be less affected. For very concentrated banking systems the first effect (lower equity capital base) outweighs the second, but it is becomes less important in favor of the second effect (higher loss transmission) for higher numbers of banks.

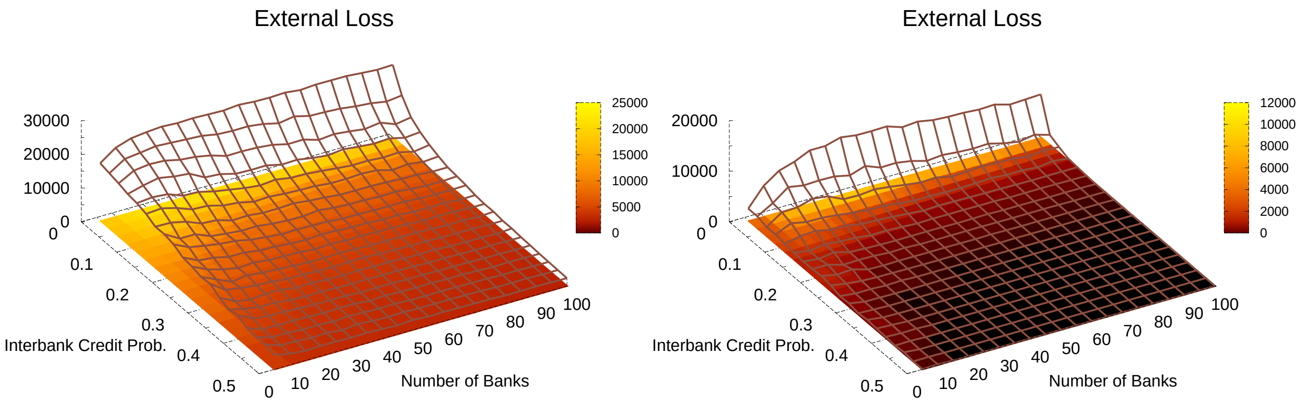


Figure 6.16: Cumulated external losses in relation to the interbank connectivity and size of the banking segment for low and high bank capitalization levels ($\gamma = 3\%$ (left) and $\gamma = 8\%$ (right)).
Parameter setting: see Fig. 6.10.

Conclusion

It can be concluded that the size as well as the connectivity degree of the banking system could play a significant role, especially if the capitalization level of banks is relatively low compared to the initial shock, so that the transmission of the shock from the initially affected bank(s) takes place. Furthermore, the capitalization of the banking system is highly significant to the way in which an increasing number of banks affects the system stability and the loss distribution between banks and external segments. In this way, the increasing number of banks (provided that external credit amounts and thus the initial shock remain unchanged) does not induce a clear effect. Moreover, a combined effect of increasing network size has been observed. The first part of the effect is similar to the impact of *increasing connectivity*, playing a negative role for the resistance of banking systems to shocks in the case of lower capitalized banking systems and stabilizing well capitalized systems by further spreading of the loss. The second part is based on the *increasing network granularity* due to the decrease of the average balance sheet total with increasing number of banks, leading to higher losses to externals due to higher shock transmission, especially when banks have low capitalization and low interconnectivity. The total effect of the increasing number of banks is then the result of the interaction of both the aforementioned drivers.

This finding, however, disputes the general claim of Nier et al., that a more concentrated banking system is more vulnerable to systemic risk.

6.4 Heterogeneity

In this section we introduce the extended core periphery concept, including semi-periphery in addition to common core and periphery as an integral part of the financial network. We focus on the impact of the heterogeneity on the stability of the total system in general, but also on the vulnerability of core and periphery banks, as well as of semi-periphery banks in particular.

6.4.1 Motivation

The network of liabilities between individual financial institutions has been frequently mentioned as an aspect of the banking system which might play an important role in identifying and evaluating contagion risks in order to assess the financial stability. *"The network structure has two important implications for policy makers. First, the network structure is ultimately determined by deeper market forces that need to be unravelled in order to anticipate monetary policy responses. Secondly, the actual distribution of links between banks affects the stability of the systems and the possible contagion after large shocks"*, van Lelyveld and in 't Veld (2012) in [65]. Unfortunately the interbank networks are not fully researched. Nevertheless, it is generally agreed that the structure and size of linkages is of significant importance for financial stability. The leading method to derive the network structure using the available information on each banks total interbank lending is an approach known as maximum entropy. One of the main assumptions thereby is that banks diversify their exposures by spreading their lending and borrowing across all other active banks. As a result of the use of this method, quite homogeneous network structures have been observed.

In fact, with the support of intensive debate among experts and empirical studies it can be stated that the network structure of interbank exposure is highly heterogeneous and interbank networks are sparse. In reality, only a small percentage of potential bilateral linkages are in active use. *"If tiering is not the result of random processes but of purposeful behavior, there must be economic reasons why the banking system organizes itself around a core of money center banks"*, Craig and von Peter (2014) in [15].

The fact that banks do not spread their borrowing and lending across the entire system can be explained by the circumstance that establishing and maintaining network linkages is associated with costs in terms of information processing, risk management and creditworthiness checks. In addition to these costs, side considerations, operating earnings as well as individual risk and business strategy, too, play a decisive role in the interbank activity often characterized by disassortative relationships describing a graph (or network) in which nodes of low degree are more likely to connect with nodes of high degree. Less-connected banks are more likely to trade with well-connected banks than with other less-connected banks. The number of counterparties per bank follows a fat-tailed distribution, with most banks having few counterparties and a small number having many.

This property is a characteristic of core-periphery networks, where multiple core banks intermediate between the peripheral banks, which in turn do not or rarely interact with each other.

6.4.2 Core-periphery networks in the literature

The most popular notion of core-periphery (CP) structure was introduced by Borgatti and Everett (1999) in [9], who proposed an algorithm for detecting both discrete and continuous versions of CP structure in weighted, undirected graphs.

Fricke and Lux (2012, 2015) have applied this CP framework to data of the electronic market for interbank deposits "e-MID", which is basically used for short-term (overnight) liquidity trading, see [29]. The authors found that the structure of the networks derived from these data can be reliably determined by a CP model. Applying an asymmetric version of the CP framework, they found that banks' roles as borrowers and lenders in the money market can be very different.

Iman van Lelyveld and Daan in 't Veld (2012) followed these analyses in [65], using data for the Netherlands and also found a significant CP structure.

Using regulatory data, Tellez (2013) analyzed the network of exposures between Australian authorized deposit-taking institutions like banks, credit unions and building societies in [62]. The author mapped the network of large bilateral exposures between financial institutions and analyzed its basic features using the tools of network theory. He found that many of the features of the Australian network are consistent with those of financial networks in other countries. In particular, most institutions in the network are only linked to a small number of other institutions, while a few, typically larger, institutions are linked to a large number of other institutions. Despite the network complexity, the author underlines the low density, of even the comprehensive version, of the Australian banking system network. Despite the fact, that only about 5% of all possible pairs of nodes have direct links between them, the indirect interconnectivity tends to be significantly higher. In the case of the Australian banking system about 30 percent of bank pairs are indirectly connected. Furthermore, financial networks tend to have a low density as they are generally comprised of a few well-connected institutions and a large number of sparsely connected institutions, see [62].

The last point can be seen, amongst others, in studies of German, Italian and Swiss interbank markets, which report ratios of actual connections to all possible connections (degrees) smaller than 1.5%. These results seem to be connected with a very large number of small credit institutions and the presence of a few larger banks, which play the role of intermediary institutions, see Fricke and Lux (2015) in [29], Craig and von Peter (2010, 2014) in [14], [15]. However, it should be taken into consideration, that the mentioned studies are based only on one part of interbank exposure. Mostly money market records have been taken into account or even large exposure statistics.

Craig and von Peter (2010) employed a German set of comprehensive banking statistics on large loans and concentrated exposures compiled by the Evidenzzentrale der Deutschen Bundesbank. The statistics include quarterly reported data of financial institutions located in Germany about each counterparty to whom they have extended credit for the amount of at least EUR 1.5 million or 10% of their liable capital, see [14]. On the basis of this data Craig and von Peter analyzed the German interbank network after consolidating banks by ownership at group level, excluding cross-border linkages. The resulting network of the German banking system, which is one of the largest in the world, is characterized by sparsity with a density on the order of 0.41 % of possible links that suggests the presence of a discernible structure. Even after the consolidation, the set of about 1800 active banks, on average, comprises, 40 private credit banks (Kreditbanken), 400 savings banks (Sparkassen), 1150 credit unions (Kreditgenossenschaften), and 200 special purpose banks.

In [15] Craig and von Peter (2014) provided evidence that interbank markets are tiered rather than flat, in the sense that most banks do not lend to each other directly but through money center banks acting as intermediaries. Using Bundesbank data on bilateral interbank exposures the authors found strong evidence of tiering in the German banking system. They captured the concept of tiering by developing a core-periphery model, and devised a procedure for fitting the model to real-world networks. Fitting the tiered structure to the German interbank network the authors realized that there are plenty of banks which borrow from, and lend to the others. But many of them do not play an essential role in the interbank market. Such banks simply transform their maturity profile by taking and placing funds in different maturities, often with a single counterparty at the core, for example. According to this finding, the authors specify the definition of the core as a strong refinement of the concept of intermediation. Therefore, by their definition, the core includes only those intermediaries that borrow from, and lend to the periphery and play an essential role in the market. By building on intermediation and by using the model of tiering Craig and von Peter identify a tighter core in the German banking network, comprising only 2 % of banks in the network (see Fig. 6.17). However, the authors underline the importance of the existence of a core, which is more important than the exact size of the core.

Note, that banks which intermediate but are not in the core could be considered as semi-periphery in the core-periphery concept, presented in this work.

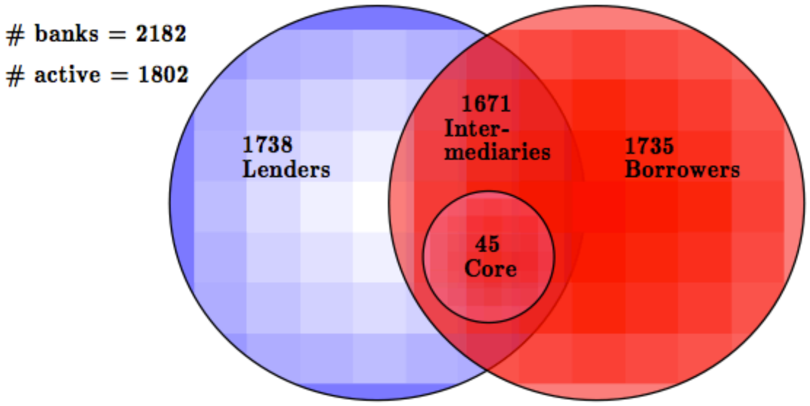


Figure 2: The core as a refinement of intermediation. This Venn diagram illustrates the relationships between various sets of banks in the German interbank market. The majority of banks intermediate, yet only a small subset of intermediaries qualify as core banks.

Figure 6.17: The tiered structure of the German interbank network.
Source: Craig and von Peter (2014), [15].

In [5], Anand, Craig and von Peter (2015) proposed the minimum-density solution as an efficient alternative to the well known maximum entropy method for estimating counterparty exposures. The authors combined information-theoretic arguments with economic incentives to produce more realistic interbank networks that preserve some characteristic features of the original interbank markets. They mentioned that the minimum-density-method loads the most probable links with the largest exposures consistent with the total lending and borrowing of each bank, yielding networks with minimum density. The authors observed that in a stress-testing context, the minimum density solution overestimates contagion, whereas maximum entropy underestimates it. In this way, both methods can be used meaningfully side by side defining a useful range for the damage of systemic stress when counterpart exposures are unknown.

Using an elementary dynamic model of the interbank market, Lux (2014, 2015) introduced an approach that shows how a CP structure might emerge from a different theoretical perspective in [45].

In [38] van Lelyveld et al. (2014) tried to find the economic explanation for the existence of CP structures in the financial markets and showed that such a network structure can form endogenously. They identified the instability of the core periphery network, where agents are homogeneous because of the large benefits of core banks from intermediating between periphery banks and incentives for periphery banks to enter the core. The authors showed that, for sufficiently large differences between big and small banks, it becomes beneficial for large banks to have direct lending relationships with all other large banks in the core, such that the CP network becomes stable. Moreover, the authors succeeded in reproducing the observed CP structure in the Dutch interbank market by modeling.

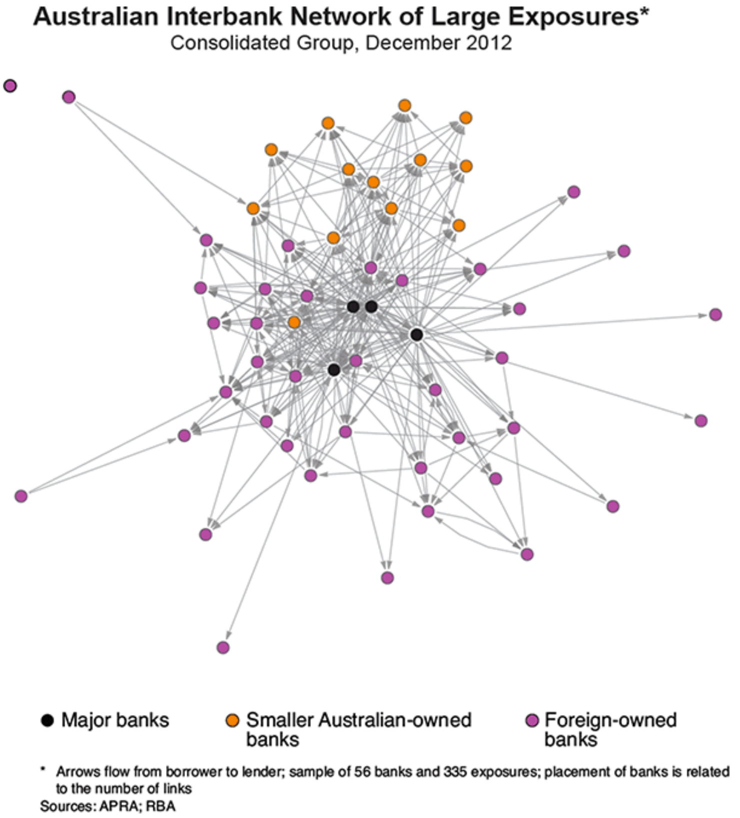
Despite the importance of the interbank exposure data for financial regulation, it is still impossible to analyze total interbank exposure even on a country basis, containing all kinds of debts and financial products which include credit risk. The interconnectivity in a real banking system would be presumedly substantially higher, than can be observed.

In this section, we try to use the knowledge achieved from empirical studies and study the impact of the heterogeneity of banks by applying the discussed properties of real banking systems in the simulation model. Here, we design simulation experiments tailored to different levels of connectivity. For further analysis of the connectivity impact we refer to section 6.2.

6.4.3 A three-tiered banking system

Here we introduce the extended core periphery concept, including semi-periphery in addition to the core and periphery of the banking network. Based on the definition of the core as a strong refinement of the concept of intermediation, introduced by Craig and von Peter (2010) in [14], we expand the common core periphery concept described in the previous part of the section by adding a semi-periphery as an integral part of the financial network, including banks that are more or less randomly linked to all other banks in the system. The percentage of such semi-peripherical banks is flexible in the model. So, in the case of "zero" we deal with a classical core-periphery structure. From our point of view, this "extended" concept should be more appropriate to simulate the financial network structures which are more complex than ones with a poor core-periphery structure.

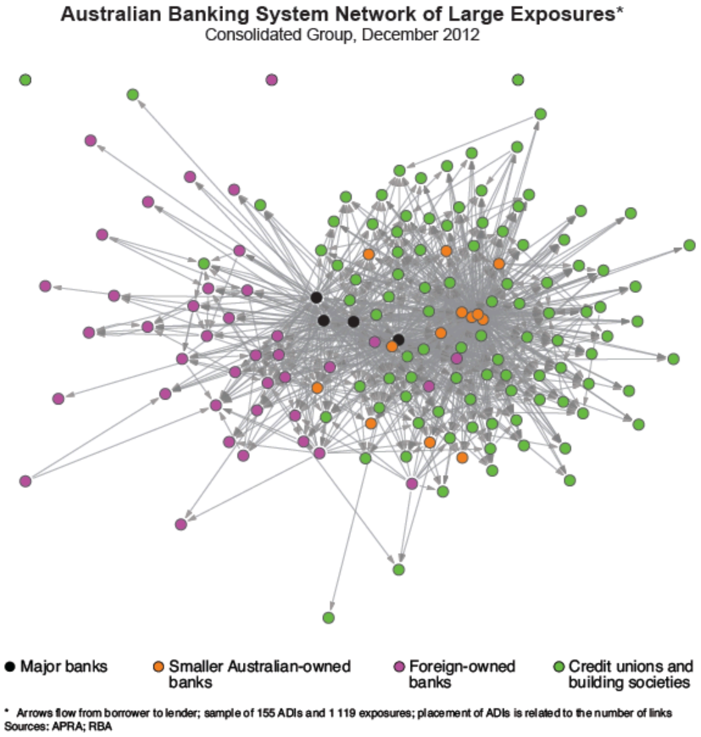
One example is the view of the large bilateral exposures between financial institutions of the Australian Banking System in a simplified and in a more complicated form, studied by Tellez (2013) in [62]. A simplified presentation of the banking system excluding the credit unions and building societies is shown in Fig. 6.18, where banks are presented as nodes, and large exposures between borrowing banks and lending banks are pictured as links between nodes. The greater the number of links related to a given node, the closer the node is to the centre of the network. The links indicate the possible paths of contagion in the case of financial distress of the borrower. The author points out the fact that *"... the major banks, which are placed at the centre of the graph, are linked to many other banks in the network. In contrast, most of the foreign and smaller Australian-owned banks are linked to only a few other banks. Also, the smaller Australian-owned banks tend to be more connected with other Australian-owned banks, while the foreign-owned banks tend to be more connected with other foreign-owned banks and the major banks."*, Tellez (2013) in [62].


Australian Interbank Network of Large Exposures*
Consolidated Group, December 2012

* Arrows flow from borrower to lender; sample of 56 banks and 335 exposures; placement of banks is related to the number of links
Sources: APRA; RBA

Figure 6.18: Australian banking system, excluding credit unions and building societies. *Source*: Tellez (2012) in [62], Reserve Bank of Australia, Bulletin June Quarter 2013

Fig. 6.19 graphically displays the Australian banking system including the credit unions and building societies, which is further complicated compared to the interbank network presented above. As the author noted, the major banks remain highly connected to other institutions, but some smaller institutions become highly connected as well. Moreover, the major banks tend to be more interconnected with foreign banks and smaller Australian-owned banks tend to be more interconnected with credit unions and building societies, as Fig. 6.19 demonstrates. In the context of our concept the major banks would represent the core; the major part of the foreign banks, credit unions and building societies, which are lowly interconnected would build the periphery, and the smaller Australian-owned banks together with the remaining banks would constitute the part of the semi-periphery.


Australian Banking System Network of Large Exposures*
Consolidated Group, December 2012

* Arrows flow from borrower to lender; sample of 155 ADIs and 1 119 exposures; placement of ADIs is related to the number of links
Sources: APRA; RBA

Figure 6.19: Australian banking system including credit unions and building societies. *Source*: Tellez (2012) in [62], Reserve Bank of Australia, Bulletin June Quarter 2013

Interconnectedness within the bank group and connectivity to other banks as well as external and interbank exposure are the group specific properties which we use for distinction between core, periphery and semi-periphery. With regard to external exposure, core banks exhibit higher external credit volume on average than each of the periphery and the semi-periphery banks. Periphery banks have the smallest external exposure on average. This external exposure difference is exogenously given in the model. In terms of interbank linkages, core banks are extremely interconnected, highly connected with the periphery and also connected with other banks, while periphery banks are disconnected within the periphery, highly interconnected with the core banks and also linked to other, semi-periphery banks. The values of in- and out-degrees and further connectivity parameter for each bank group are endogenous and depend, among other factors, on the size of each group in the network. As a result of external exposure differences and specific interbank linkage properties of the mentioned bank groups, significant differences in interbank exposure especially between core and periphery will be observed. More formal definitions of core, periphery and semi-periphery are presented in section 2.3.5.

Taking into account the multi-linkage network structure of the ABN-model, in which any two banks can be connected via multiple links, we developed an algorithm to reconstruct the random network to the (extended) core periphery network with the described characteristics under the condition that other properties of the network, like number of active links and external credit volume, remain unchanged. This condition is necessary in order to separate the effects of the network structure and to make the results of simulation experiments comparable. For details, we refer to section 2.3.5.

The main steps of the core-periphery formation procedure can be summarized as follows:

1. redistribute external assets between banks in the network to get bank groups with different size on average after the initial asset allocation (a suitable method here because of the random distribution of the assets between banks in the model initially)
2. determine relationships between banks by changing the initial random matrices for credit and investment linkages R_b^c and R_b^i according to the predefined characteristics of bank groups.

The presented procedure requires the following exogenous parameters, which will be stressed in the simulation analyses:

- ψ_1 and ψ_2 - fractions of core and periphery banks,
- ξ - percentage of external assets to be reallocated from periphery to the core banks.

As result of the mentioned procedure the new network structure is obtained, as shown stepwise in the example in Fig. 6.20 to Fig. 6.22, where 30% of banks (with indices

71-100) belong to the periphery and 10% (indices 1-10) of banks are the part of the core. On the left hand side the initial lending relationships according to the random matrix R_b^c are pictured, while the figure on the right side shows the new structure for interbank credit links. It can be seen, that the relationships within the periphery do not exist any more, while the core is higher interconnected and more intensively linked to the periphery. The structure of the semi-periphery remains nearly untouched.[1] Fig. 6.21 pictures the redistribution of the external credit exposure from periphery to core banks.[2] Fig. 6.22 shows weighted lending links after the core-periphery formation process described above. It is obvious that core banks have significantly higher refinancing needs due to their higher volume of external credit exposure, which should be covered by other banks' resources connected to them via lending links and by external deposits.

6.4.4 Simulation results

In this section we study the impact of the network structure in terms of heterogeneity of banks with respect to the individual interbank lending preferences and the initial amount of external debts. We conduct our research on potential effects of the network structure on the resilience of the banking system. To separate single effects we analyse the differences between the core and the periphery in the complete core-periphery network as defined above, as well as in the networks in which the core periphery properties have been implemented in part. We define three groups of simulation experiments to separate the core-periphery properties. The first group provides only the differences in the size of the

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[1] "Nearly" untouched because only some links of the semi-periphery have been redistributed to the core to make it completely interconnected. See more in the description of the core formation procedure in section 2.3.5.

[2] Different credit volumes of external segments as well as their different connectivity degrees to banks are quite well pronounced in the presented network to demonstrate a heterogeneity of the network structure . Segment one, for example, is connected to many banks but characterized by a relatively small credit volume in total, while segment six is the largest borrower, but its claims relate to a relatively small number of banks. The first of both segments can be understood as a private borrower market, while the later can be compared with the shipping market, for example. It can be clearly seen that the implemented redistribution of external assets changes neither the external credit volume nor the number of connected banks in total or for each segment.

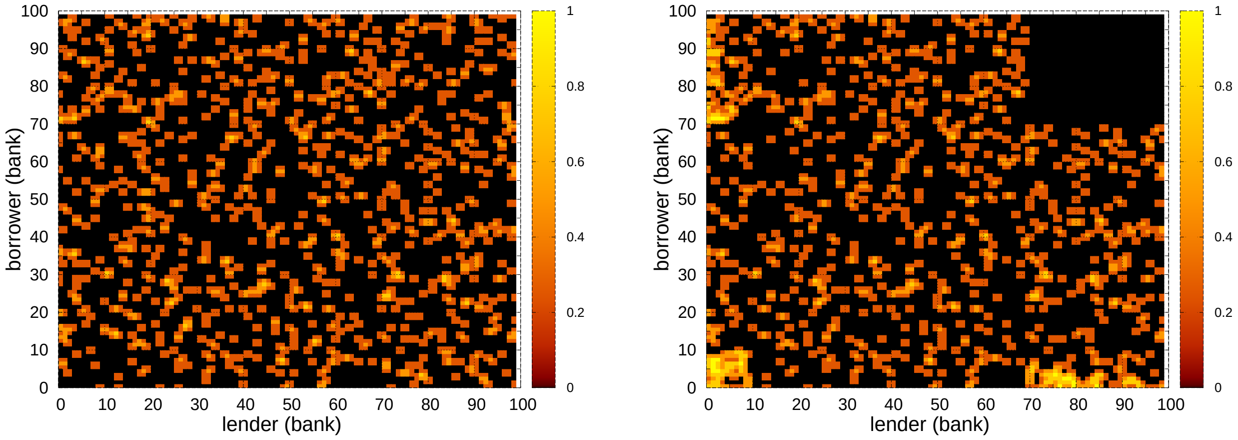


Figure 6.20: Example: Interbank lending relationships in a random network (left) and in the derived core-periphery network (right).
Parameter setting: $N = 100$, $p^c = 0.1$, $\psi_1 = 0.1$ and $\psi_2 = 0.3$.

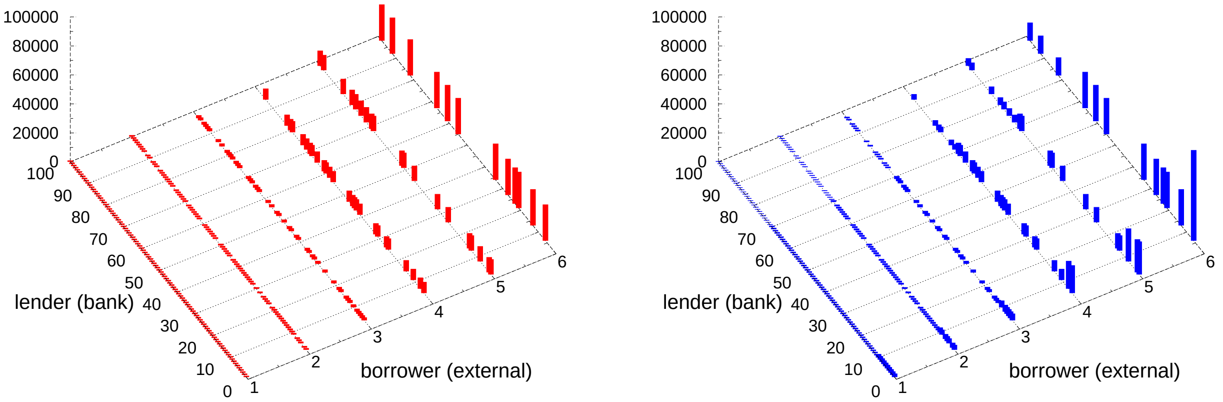


Figure 6.21: Example: External lending in a random network (left) and in the derived core-periphery network (right).
Source: $N = 100$, $p^c = 0.1$, $p^i = 0.1$, $\psi_1 = 0.1$ and $\psi_2 = 0.3$, $\xi = 0.5$. For the remaining parameters please refer to Tables A.1 to A.3 in the appendix (A.1.1).

external credit exposure between core and periphery banks (exposure difference). The second group considers only the difference in the connectivity (structural difference). The

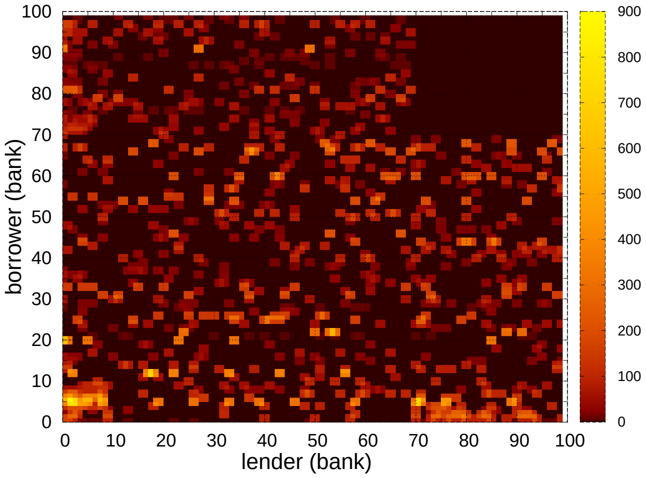


Figure 6.22: Example: Final (wighted) interbank lending structure. *Parameter setting*: see Fig. 6.21.

third type includes both these characteristics (core-periphery network).

We illustrate the selected simulation results graphically considering an idiosyncratic initial shock (single external segment default) for various levels of banks capitalization. We assume that 10% of banks belong to the core, while 50% are part of the periphery, and 80% of external debts of the periphery are redistributed to core banks: $\psi_1 = 0.1$, $\psi_2 = 0.5$ and $\xi = 0.8$.

The results of the mentioned simulation experiments are pictured in Fig. 6.23. In addition, two further constellations with the same risk parameter setting will be considered here: a random and a homogeneous (and completely interconnected) network. It is obvious that the difference in the external credit amount between core and periphery banks shows a significantly positive influence on the stability of the system for low capital levels compared to the random network, while for higher equity rates, negative effects can be obtained. We explain these effects by a higher heterogeneity degree of the network if substantial exposure differences between banks exist. The increase of the heterogeneity in the banking system displays the following properties: higher stability of the system for substantially higher shocks or lower capitalization of banks, i.e. the total collapse of the system becomes less likely; higher susceptibility for less dramatic shocks or better capital endowment of the banking system – bankruptcies of banks are more likely than in less heterogeneous systems. This can be clearly seen when comparing the green line presenting the completely homogeneous network structure with other lines in Fig. 6.23.

Similar findings had been made by Eboli (2013) in [22], where the author investigated the relation between the shape of financial networks and the share of defaulting agents. Eboli (2013) characterized the first and the final contagion thresholds as the value of the smallest shock inducing at least one default and the value of the smallest shock inducing the total systemic collapse, respectively. He demonstrated that the first and the final thresholds coincide in complete networks, which can be also seen in Fig. 6.23 with regard to the equity ratio, considering the homogeneous network presented by the green line. However, the differences in default rates of a core-periphery network and the random network are

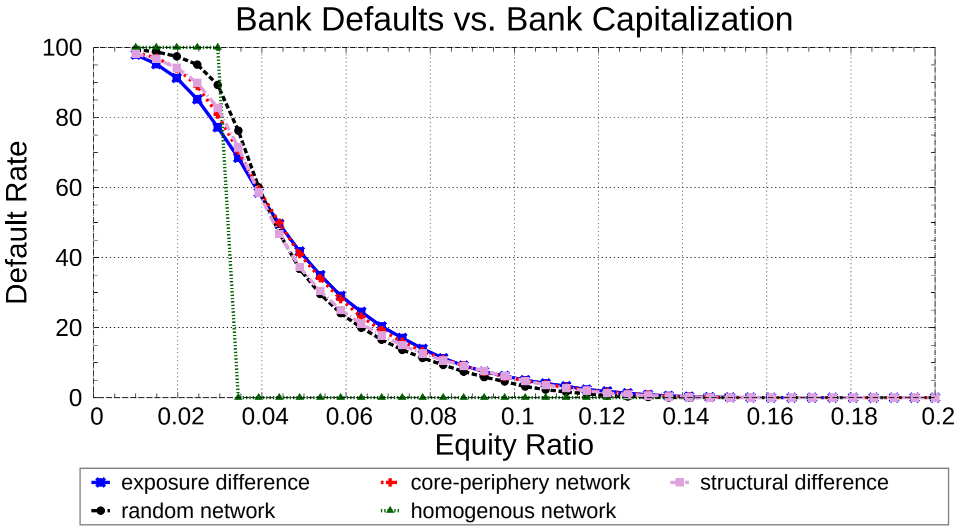


Figure 6.23: Impact of network structure on the banking system stability in the case of idiosyncratic shocks, high risk appetite of banks and absence of liquidity risk ($\tau = 0$).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.8$ if exposure difference exists ($\xi = 0$ otherwise), $\zeta = 0.1$. For the remaining parameters please refer to Tables A.1 to A.3 in the appendix A.1.1.

significantly less pronounced than such differences between a core-periphery network and the homogeneous network because of the already quite heterogenous structure of the random network in the model. Although the implementation of the core-periphery properties in the random but heterogenous network enhances its heterogeneity, the effects are less impressive.

Let us take a look at networks, in which only structural differences with regard to the interbank links exist, and this without any systematic differences in external lending exposure between the core and peripheral banks with $\xi = 0$ (Fig. 6.23, pink line). A positive impact of such structural differences on the resilience of banks compared to the random networks (black line) can be observed for less capitalized systems, even if this effect is smaller than the effect of the difference in the external lending exposure (blue line). Core-periphery differences in the interbank linkage structure cause a higher concentration of interbank claims and investments compared to the random network, which will be shown below in Fig. 6.31, increasing the heterogeneity of the network, which explains the obtained result. For better capitalized banks only small negative effects of pure structural differences compared to the random network have been observed.

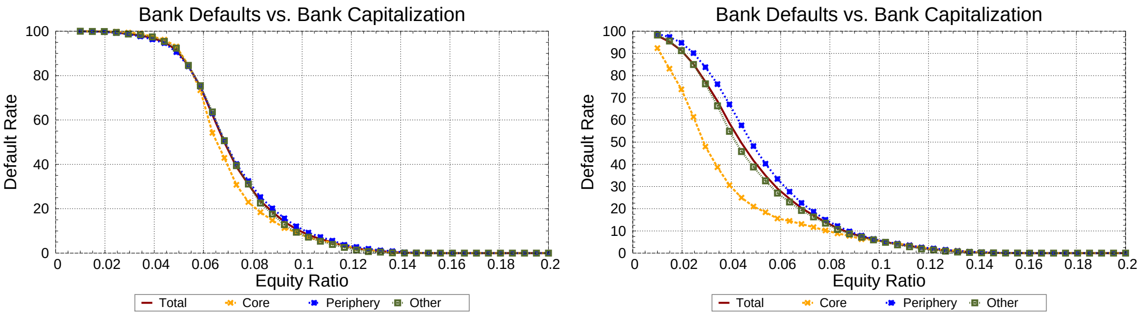
From the acquired results it can be inferred that core periphery linkage structure tends to have positive impact on the systemic stability of low capitalized systems without substantial increase of the systemic risk in better capitalized systems, while higher concentration of the external exposure may stabilize lower capitalized networks but tends to make higher capitalized systems more vulnerable against shocks. The total impact of the core-periphery network properties consists of the partially opposite effects and tends to be rather positive for core banks if the external difference is pronounced. Otherwise the negative effect of contagion and riskier exposure structure could predominate, in particular for lower equity ratios or higher shocks.

To analyze the impact on the vulnerability of core, periphery and semi-periphery banks, let us look at the following results. Fig. 6.24 - 6.25 show final and immediate default rates, respectively, as results of various bank capitalization for scenarios with liquidity risk (on the left) and without possibility of deposit withdrawals (on the right). It can be seen that the existence of the core periphery structure and so the higher heterogeneity can be significant for the individual bank clusters: core, periphery and semi-periphery.

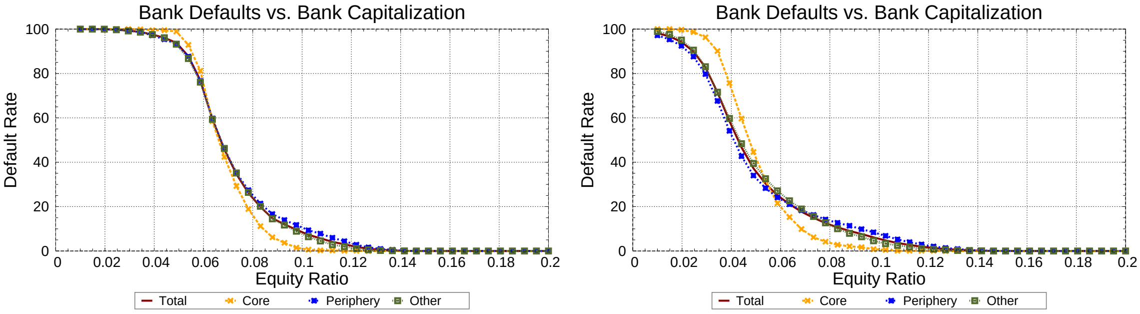
Furthermore, we can see that resistance of banks significantly depends not only on network properties of the banking system but also on its capitalization level or magnitude of the initial shock: core banks are generally better off if significant exposure differences exist. If there are only differences in the interbank linkage structure between the core and the periphery, core banks are significantly more vulnerable than periphery banks in low capitalized banking systems. This vulnerability corresponds to the higher contagion risk of significantly higher connected core banks on the one hand, and higher connectivity of core banks via investment links on the other. This can be obtained by the immediate default rates of banks for the same scenarios as before, pictured in 6.25, which demonstrates the default rates of banks before contagion takes place. Even without contagion, core banks become bankrupt more often than other if capitalization of the system is sufficiently low. This effect could disappear if banks tend to invest in less risky assets.

The high connectivity of core banks via investment links increases the default risk of core banks as long as increasing investments increase the degree of risk of their assets and sufficient level of capital adequacy is not ensured. The negative effect of increasing high-risk investments become smaller or disappears with enhanced capital requirements. In such a case investments will stabilize the shareholder banks against moderate idiosyncratic shocks due to the higher (risk adjusted) capital requirements, since the riskier banks are significantly better capitalized in absolute terms. In the case of substantially higher shocks or a lower capitalization level, riskier assets tend to cause higher default rates of core banks compared to other banks because of a higher affectedness by the initial distress. We demonstrate this effect in Figures 6.26 and 6.27. The higher risk of banks is connected to the exclusive investments of banks in the most risky CDO-Tranches B and

case with exposure difference: WD no WD



case with structure difference: WD no WD



case with exposure and structure differences: WD no WD

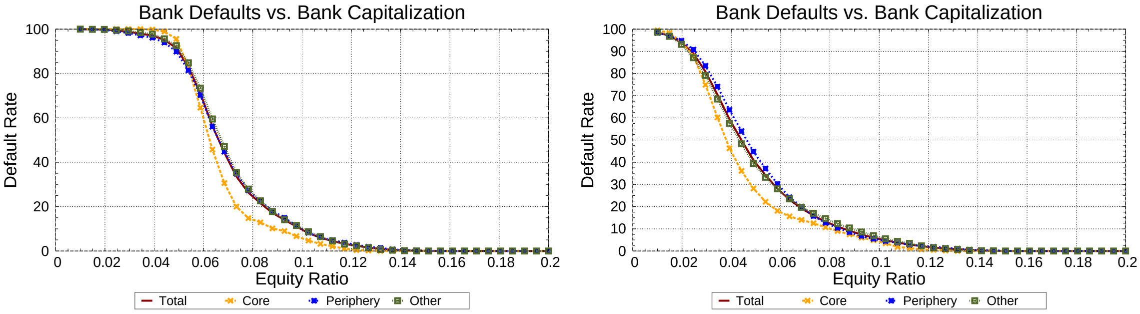
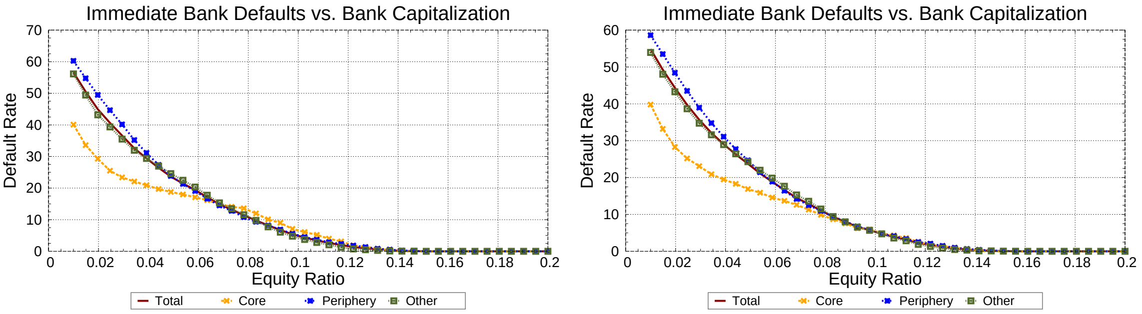


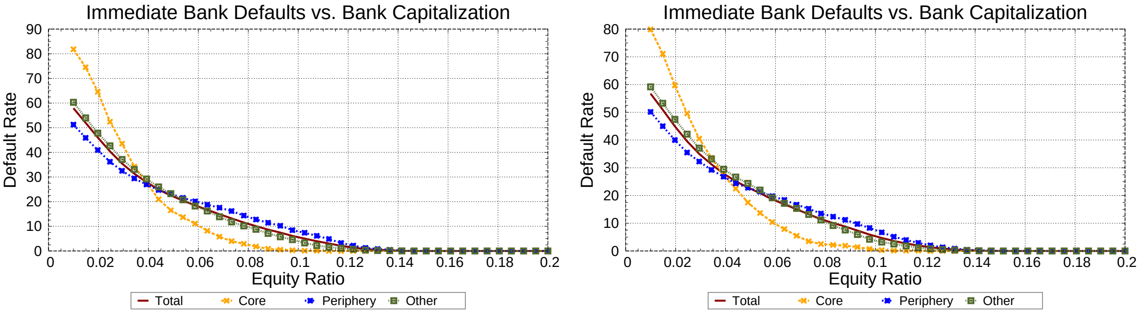
Figure 6.24: Bank defaults in CP-networks with different properties in the case of idiosyncratic shocks, high risk appetite of banks with or without liquidity risk related to withdrawal of deposits (WD with $\tau = 0.1$ (left) or no WD with $\tau = 0$ (right)).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.8$ if exposure difference exists and $\xi = 0$ otherwise, $\zeta = 0.1$. For the remaining parameters please refer to Tables A.1 to A.3 in the appendix A.1.1.

C and in the case of the lower risk banks solely hold CB and the CDO Tranche A, see Tab. 6.1.

case with exposure difference: WD no WD



case with structure difference: WD no WD



case with exposure and structure differences: WD no WD

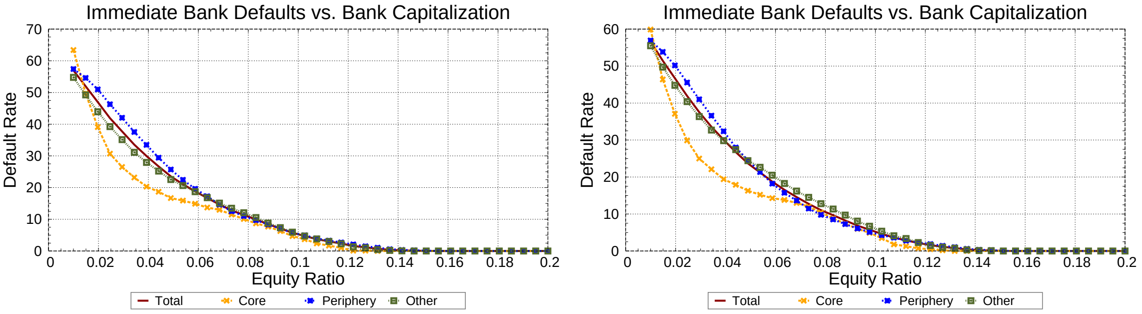


Figure 6.25: Immediate bank defaults in CP-networks in the case of idiosyncratic shocks, high risk appetite of banks with or without liquidity risk related to withdrawal of deposits (WD with $\tau = 0.1$ left or no WD with $\tau = 0$ right).

Parameter setting: see Fig. 6.24.

Bank shares of investments β^{CB}, $\beta^{CDO}_t \quad (t \in T)$	**CB** β^{CB}	**Tranche A** β^{CDO}_A	**Tranche B** β^{CDO}_B	**Tranche C** β^{CDO}_C
Low risk of banks	1	1	0	0
High risk of banks	0	0	1	1

Table 6.1: Tranche-specific (CB and CDO) parameters and their benchmark values specified for modified scenarios (connectivity experiments).

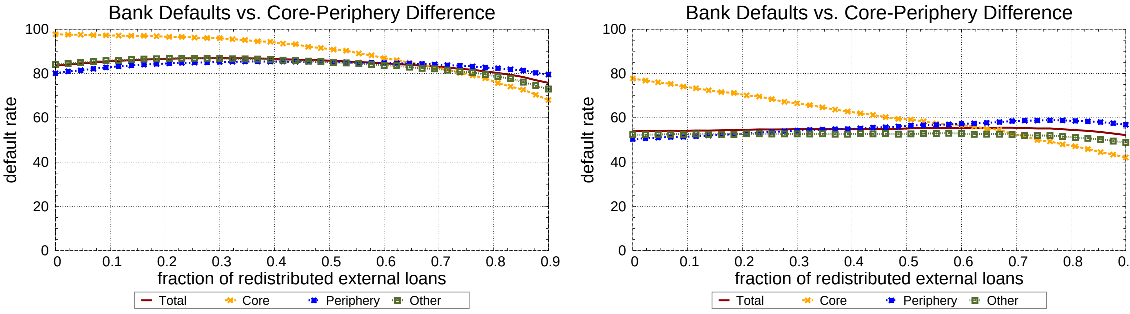


Figure 6.26: Resilience of banks in relation to the core-periphery exposure difference related to ξ in the case of idiosyncratic shocks without liquidity risk (absence of withdrawal of deposits, $\tau = 0$) with higher (left) and lower risk of banks (right).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\zeta = 0.1$, $\gamma = 3\%$. For the remaining parameters please refer to Tables A.1 and A.2 in the appendix A.1.1.

For very low differences in external exposure, core banks tend to fail more often than other banks in the system with low capitalization, regardless of risk level of their investments,

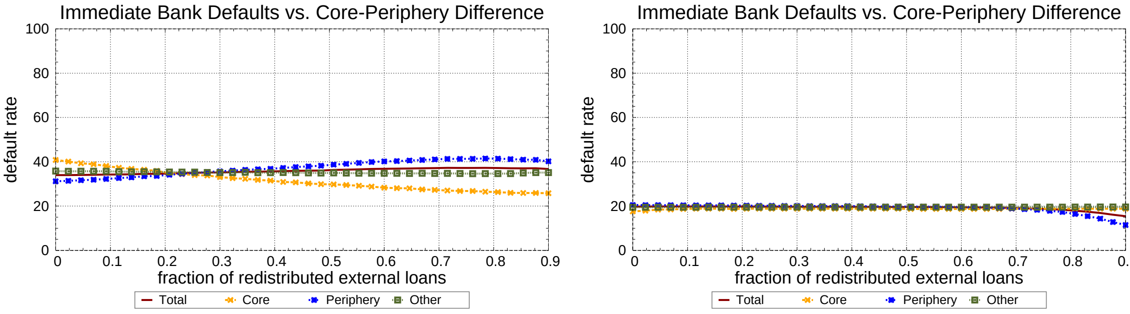


Figure 6.27: Direct defaults of banks (before contagion) in relation to the core-periphery exposure difference related to ξ in the case of idiosyncratic shocks without liquidity risk (absence of withdrawal of deposits, $\tau = 0$) with higher (left) and lower risk of banks (right).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\zeta = 0.1$, $\gamma = 0.03$. For the remaining parameters please refer to Tables A.1 and A.2 in the appendix A.1.1.

which can be explained above all by higher contagion of core banks via interbank lending links. It can be also seen, that even before contagion processes start, default rates of core banks are higher if bank investments are sufficiently risky (Fig. 6.27 on the left). Even higher differences in bank default rates between a core and a periphery can be observed with lower capital rate (Fig. 6.25 middle right). For a lower risk of banks or high capital levels, the difference in immediate default rates between core banks and others is very small or none at all, as shown in Fig. 6.27 on the right. Please note, that a relatively low equity quote is assumed for these simulation experiments. In such a case defaults of the core banks decrease with increasing difference in external credit exposure between the core and the periphery, as illustrated in Fig. 6.26.

The figures above indicate a considerable importance in the difference between the core and periphery regarding the amount of the external credit exposure. We would like to take a closer look at this property of core-periphery networks. The understanding of its impact is not a trivial matter, because of the externalities connected to the distribution of the loans to externals among banks. First of all, we would like to emphasise the changes in the network structure connected to an increase of external loans in the core as a result of redistribution of them from the periphery.

Increasing redistribution of the external lending exposure from the periphery to core banks implies the following changes in the system:

1. Increasing / decreasing external lending by the core / periphery and thus increasing concentration of the external credit exposure will be expected, which can be seen in Fig. 6.28.
2. Increasing / decreasing origination of CBs and CDOs by core / periphery banks, as a result of changes in the external lending exposure and related securitization of loans by banks. This is determined by formula [2.10], explained in section 2.2.5.
3. Decreasing interbank lending of core banks and an increasing interbank lending of

other banks to the core because of increasing refinancing needs of core banks, which is determined by formula [2.7] in section 2.2.5. As a result, increasing concentration of the interbank lending is expected if there are not structural differences related to the connectivity degrees of banks. Increasing interbank lending of a small number of banks connected to the core will be observed. But decreasing concentration can be expected if structural differences exist, because of the high connectivity of the core via lending links. Higher connectivity of the core implies broader diversification of lender banks connected to the core banks and smaller weighting of these connections. Remember, that all initial interbank loans to any bank are at the same amounts for all its lenders by the model assumption related to formula [2.10]. The higher the refinancing needs of core banks, the higher the share of interbank loans which are more broadly distributed among banks. In both cases interbank loans of core banks decrease on average with exposure difference to the periphery banks if the total amount of lending is fixed. This is explained by decreasing refinancing needs of other banks in the system. Interbank lending of periphery banks increases instead. However, in the case of higher connectivity of the core, decreasing interbank lending of core banks tends to reduce the differences between banks and so the concentration

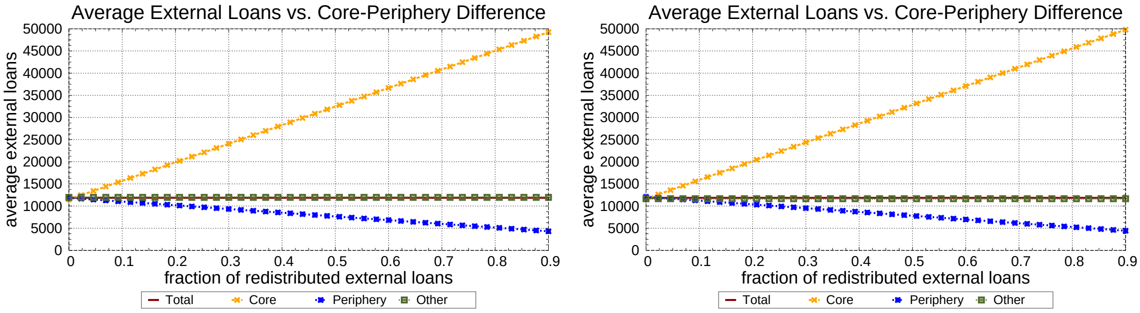


Figure 6.28: Loans to the external sector in bank balances on average of the peer-group (core, periphery, semi-periphery or other and the banking system as whole) via core-periphery exposure difference related to ξ. Similar results in both cases: with structural difference (left) and without structural difference (right).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\zeta = 0.1$. For the remaining parameters please refer to Tables A.1 to A.3 in the appendix A.1.1.

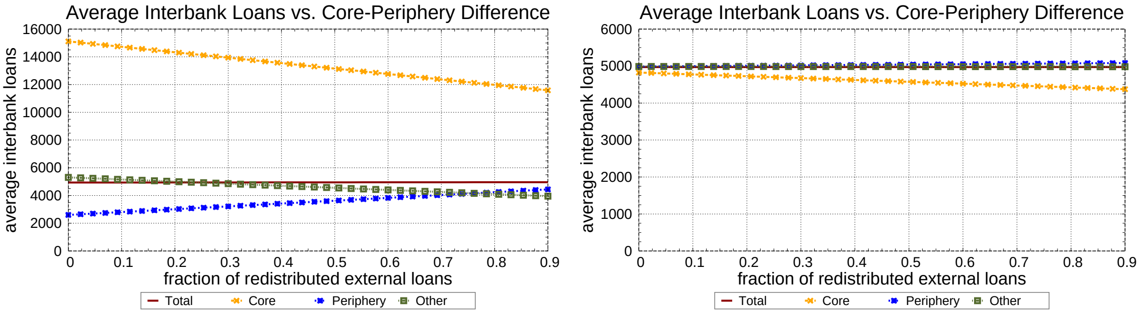


Figure 6.29: Interbank loans in bank balances on average of the peer-group (core, periphery, semi-periphery or other and the banking system as whole) in relation to the core-periphery exposure difference related to ξ in the case of the structural difference (left) and without structural difference (right).
Parameter setting: see Fig. 6.28.

of the interbank lending. Fig. 6.29 left shows the relation between the average interbank loans and the fraction of external loans redistributed from the periphery to the core if structural differences and therefore the higher connectivity of core banks exist. The graph on the right demonstrates the results of similar experiments, given that there are not structural differences between the bank clusters - all banks are interconnected with the same probability. Even if interbank loans of core banks decrease with the external exposure difference between the core and the periphery again here, the concentration of interbank lending increases because of the increasing heterogeneity of banks related to interbank lending.

4. Decreasing investments of core banks in assets, that are originated by other banks and increasing investments of other banks, which are shown in Fig. 6.30 and follow the similar argumentation as above with regard to the increasing amount of securitized external loans instead of refinancing needs of core banks. As a result, decreasing concentration of interbank investments would be expected if structural differences exist.

To illustrate the relationship between the allocation of external credit exposure in the system and heterogeneity of the network we will add some further analyses. We use the

Herfindahl index (also known as Herfindahl – Hirschman Index, or HHI) as an indicator of the economical concentration among banks to support the explanation of the impact of the core periphery properties on the financial system stability. We focus on the interbank and external loans, respectively, and their distribution between banks:

$$HHI_e = \frac{\sum_{i \in N} (c_i^e)^2}{(\sum_{i \in N} c_i^e)^2} \qquad \text{and} \qquad HHI_b = \frac{\sum_{i \in N} (c_i^b)^2}{(\sum_{i \in N} c_i^b)^2},$$

where e_i and b_i are the external and interbank loans of bank $i = 1, \dots, N$ in the network, respectively, and N is the number of banks.

We adopt the normalized Herfindahl index, which ranges from $1/N$ to one and is computed as

$$HHI_e^* = \frac{(HHI_e - 1/N)}{1 - 1/N} \qquad \text{and} \qquad HHI_b^* = \frac{(HHI_b - 1/N)}{1 - 1/N}$$

for external and interbank loans, respectively.

Fig. 6.31 shows the concentration of external and interbank lending depending on the exposure difference between the core and the periphery determined by ξ. It is obvious

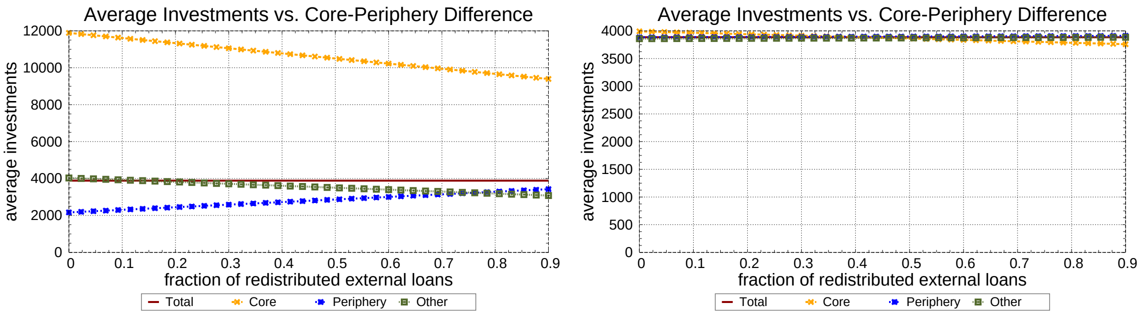


Figure 6.30: Interbank investments in bank balances on average of the peer-group (core, periphery, semi-periphery or other and the banking system as whole) in relation to the core-periphery exposure difference related to ξ in the case of the structural difference (left) and without structural difference (right).
Parameter setting: see Fig. 6.28.

that the concentration of the external lending HHI_e^* increases with increasing external exposure difference, regardless of the existence of differences in the interbank relationships in the system. However, the concentration of the interbank lending HHI_b^* increases with increasing exposure concentration only if interbank lending links are randomly distributed, while in the case of a core-periphery network the concentration of the interbank lending decreases. As we discussed above, if all banks are interconnected with the same probability and core banks grow with respect to their external lending, which induces their refinancing needs, the interbank lending of banks which are connected to the core and subsequently the concentration of the interbank lending increases. In a typical core-periphery network, core banks are more strongly connected than other banks. Increasing refinancing needs of core banks will also increase the amount of interbank loans to core banks, which will be more widely distributed among banks in the system than previous levels of loans to periphery banks. The effect is stronger the larger the redistributed external credit exposure from the periphery to the core is. Hence, the concentration of the interbank lending will decrease with an increasing difference between the core and periphery in core periphery-networks.

We now want to show the impact of the growing external exposure difference between

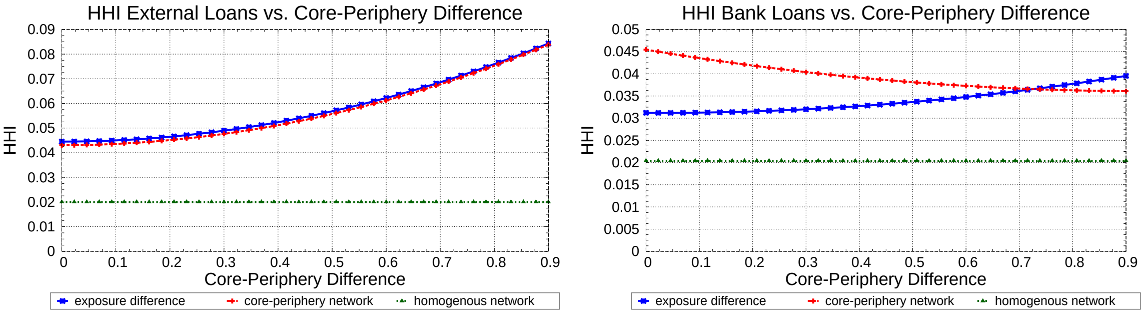


Figure 6.31: Normalized Herfindahl – Hirschman Index for various levels of external exposure difference between core and periphery banks, related to $\xi = 0$ to $\xi = 0.9$: HHI_e^* (left) and HHI_b^* (right).
Parameter setting: see Fig. 6.28.

the core and the periphery on the resilience of the banks. As before this difference is expressed as a fraction of external loans ξ which is redistributed from periphery banks to the core. We vary ξ between 0 and 0.9 and fix the core and periphery fractions by $\psi_1 = 0.1$, $\psi_2 = 0.5$ to study the impact on resilience of banking systems with different levels of capitalization with the equity rate of banks $\gamma = 8\%$ or $\gamma = 4\%$.

Fig. 6.32 presents the results of these simulation experiments, showing the relation between the difference in the external lending exposure and bank defaults in the clusters. Without loss of generality, we will focus on cases where liquidity risk does not exist. As before, we will look at a typical core-periphery network structure characterized by a highly interconnected core and a disconnected periphery, plotted in (a) and (b), as well as at the banking systems with randomly distributed interbank linkages in (c) and (d). Plots (a) and (c) show average default rates for lower capitalized banking systems, while (b) and (d) picture results of the same experiments but for better capitalized banks.

As before, we can see different effects for lower and better capitalized banking systems. Moreover, we can observe different consequences of the external credit exposure allocation for single banking groups and also the effects on the total system stability, which can be positive or negative.

In Fig. 6.32 (a), which shows simulation results for a low equity rate and structural differences between the core and periphery, we observe higher defaults of core banks compared to the periphery and semi-periphery if differences in external lending are sufficiently small. We have already considered this effect above and explained it by risky investments and higher contagion risk of core banks via interbank lending links, which have significantly negative effects on the resilience of core banks in the case of low capital requirements. For low equity rates, increasing external lending of core banks will improve their resilience, which is connected to their decreasing interbank lending reducing the risk of contagion (Fig. 6.32 (a) and (c)). For higher equity rates, contagion is not significant and structural differences have a small positive effect on the resilience of core banks be-

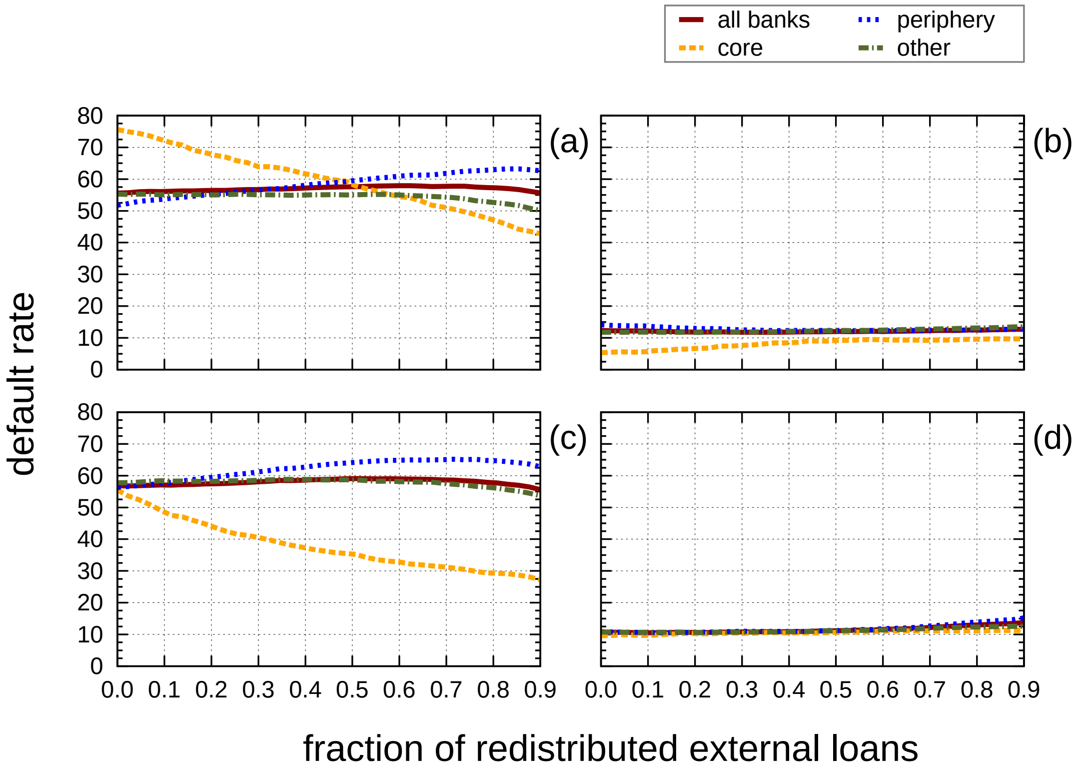


Figure 6.32: Resilience of the bank groups (core, periphery, semi-periphery or other and the banking system as whole) against idiosyncratic shocks without liquidity risk (absence of withdrawal of deposits, $\tau = 0$) in relation to the core-periphery exposure difference related to ξ: (a) structural difference, $\gamma = 4\%$; (b) structural difference, $\gamma = 8\%$; (c) no structural difference, $\gamma = 4\%$; (d) no structural difference, $\gamma = 8\%$.
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\zeta = 0.1$. For the remaining parameters please refer to Tables A.1 to A.3 in the appendix A.1.1.

cause of more interbank loans, which serve to increase the required equity of banks but stay safe after the shocks. But one can also see that the advantage of core banks slightly decreases with an increasing external exposure difference, which can be explained by a decreasing interbank lending of core banks, see Fig. 6.32 (b) and (d).

Increasing differences in the external exposure have smaller, but mostly opposite impacts on the resilience of the periphery banks. However, the high vulnerability of core banks may weaken the periphery by contagion and a rise in the total defaults in the banking system, as can be seen in Fig. 6.32 (d). The total effect on the systemic stability will be negative, if contagion effects outweigh the advantages of the periphery banks in terms of being initially less affected by the external credit defaults. And vice versa, increasing vulnerability of core banks may positively affect the resilience of the total financial system, reducing the total default rate of banks. We observed again that, if the contagion risk is low, banks with higher interbank loans are more stable. If the contagion risk is high, this advantage disappears.

Remark: In addition to the analyses discussed above, we also studied the impact of systematic initial shocks using the same network characteristics as before. Generally, we did not find such pronounced effects as in the case of idiosyncratic shocks.

Conclusion: We can summarize that more heterogeneity in banking systems has stabilizing effects on low capitalized systems and may have a negative effect on the banking stability if banks are better capitalized or shocks are sufficiently small. A core periphery structure presents two major differences compared to the random network. Firstly, the external credit exposure is more concentrated: core banks do more or larger lending deals. Secondly, the interbank lending is generally more concentrated in complete (including structural differences) core-periphery networks compared to the random or incomplete (without structural differences) networks because of the intermediary role of core banks. But the concentration of the interbank lending is decreasing with increasing exposure differences between core and periphery if structural differences with regard to the interbank relationships exist. These properties may have different impacts on the systemic stability and on the resilience of single bank groups, depending on the capitalization level of the banking system or intensity and concentration of the initial shock. Furthermore, core banks tend to be more stable, while periphery banks are more prone to shocks in core-periphery networks if significant differences between the core and periphery exist.

Chapter 7

Loss of confidence and liquidity risk

The present chapter primarily has its focus on the effects of loss of confidence in the banking system, defined by an increase of creditor and depositor intolerance for under-capitalization of banks. The impact of deposit withdrawal in conjunction with the initial shock properties as well as with the capitalization of banks and their risk appetite has been already analyzed in Chapters 4 and 5, respectively. Chapter 6 has treated the withdrawal risk in connection with such banking system properties like network structure and connectivity. Because of the close link between confidence, regulatory capital (minimum requirements) and bank equity level in order to trigger deposit withdrawal, we will consider the interplay of these factors in Chapter 8. Furthermore, we will turn to look at how the discovered effects will be influenced by the willingness of the central bank to support the banking system in Chapter 9.

7.1 Confidence in banks

One of the important properties of the financial network environment is the confidence in the banking system. A coherent, effective and transparent set of laws which ensure the respect of property rights and the operation of a functioning bankruptcy regime, as well as certainty and effectiveness of safeguards and guarantees are of key importance for investor and creditor protections and thus for the confidence in the banking system.

Numerous papers have established that countries with better functioning legal institutions and effective protection of investor and creditor rights enjoy better developed and more stable financial markets. According to the widespread belief in academic and political circles, the depth of the 2007-09 financial crisis, its longevity and its impacts on the real economy resulted from an erosion of confidence, see [21].

E. Perotti and E. Feijen (2005) addressed the question of investor protection in [26] and demonstrated that, under weak regulatory institutions, financial liberalization, which should free financial institutions from direct political control and lead to better access of firms to finance, is often followed by financial crises. The authors explained this conclusion by poor investor rights, which may induce ex post incentives to default for firms requiring more external finance and would cause investors to refuse new project financing or to exit from ongoing projects after an external shock.

A.J. Galindo and A. Micco (2007) focused on creditor protection in [34] and studied the relationship between creditor protection and the response of credit to external shocks by using a panel constructed gathering information between 1990 and 2004 for a broad set of countries. The authors detected empirical support for the idea that weak creditor protection makes credit markets more volatile, which means that poor creditor protections induce an overreaction of credit markets to exogenous shocks. They showed, for example, that in countries with a common law tradition, characterized by high creditor protection and good contract enforcement, the elasticity of credit to external shocks is half of that in other economies.

M. Dailami and P. Masson (2009) underlined the connection between the willingness of investors to allocate assets to equities, and their risk appetite and confidence in [16]. The authors postulated four dimensions of investor confidence: market volatility, market performance, macroeconomic news, and government responses. According to them, investor psychology is strongly influenced by volatility in the marketplace, which signals uncertainty and risk aversion. Moreover, investor confidence is related to the performance of their investments, as measured by wealth creation or destruction. Furthermore, investors typically look at current economic fundamentals and predictions concerning the future state of the economy and pay close attention to the stance of government policy makers and continually assess the credibility of their responses, see [16].

The mentioned studies underpin that the occurrence or even the reasonable possibility of a financial crisis will naturally lead to contraction in credit and willingness to invest. However, this effect is not in the scope of the present work.

The main focus of the present research is creditor confidence in banks in connection to the deposit withdrawal risk and the question, how the regulatory requirements and central bank policy maintain financial stability and confidence in banks.

7.2 Liquidity risk

The financial crisis, that began in 2007, was in essence a collapse in confidence, as summarized by Stefan Ingves during the 15th Annual Convention of the Global Association of Risk Professionals in New York (2014) [1]. Starting from the real estate market in the USA, the financial turmoil spread rapidly beyond the United State's borders. Shortly after the outbreak of the crisis, the interbank market froze nearly completely. Banks stopped giving short-term loans on the interbank market activating a further spiral of liquidity problems.

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[1] see "Restoring confidence in banks" in "Keynote address to the 15th Annual Convention of the Global Association of Risk Professionals" in New York, 4 March 2014.

At this point, it would be appropriate to define the term "liquidity". In accordance with M. Dailami and P. Masson (2009), the term liquidity has two principal meanings: one of them is the global liquidity measure capturing the volume of funds available for investment. Another meaning is the ease and quickness with which assets can be converted to cash. Liquidity in this sense has decreased dramatically for all except government securities during the financial crisis, which started in 2007, in contrast to the global volume of funds, see [16]. The liquidity term in the sense of the amount of highly liquid assets is connected to liquidity problems to be studied here.

Here, we will focus on creditor and depositor confidence, the loss of which would lead to withdrawal of liquidity. In this way, we try to pay the necessary amount of attention to the role of the borrowed capital here. To model the loss of confidence we use one additional exogenous parameter 'intolerance of bank undercapitalization', hereinafter referred to as the 'intolerance', that characterizes a degree of mistrust in the safeguards of the banking system. The intolerance is connected to the undercapitalization degree of banks. Thus, the intolerance τ is defined as a threshold for the quotient of individual bank capital ratio γ_i and the regulatory capital ratio γ^r. If the equity ratio of any bank falls so that $\frac{\gamma_i}{\gamma^r} \leq \tau$, externals and other banks would withdraw their funds from this undercapitalized bank. In this way the withdrawal risk is also connected to the regulatory capital requirements, which serve as an orientation for the depositors, thinking that the regulations define the appropriate benchmarks and stability criteria. Please note, that banks are allowed in the model to have a 'thin capitalization' in the short term. There is no need to wind up the undercapitalized banks immediately. For details on the implementation of the withdrawal risk and the according dynamic processes we refer to the description in section 2.3.4.

7.3 Simulation results

Impact of withdrawals for each subject of the economy is not clear because of the accumulation of several effects. On the one hand, withdrawals of deposits could prevent externals and banks from losing their funds on deposit. But, on the other hand, withdrawals may cause serious liquidity problems to the affected banks and their need to sell assets. This option, in turn, allows the better capitalized banks to reap profits buying the assets at fire-sale prices. Thereby, fire-sale prices will largely depend on the demand for the fire-sale assets, which in turn is limited by capital restrictions. In addition, central banks or other supporting institutions may play an important role in the price formation process. In particular, the arrangements of the central bank for providing the suddenly lacking liquidity or buying the excess assets may have significant implications.

In the following we investigate the impact of intolerance for bank undercapitalization and thus of confidence in the banking system on losses to externals and banks as well as the resilience of the banking system. In order to keep the analysis as simple as possible and to avoid a mixing of effects, we will abstain from including into the analysis the external credit decline as a reaction on the financial turmoil. So, we will keep the initial external credit volume constant and allow its deterioration only by the initial shock.

Resilience of the bank system

We observe, in general, that the number of defaults rises with an increasing intolerance, provided that the intolerance is high enough to trigger withdrawal of deposits, see Fig. 7.1. The increase of bank defaults is stronger if the debtors are less tolerant. The default curves follow a similar course as the according external loss curves. Note, that similar to external losses, bank defaults after deposits withdrawal can not be lower than in similar scenarios but without liquidity risk.

In addition, we note that the impact of the intolerance is highly dependent on the initial

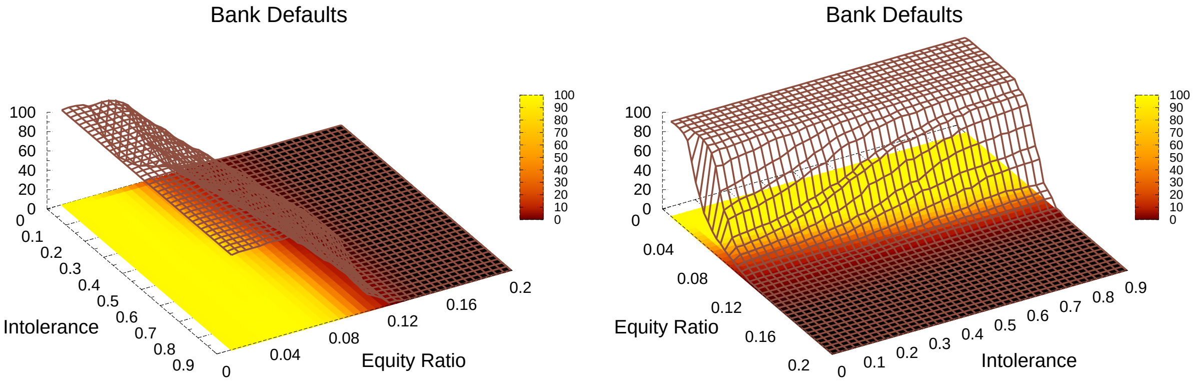

Figure 7.1: Resilience of the bank system in relation to the intolerance for capital gap of banks τ and initial bank capitalization γ in the case of high concentration of shocks and high risk appetite of banks (NW 01). The (same) results are presented taking into consideration two different spatial perspectives.
Parameter setting: see Tables A.1 to A.3 in the appendix A.1.1.

capitalization of banks. The influence of the intolerance is particularly high for some medium equity levels. The level of the intolerance does not play a significant role if the initial equity is high compared to the initial shock and likewise, if the equity is very low or the initial shock is very high, so that the banking system would collapse completely, regardless of the level of intolerance. However, the level of the initial equity rate, which is small enough to cause withdrawal, increases with increasing intolerance.

Bank losses:

Fig. 7.2 pictures the cumulated losses within the banking system depending on the level of the intolerance. It can be observed that bank losses increase with increasing intolerance if withdrawals can be triggered. Withdrawal of deposits depends not only on the intolerance level, but also on the level on the initial bank capitalization as well as on the intensity and allocation of the initial shock across the system. Furthermore, the influence of intolerance is especially high at certain medium equity levels. Moreover, the interval of equity in which withdrawals occur becomes broader with the intolerance becoming higher. This result emphasizes that higher intolerance requires a higher bank capitalization level to make the banking system more resistant against withdrawals. The following analysis

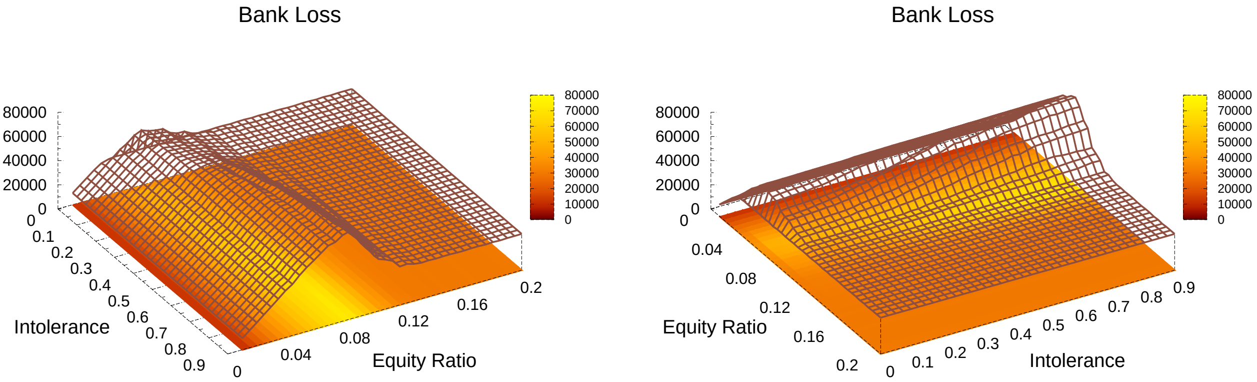

Figure 7.2: Cumulated bank losses in relation to the intolerance for capital gap of banks τ and initial bank capitalization γ for high concentration of shocks, high risk appetite of banks and deposit withdrawals (NW 01). The (same) results are presented taking into consideration two different spatial perspectives.
Parameter setting: see Fig. 7.1.

of the system resistance confirm this statement.

External losses:

As before we are using the simulation engine, implementing the risk of withdrawals after the first absorption of the initial shock is completed. Therefore, it is not surprising that, compared to the cases in which no withdrawals are possible (intolerance level is equal to zero), the total external losses should be higher or remain at the same level after withdrawals occur, see Fig. 7.3.

We observe that external losses increase with increasing intolerance, provided that the intolerance is high enough to trigger withdrawal of deposits, and remain constant at a sufficiently high level of intolerance (very strong bank run, total bankruptcy). We see that this increase is slight if the intolerance is low; and it is very strong if the intolerance is sufficiently high but not enough to trigger the total collapse of the banking system. If banks are still well capitalized, withdrawals are averted or do not have any influence on externals. It is also possible that withdrawals do not lead to external losses. Thereby, the additional losses to banks, caused through fire-sales, can be completely covered by

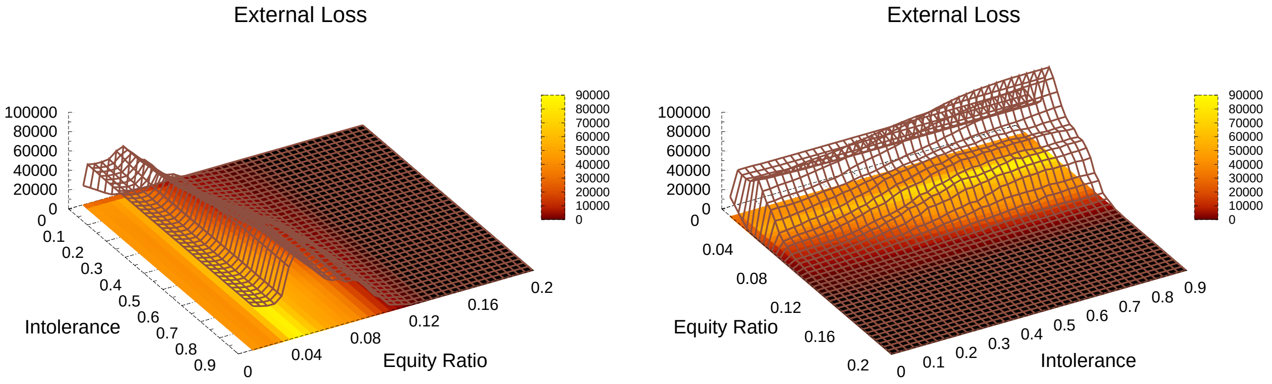

Figure 7.3: External losses in relation to the intolerance for capital gap of banks τ and initial bank capitalization γ for high concentration of shocks and high risk appetite of banks with the possibility of deposit withdrawals (NW 01). The (same) results are presented taking into consideration two different spatial perspectives.
Parameter setting: see Fig. 7.1.

the banking system. But, at a sufficiently high level of intolerance, external losses would increase disproportionately strongly compared to the further increase of the intolerance, which means that a marginal loss of confidence would lead to the heavily growing losses to the external segment, if the confidence has been already considerably damaged.

Conclusion:

If banks are still well capitalized after the shock, withdrawals are averted, whatever the level of intolerance is. At a sufficiently high level of intolerance, in other words if the confidence has been already considerably damaged, the negative impact of withdrawals would increase disproportionately strongly compared to the further increase of intolerance, which means that a marginal loss of confidence would lead to heavily growing losses to banks and externals and destabilize the banking system substantially.

One interesting aspect is here, that the more rigorous the capital regulations are, the stronger this effect will be. In contrast, central bank support could positively counteract, stabilizing the banking system. Both mentioned effects will be discussed later. Furthermore, the effects of deposit withdrawal risk can be influenced not only by capital regulations, willingness of the central bank to support the banking system or the initial bank capitalization, but also by the network structure, intensity and distribution of shocks and not least by the risk appetite of banks and externals.

Furthermore, the interval of equity values, in which withdrawals occur, grows with increasing intolerance against undercapitalization of banks. This result emphasizes that higher intolerance requires higher bank capitalization level to make the banking system more resistant against withdrawals.

It should be mentioned here, that despite the multiplex analysis we had implemented in the simulation engine, we believe that parameter settings and network topology have a considerable influence on structural loss trends in the economy. It cannot be excluded, for example, that cumulated bank losses decrease with increasing intolerance for some parameter constellations. It could be possible that in the low interconnected system, only some banks which are not well connected to others get affected after a strong idiosyncratic initial shock is very concentrated. In this case, only a few banks would run into trouble, significantly transmitting their losses to externals. Buying assets at fire-sale prices banks would reap profits, which could be higher than the losses covered by capital of defaulted banks. In such a hypothetical case the banking system as a whole may face lower losses with increasing intolerance.

Chapter 8

Capital adequacy

Governments may influence the confidence of investors in many ways: through macroeconomic and regulatory policy as well as through other legislative actions that can strengthen transparency and enhance corporate financial disclosure and integrity, see [16].

Basel III has added additional safeguards as an answer to the financial crisis started in 2007. Particularly, the revised capital requirements should help to restore confidence in banks by attaching greater importance to core capital, which serves as a buffer for the real economy against financial distress. Especially worthy of mention here are the regulations in order to strengthen the quality of risk-based capital ratio and to prescribe additional capital for institutions of systemic importance. Furthermore, the increase of requirements on leverage has been established, characterized by the introduction of a non risk-based leverage ratio serving as a complement and a constructive corrective to the risk-based capital requirement. Moreover, the international standards for bank liquidity and funding in the shape of the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) have been introduced.

The mentioned steps are in line with the principles of requiring higher capital for activities of greater risk and a stable funding concept. All in all, they should serve to stabilize the financial system by increasing transparency and by restoring and solidifying investor, creditor and market confidence in the banking system. The mentioned structures and requirements, which would increase transparency and confidence in banks, are of particular interest in the presented work. The impact of liquidity endowment will be treated in the subsequent chapter.

This chapter is organized as follows. Section 8.1 deals with the impact of the regulatory capital restrictions for minimum bank capitalization. Section 8.2 analyzes the implications of the more stringent capital requirements and of a capital surcharge for systemically important banks, in particular.

8.1 Impact of the regulatory capital restrictions

As noted in the previous section, the equity level of banks depends on the willingness of investors to provide the equity and is connected to the confidence in the banking system. But, to a much higher degree the bank capitalization level is linked to the regulatory minimum capital requirements.

Theoretical papers about how banks react to capital requirements often demonstrate contradicting results because of the high sensitivity to the underlying assumptions. Not least, for that reason, a substantial number of empirical work has tried to evaluate the impact of capital requirements on bank behavior over the recent decades, see [36]. Various studies proved that minimum capital requirements significantly affect capital and risk levels in banking systems. The researchers found that reactions of banks differ in terms of adjusting their capital ratios primarily through capital or risk, or by using both instruments. However, it should be added that the different statements are results of analyses of various banking systems. The differences can be explained, for example, by different access to capital and a developed market for securitization and credit derivatives. While in the 90s US banks seemed to adjust capital and risk assets in order to meet the capital regulation, UK and Swiss banks seemed to exclusively adjust their capital, see Heid, Porath and Stolz(2003) in [36], Aggarwal and Jacques (1998) in [2], Rime (2001) in [58] and Van Roy (2005) in [60].

Heid, Porath and Stolz (2003) examined in [36] the impact of capital requirements on capital and risk levels of German savings banks. They found evidence that banks' responses to the regulatory requirement adjustments depended on the amount of capital buffer, defined by the capital the bank holds in excess of the regulatory minimum. Banks with low capital buffers tried to rebuild an appropriate capital buffer by raising capital and simultaneously lowering risk. In contrast, banks with high capital buffers tended to keep their buffers by simultaneously increasing both capital and risk levels.

Brei and Gambacorta (2014) analyzed how the risk-weighted regulatory capital ratio and the Basel III leverage ratio behaves over the cycle, using a large data set for the period 1995-2012.[1] They found that both are countercyclical: it is a tighter constraint for banks in booms and a looser constraint in recessions. Moreover, the leverage ratio, which includes guarantees and other off-balance sheet positions, is significantly more countercyclical than the risk-weighted regulatory capital ratio, see [10]. Furthermore, the authors have shown, that exposure measures, total assets, as well as RWA are positively correlated with cycle indicators. They noted that the correlation is somewhat lower during the crisis and explained this finding by the effect of a sharp lending and investment reduction during the crisis.

As the mentioned works demonstrate, it is indisputable that regulatory capital requirements influence the level of the initial bank capitalization at least in the mid-term. We analyzed the influence of the capitalization of banking systems in section 5.1 and showed

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[1] The leverage ratio indicates the maximum loss that can be absorbed by equity, while the risk-based requirement refers to a banks capacity to absorb potential losses, see [10].

its common positive impact on system stability. In order to separate the short-term effects of the obligatory minimum capitalization of banks, like cutting back or expending new business, from effects of the initial capitalization, we don't adjust the initial bank capitalization according to the changing capital requirements in our simulation analysis. Here we take into account only the short-term impact of capital requirements. To be exact, we suppose that capital requirements influence the new business by capital restrictions and, thus, the demand for assets during the fire sale process.

Furthermore, as presented in section 2.3.4, liquidity risk is connected to the regulatory capital requirements in the model.

We are looking at impacts of the regulatory capital by varying the regulatory capital ratio γ^r. We begin by analyzing the losses to external counterparts.

Resilience of the bank system and losses to banks

As shown in Fig. 8.1, cumulated bank losses increase with increasing capital requirements if withdrawals occur. Similarly, bank defaults increase with increasing capital requirements if withdrawals happen, see Fig. 8.2. Moreover, the increase of the regulatory capital level can substantially intensify the impact of intolerance for undercapitalization of banks. The reasons for the observed effects are capital restrictions on new business and an earlier start of withdrawals, which will be discussed below in relation to the losses to externals.

External losses

In Fig. 8.3 we observe that external losses increase with increasing capital requirements if withdrawal risk exists because of withdrawals being triggered earlier and prices for the fire-sale assets decreasing more strongly. The first effect is connected to the condition $\frac{\gamma_i}{\gamma^r} \leq \tau$, which determines the state when depositors withdraw their funds from the bank i. In this way the withdrawal risk is increasing in the regulatory capital γ^r (see 2.3.4 for

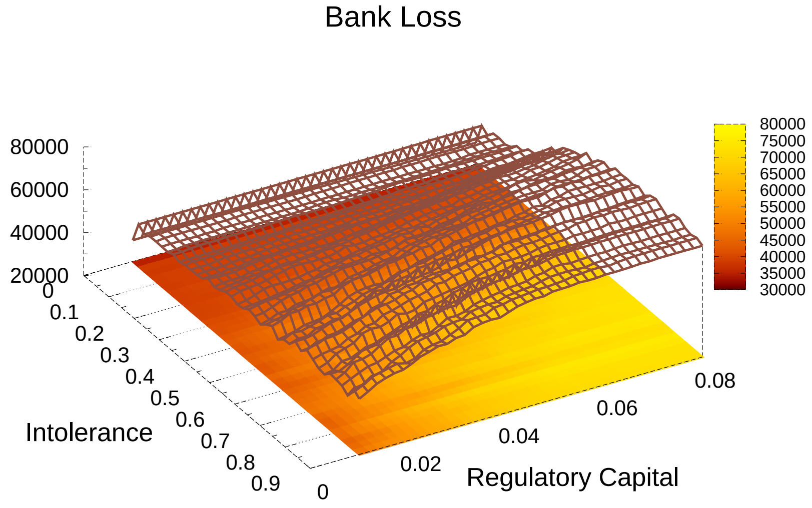

Figure 8.1: Cumulated bank losses in relation to the intolerance for capital gap τ and regulatory capital λ^r with high concentration of the shock and risk of withdrawal of deposits.
Parameter setting: see Tables A.1 to A.3 in the appendix A.1.1.

more details) given a constant initial capital determined by γ_i. The second effect is linked to the fact that stricter regulatory requirements allow solvent banks limited leeway for

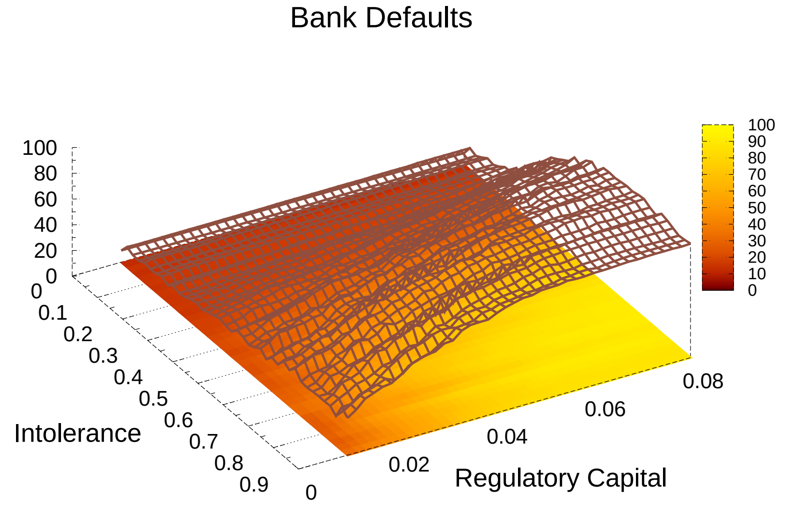

Figure 8.2: Resilience of the bank system in relation to the intolerance for capital gap τ and regulatory capital λ^r with high concentration of the shock and risk of withdrawal of deposits.
Parameter setting: see Fig. 8.1.

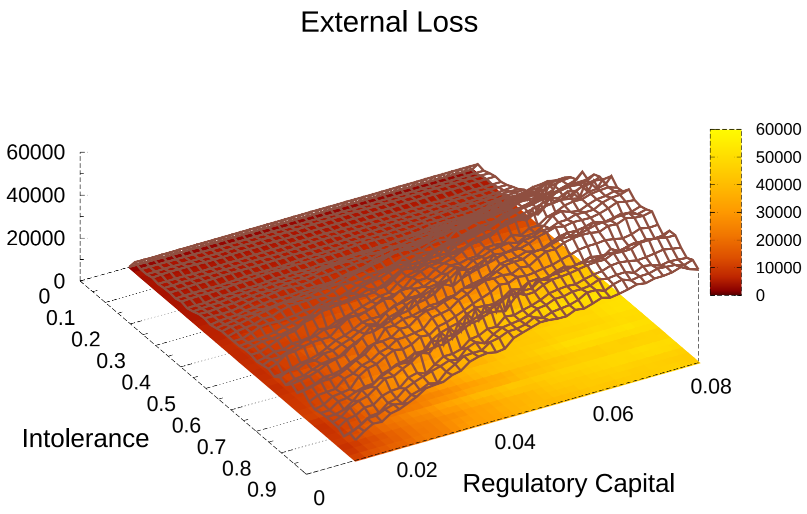

Figure 8.3: External losses in relation to the intolerance for capital gap τ and regulatory capital λ^r with high concentration of the shock and risk of withdrawal of deposits.
Parameter setting: see Fig. 8.1.

new business which negatively affects demand for offered assets and, thus, the fire-sale prices.

We can say, taking into account the results of the previous chapter, that similar to the higher intolerance stricter capital requirements would lead to a higher withdrawal of deposits and thus to higher external losses, in general. The according results are illustrated in Fig. 8.3.

Conclusion

In this section we have looked at the impact of the tightening of regulatory capital restrictions followed by two short-time consequences: deceleration of new business activities and, thus, pressure on the demand and prices for fire sale assets, firstly, and maintaining uncertainty about appropriate capitalization of the banking system among depositors, secondly, using the regulatory capital requirements as an orientation marker with regard to the safety of the deposits. We can summarize that the tighter capital requirements may increase the vulnerability of the banking system from the short time perspective and, even more, the losses to both, banks and externals due to the increasing liquidity risk. Nevertheless, we recognize that at least in the medium run, banks would react by increasing their equity base or reducing their (risk) assets, strengthening the systemic stability.

8.2 Modifications of capital requirements and capital surcharge

In the previous chapters we examined the (mostly positive) effect of higher capitalization of the banking system at different points. Here we focus on the impact of the additional capital requirements. Thereby we analyze the case that all banks are treated equally, and the case of different allocation of the additional capital assuming that only systemically important banks are subject to the capital surcharge. Furthermore we take a look on the risk adjusted capital requirements compared to the "flat" capital adequacy. The last can be regarded as a "prototype" of the Basel III's Leverage Ratio which represents the relationship between core capital and total assets. It should basically restrict the excessive credit growth accompanied by excessive leverage.

8.2.1 Treatment of systemically important banks by Basel III

The great impact of the disruption or failure of large and internationally active financial institutions on the financial system and, even beyond, on the real economy became obvious during the financial crisis that started in 2007. To prevent further damage to the economies and to restore the confidence in the banking systems plentiful and costly interventions of public sector were needed. The financial and economic costs of these interventions and the increase in moral hazard associated with the behaviour of systemically important financial institutions have required reconsideration of the regulatory requirements.

The Bank of International Settlements (BIS) published new regulatory rules for commercial banks in December 2010, known as Basel III (or the Third Basel Accord), with the aim of increasing the stability of the financial sector. These guidelines, developed by the Basel Committee on Banking Supervision (BCBS), strengthen capital requirements amongst others. In addition to the increase for the core capital quota (CCQ), defined as the minimum ratio of core equity capital that a bank has to hold in relation to its risk weighted assets, the globally important financial institutions (G-SIBs) shall be subject to tighter capital requirements. In particular, the "cross-border risk" is addressed with capital surcharges on G-SIBs. The final rules for G-SIBs were published in [54] and revised in [56].

Furthermore, in addition to the rules for G-SIBs the Basel Committee developed a set of principles on the assessment methodology and the higher loss absorbency requirement for domestic systemically important banks (D-SIBs) in response to the appeal by the G20 leaders. The idea is that some banks which are not significant to systemic risk from a "cross-border" perspective, can be of prime importance with a view to their domestic financial system stability. Moreover, the failure or distortion of any of them would likely have significant cross-border side effects. The D-SIB framework was published in [55] allowing for an appropriate degree of national discretion to be able to accommodate the specific features of domestic jurisdictions. It is complimentary to the rules applied to the G-SIB. Thereby, the focus is placed on the negative externalities created by local and international banks at a domestic level, see [55].

The special purpose of these rules for G-SIBs is to enhance the loss absorbency on a going concern basis of G-SIBs and reduce their probability of default. The intent is to protect the system from the risks of spillover effects created by G-SIBs. The abovementioned externalities include the impact of the failure or impairment of G-SIBs that can trigger shocks causing widespread financial distress and damaging the real economy. One further impact is connected to the, probably not optimal, outcomes of G-SIBs from a systemic perspective because of the negligence of negative externalities. And not least, the moral hazard risk created by the incentive of large and highly interconnected banks to take on excessive levels of risk in anticipation of direct support and implicit government guarantees should be mentioned, see [56].

According to BIS, the global systemic importance should be measured in terms of the impact that a banks failure can have on the global financial system and wider economy, rather than the single bank default risk. The assessment methodology for G-SIBs is based on an indicator-based approach and comprises five broad categories which reflect the size of banks, their interconnectedness, the lack of readily available substitutes or financial institution infrastructure for the services they provide, their global (cross-jurisdictional) activity and their complexity. With the exception of the size category, multiple indicators in each of the categories have been identified, with each indicator equally weighted within its category. In accordance with the Basel Committee on Banking Supervision the quantitative indicator-based approach can be supplemented with qualitative information that is incorporated through a framework for supervisory judgment because no approach will perfectly measure global systemic importance across all banks, which vary widely in their structures and activities, and therefore in the nature and degree of risks they pose to the international financial system.

The indicators applied for assessment of G-SIBs are chosen to reflect the different aspects of negative externalities that could make a bank critical to the stability of the financial system, according to [56].

1. Cross-jurisdictional activity The objective of this indicator is "*. . . to capture banks global footprint*". Two indicators should grasp the significance of a bank with respect to its activities outside its local jurisdiction relative to overall activity of other banks in the system: cross-jurisdictional claims and cross-jurisdictional liabilities. The assumption is that the international impact of a banks distress or failure depends on its share of cross-jurisdictional assets and debts. The greater these items, the more widespread the spillover effects from the failure of the bank.

2. Size Size is a key measure of systemic relevance. The indicator used here is a simple indicator as a measure of total exposures used in the Basel III leverage ratio. The idea is that a large bank's distress or failure is more likely to harm the financial markets or even the global economy. The larger the bank, the more difficult its replacement therefore the greater the probability of the disruption of the relevant financial markets. Moreover, the impairment of a large bank is more capable of damaging confidence in the financial system as a whole.

3. Interconnectedness A banks systemic importance is expected to be positively related to its interconnectedness within the system. Three indicators are used to measure interconnectedness here: intra-financial system assets, intra-financial system liabilities, and securities outstanding.

4. Substitutability/financial institution infrastructure The systemic importance of a bank seems to be negatively related to its degree of substitutability. Three indicators are used to estimate substitutability/financial institution infrastructure: assets under custody, payment activity, and underwritten transactions in debt and equity markets.The greater a banks role in the financial infrastructure, the larger the probable disruption following its failure. Subsequently, the cost to the failed banks customers or business partners of substituting the relatively larger service provider or consumer is likely to be higher.

5. Complexity The systemic importance of a bank is expected to be positively related to its overall complexity. Three indictors are used to measure complexity: firstly, notional amount of over-the-counter (OTC) derivatives; secondly, Level 3 assets like complex OTC derivatives, illiquid loans, certain structured bonds, and further typically very illiquid assets which fair values usually can only be calculated using estimates or risk-adjusted value ranges; finally, trading and available-for-sale securities. The idea is that the failure of a more complex bank would cause greater costs and time needed to wind up the bank.

The impact of impairment or failure of a D-SIBs on the domestic economy should be assessed with regard to the size, interconnectedness, substitutability/financial institution infrastructure (including considerations related to the concentrated nature of the banking sector) and complexity (including the additional complexities from cross-border activity) in terms of bank-specific factors, see [55].

8.2.2 Capital Surcharges on SIBs in the ABN Model

The tighter capital requirements for SIBs can be understood as penalties for their importance to the global financial stability or stability of a country and its economy. Such an instrument should not only actively support the robustness of the SIBs, but also reduce incentives to increase the systemic importance, that would otherwise arise in anticipating advantages as a result of being 'to important to fail'.

We try to adopt the principles contained in the assessment methodology for SIBs of the BCBS that are based on the scores as described in 8.2.1. We adapt this methodology to the features of the ABN-Model. Since we model a closed economy, cross-jurisdictional activity does not really matter here. Moreover, only indicators which seem to be connected to the individual or systemic risk in the given stylized network should be included. So, for example, payments activity plays no role in the ABN-Model and therefore cannot be regarded as an indicator. Among these considerations, five indicators will be incorporated in the model structure, which can be classified into four categories as follows:

Size: Large banks increased in size during the several years before the last financial crisis. Their complexity and wide variety of market-based activities grew rapidly. The banking systems became increasingly global and interconnected. Therefore, it is hardly surprising that bank size is typically an important driver of systemic risk measures. Thus, large institutions are commonly regarded as banks of systemic importance. The larger the bank, the higher the amount of its exposure will be expected to be stressed by the initial shock, and the greater the interbank exposure will be, which can be affected by contagion triggered by the failure of the bank. We define size as total assets of the bank:

$$i_i^1 = a_i \qquad (Size) \tag{8.1}$$

Interconnectedness: The higher the bank is connected within the system, the higher the probability of being affected by contagion and also the larger the number of banks that could be distressed through the loss transmission from this bank. The interconnectedness will be defined as the number of banks connected via debts or deposits to the observed financial institution:

$$i_i^2 = \sum_{j=1}^{N} R_b^c[i,j] + \sum_{j=1}^{N} R_b^c[j,i] \qquad (Interconnectedness) \tag{8.2}$$

Substitutability (in the broadest sense): The higher the interbank exposure, the higher the material interdependency between this and the other connected banks, including the indirectly connected financial institutions. The total lending to the external segments (private and commercial customers) indicates the importance of the bank for the real economy, but it is also connected to the probable intensity by which the initial shock may concern the bank. We define the substitutability in the broadest sense as interbank loans and deposits on the one hand, and the external credit exposure on the other hand.

$$i_i^3 = c_i^b + d_i^b \qquad (Substitutability(1)) \tag{8.3}$$

$$i_i^4 = c_i^e \qquad (Substitutability(2)) \tag{8.4}$$

Complexity: Comparing two banks which are similar in size, the bank with riskier assets will be presumably more complex and more vulnerable. The absolute amount of the risk weighted assets (RWA) is closely linked to the intensity of the shock, which has to be absorbed by the bank, but also to the possible loss transmission from the bank into the system. We define the complexity as volume of the risk weighted assets:

$$i_i^5 = RWA_i = \tilde{c_i^b} + \tilde{c_i^e} + \tilde{i_i^b} \qquad (Complexity) \tag{8.5}$$

with risk-weighted interbank loans $\tilde{c_i^b}$, risk-weighted loans to externals $\tilde{c_i^e}$ and risk-weighted CB and CDO-investments $\tilde{i_i^b}$, see 2.3.

For the determination of an overall score over all five criteria, we firstly determine single scores for each criteria. Let $\underline{N} := \{1, \ldots, N\}$ be the set of bank indices. For each $k \in \{1, \ldots, 5\}$ let $\sigma_k : \underline{N} \to \underline{N}$ a permutation with the property

$$\sigma_k(i) < \sigma_k(j) \quad \Longleftrightarrow \quad (i_i^k > i_j^k) \text{ or } (i_i^k = i_j^k \text{ and } i < j) \quad \forall i, j \in \underline{N}.$$

Hence, $\sigma_k(i)$ is the position of bank i considering criteria k, only. All σ_k are uniquely defined. The overall position (score) is then given by a further permutation $\sigma : \underline{N} \to \underline{N}$ with the property

$$\sigma(i) < \sigma(j) \quad \Longleftrightarrow \quad (s_{ij} < 0 \text{ or } (s_{ij} = 0 \text{ and } i < j)) \quad \forall i, j \in \underline{N},$$

where the quantity s_{ij} is given by

$$s_{ij} := \sum_{k=1}^{5} \left(\sigma_k(i) - \sigma_k(j) \right). \tag{8.6}$$

The permutation σ is also uniquely defined. The importance of all criteria are assumed to be equal. However, placing greater importance to individual criteria is easily possible by considering a weighted sum in (8.6).

The following relation will be then assumed: the lower the position $\sigma(i)$, the more important bank i is for the considered financial system. We determine the SIBs as those banks within the first 25% positions. The set M contains the indices of the SIB banks:

$$M = \big\{ i \in \underline{N} \mid \sigma(i) \leq N/4 \big\}. \tag{8.7}$$

As mentioned above we will analyze the impact of capital surcharges by increasing the initial capital base of the banking system. In the previous chapters, we have already demonstrated that the additional capital has a positive stabilizing effect and reduces systemic risk. The question that we face now is which effects are to be expected when the new rules impose the additional capital requirements only on the SIBs as opposed to the uniform tightening of the initial capital ratio for all banks. To avoid unwanted side effects in the analysis, we ensure an equal total amount of capital for the scenarios to be compared. For this reason we implement the following algorithm.

Assume that $\tilde{\gamma}$ determines the additional capital in the financial system, so that the total capital of the banking system is given by

$$E^{new} = E + \tilde{\gamma} RWA = (\gamma + \tilde{\gamma}) RWA, \tag{8.8}$$

where E and γ are the initial capital of banks or capital ratio, respectively, before the capital surcharge, while $RWA = \sum_{i=1}^{N} RWA_i$ is known as the total risk wighted assets in the banking system from section 2.3.

Supposing the special treatment of the SIBs, we have to calculate the RWAs of the SIBs $m \in M$, $M \subset N$ firstly and to determine the equity surcharge for the SIBs $\tilde{\gamma}^{SIB}$ secondly.

$$\tilde{\gamma}^{SIB} = \tilde{\gamma} \frac{RWA}{\sum\limits_{m \in M} RWA_m} \tag{8.9}$$

In this way we can calculate the initial capital for each bank by

$$e_i = (\gamma + \tilde{\gamma}_i) RWA_i, \quad \forall i \in N \tag{8.10}$$

where $\tilde{\gamma}_i = \tilde{\gamma}^{SIB}$ for SIBs ($\forall i \in M$) and $\tilde{\gamma}_i = 0$ for other banks.

When all banks are treated equally with $\tilde{\gamma}_i = \tilde{\gamma}\ \forall i \in N$, the application of the additional capital would be as follows:

$$e_i = (\gamma + \tilde{\gamma}) RWA_i, \quad \forall i \in N \tag{8.11}$$

Simulation Experiments and Results

Using the simulation engine we study the influence of the risk adjusted bank capitalization dependent on the sensitivity of bank capital to two different kinds of expected risk. Thereby we compare four basic scenarios characterized by the sensitivity of banks' capital to the individual (IRS) and/or systemic risk (SRS) as follows:

	IRS	
SRS	no	yes
no	**a**	**c**
yes	**b**	**d**

Table 8.1: Notation of the scenarios with respect to the sensitivity of bank capitalization to the individual and systemic risk.

Scenario "**a**" represents the case where individual bank's capital depends neither on the individual risk nor on the systemic risk, implying that capital requirements are proportional to the volume of the bank's risk assets as defined in section 2.2.5 by (2.13). In that respect, it implies that the calculation of required equity is based on risk weights which are equal to 100% for all claims with exception of the bank claims wighted by 50% (flat-rate capital adequacy). Moreover, the equity surcharge relating to $\tilde{\gamma}$ equally applies to all banks, as defined by (8.11).

The next two scenarios relate to the dependency on one of the two aforementioned types of risks. Scenario "**b**" represents the case of the systemic risk sensitive capitalization of banks (SRS), which means that the (additional) capital buffer of a bank only depends on its importance for the stability of the financial system, implying that the equity surcharge relating to $\tilde{\gamma}$ applies only to SIBs, see (8.8) to (8.10) above. Initial capital of a bank do not depend on its individual asset risk characteristics. Scenario "**c**" denotes the case in which the level of the initial bank capital depends on the individual asset risk characteristics for each bank (IRS) as presented in section 2.3, while the equity surcharge relating to $\tilde{\gamma}$ equally applies to all banks in the same way: $\tilde{\gamma}_i = \tilde{\gamma} \quad \forall\, i = \{1, \ldots, N\}$. However, this scenario corresponds to the simulation experiments which we considered in the previous sections.

In contrast, scenario "**d**" is characterized by sensitivity of bank capitalization to both individual and systemic risk (SRS&IRS).

Further, for all scenarios we assume highly heterogeneous banking systems applying the core periphery network structure with a high difference in the external exposure between the core and the periphery as presented in section 6.4.3.[2] Furthermore, we create various types of experiments considering strong idiosyncratic or systematic shocks, high or low risk appetite of banks and allowing or not the withdrawal of deposits. To make the scenarios comparable, we use the same parameters, unless the parameters specify the individual scenarios as described above. Note, that we also use the same size of shock for all scenarios. We do not present the case of low risk appetite of banks if a systematic

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[2] The scenarios a, b, c, d correspond then to the modes 07, 08, 15 and 16 according to the structure in Tab. A.7.

shock occurs, because of a very high stability of the banking system in this case for the given parameter setting and thus indiscriminate results of various experiments. The results relevant to the following discussion are displayed graphically in Figures 8.4 to 8.8. Tables 8.3 to 8.5 summarize the observed effects of the risk-sensitive compared to the non-risk-sensitive capitalization of banks on the resilience of banking systems and losses to banks and externals.

Here, a higher risk of banks is connected to the exclusive investments of banks in the most risky CDO-Tranches B and C. In the case that lower risk banks and externals hold CBs and each tranche of CDOs in equal shares, see Tab. 8.2.

Bank shares of investments β^{CB}, β_t^{CDO} $(t \in T)$	**CB** β^{CB}	**Tranche A** β_A^{CDO}	**Tranche B** β_B^{CDO}	**Tranche C** β_C^{CDO}
Low risk of banks	0.5	0.5	0.5	0.5
High risk of banks	0	0	1	1

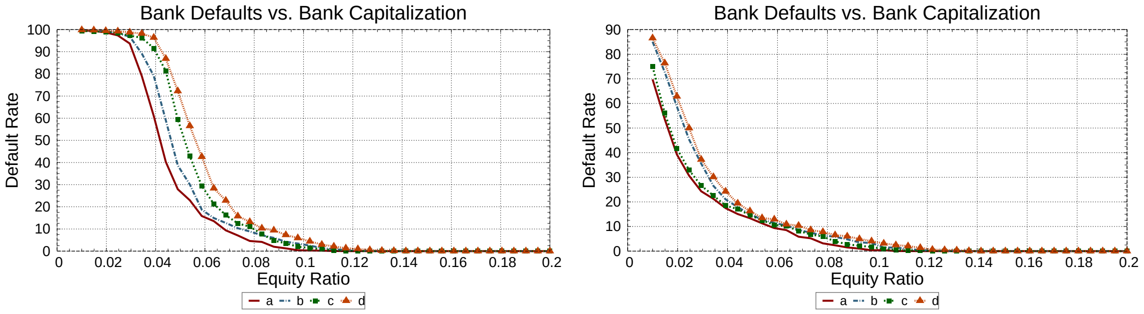
Table 8.2: Tranche-specific (CB and CDO) parameters and their benchmark values.

Resilience of the banking system

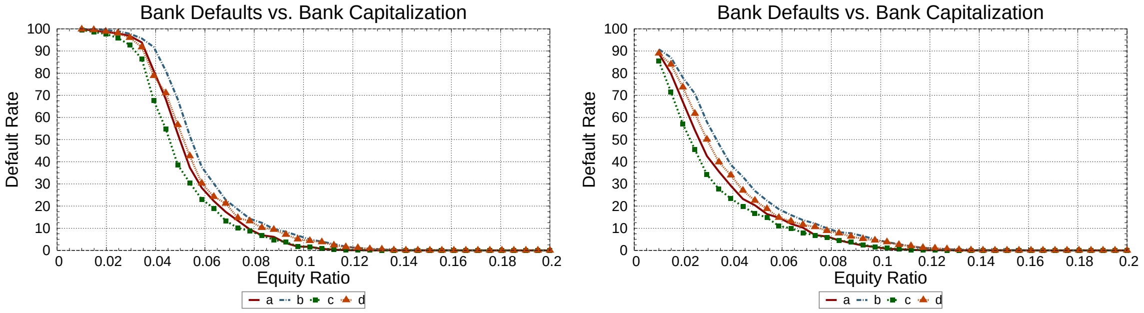
We begin the analysis taking into consideration average default rates within banking systems for the presented scenarios. Fig. 8.4 and 8.5 graphically illustrate the results of the simulation experiments. Thereby the bank default rates are displayed in relation to the equity rate γ or the magnitude of the initial shock λ for number of experiments and 100 runs for each of them. The curve slopes have already been analyzed in section 5 and chapter 4. We focus here on the comparison of the curves. The results of the comparative analysis are summarized in Tab. 8.3 and described below.

Low risk appetite / idiosyncratic shock: Risk sensitivity of bank capitalization raises the default rate of banks which could be observed for sensitivity to both individual and systemic risk. Withdrawal of deposits seems to lead to the more pronounced effects for nearly all considered levels of bank capitalization and external shocks. With regard to the effect of IRS we explain this finding with the following argumentation. Note, that as a definition of the lower risk appetite in comparison to the higher risk appetite of banks we

Low Risk (idiosyncratic shock) WD no WD



High Risk (idiosyncratic shock) WD no WD



High Risk (systematic shock) WD no WD

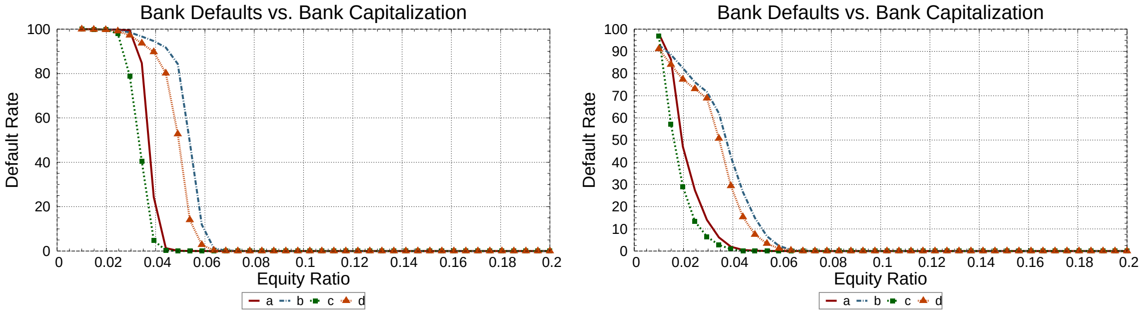


Figure 8.4: Bank defaults for LR (idiosyncratic shock), HR (idiosyncratic shock), HR (systematic shock) for scenarios (a) - lumpsum capital adequacy; (b) - SRS; (c) - IRS; (d) - SRS&IRS; liquidity risk (left); no liquidity risk (right).
The nomenclature of scenarios is presented in appendix A.1.3. For a detailed explanation of the curve shapes please refer to section 5.1. *Parameter setting*: $\zeta = 0.1$; $\tilde{\gamma} = 0.02$; $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.2$; investment parameters are presented in Table 8.2 for low (LR) and high investment risk of banks (HR). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

assumed that all investments will be equally purchased by banks and externals. In such a case the average risk content of the banking investment portfolio is equal to the average risk content of the external credits by the model, see section 2.2.5. The introduction

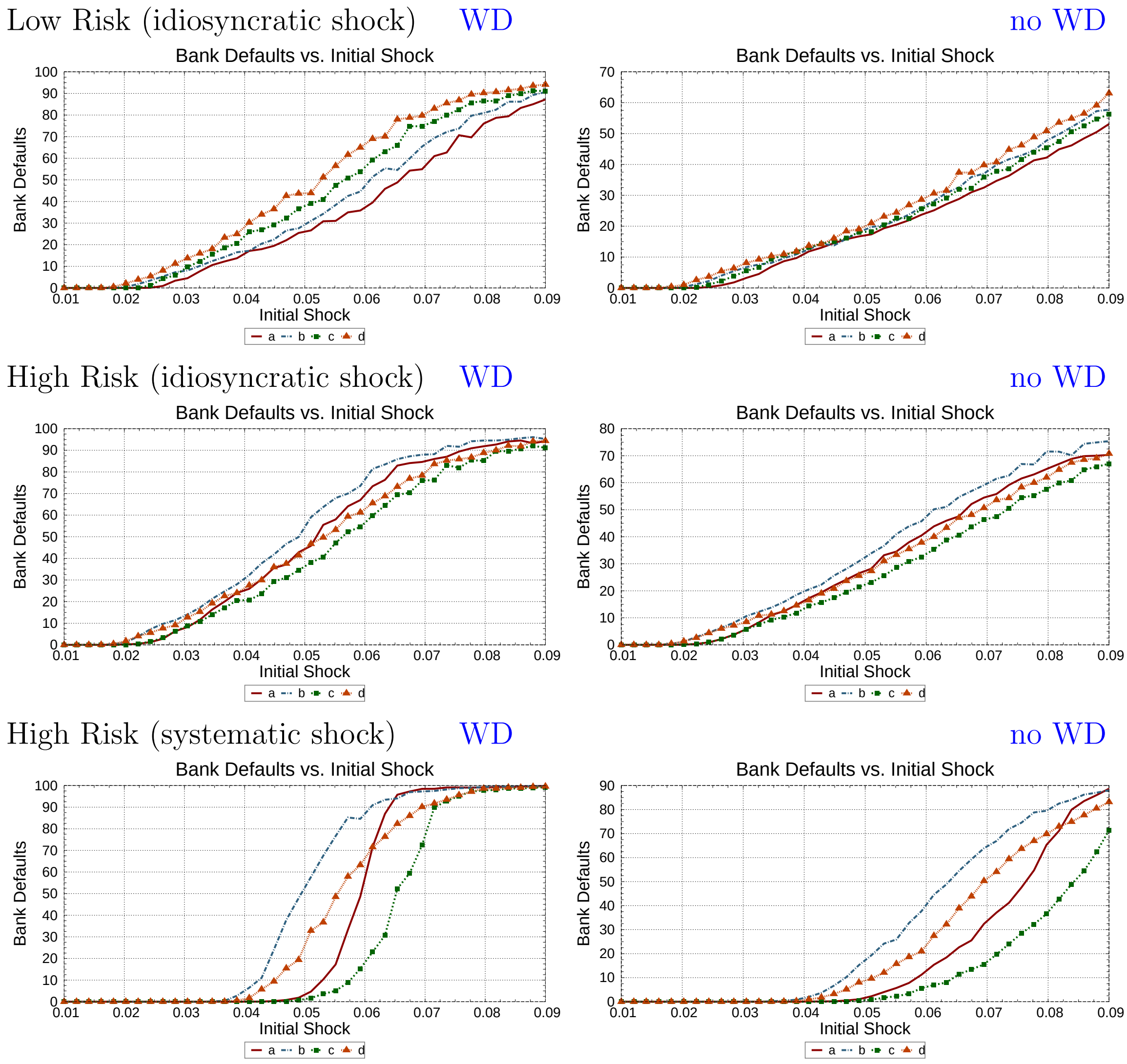


Figure 8.5: Bank defaults for LR (idiosyncratic shock), HR (idiosyncratic shock), HR (systematic shock) for scenarios (a) - lumpsum capital adequacy; (b) - SRS; (c) - IRS; (d) - SRS&IRS; liquidity risk (left); no liquidity risk (right).
The nomenclature of scenarios is presented in appendix A.1.3. For a detailed explanation of the curve shapes please refer to chapter 4. *Parameter setting*: see Fig. 8.4.

of the risk-sensitive weighting of assets does not affect the total capital of the banking system but of the individual banks. So banks with lower risk investments need relatively less equity then banks with a riskier investment portfolio, see section 2.3. We did not observe any substantial influences of IRS on the stability of the banking system in the case of systematic initial shock with the same magnitude as the idiosyncratic shock analyzed

Changes in bank defaults through the risk sensitivity of bank capital to the

	individual risk		**systemic risk**	
	withdrawal	no withdrawal	withdrawal	no withdrawal
Low Risk Idiosyncratic Shock	↑	↑	↑	↑
High Risk Idiosyncratic Shock	↓	↓	↑	↑
High Risk Systematic Shock	↓	↓	↑	↑
Hints: association between results here and Fig. 8.4 - 8.5.	↑≡ c above a and d above b *and vice versa*		↑≡ b above a and d above c *and vice versa*	

Table 8.3: General impact of risk-sensitive bank capitalization in relation to the non-risk-sensitive capitalization on default rate in the banking system (↓ and ↑ mean higher or lower default rates respectively.

here. But the effect may be somewhat positive for larger shocks, because (all) banks with more risky CDOs would be affected more but require also more capital than other banks in the case of the (individual) risk adjusted capital requirements. By contrast, an idiosyncratic shock affects only a few banks but with a much stronger force, so that not only more riskier CDO tranches are hit by the shock but also the a-priori less risk investments. In such a case the damage caused considerably deviates from the expected risk, which is a deciding factor in estimating the level of equity of banks. This deviation is higher in the case of risk adjusted capital requirements on average, provided that the total capital of the banking system remains the same, which is connected to more bankruptcies of banks.

The deviation of the expected risk from the incurred losses shall likewise be responsible for the negative impact of the capital requirements which are sensitive to systemic risk. Remember, that the indicators for the systemic relevance of banks reflect the aspects of negative externalities that could make a bank critical for the stability of the financial system, but do not necessarily try to indicate the vulnerable banks. Note that we compare the cases in which the total equity of the banking system is the same, so that only the distribution of the capital surcharges matters. From the SIB-indicators, it is possible to derive that the core-banks regarding section 6.4.3 will be mainly identified as SIBs and be subject to additional capital rules in the SRS case. But, it has been demonstrated in section 6.4.4 that core banks tend to be more stable, while periphery banks are more prone to shocks in core-periphery networks if significant differences between the core and periphery exist, which is also the case here. Thus, the negative effect of the SRS corresponds to the fact that the more vulnerable banks face lower capital requirements than in the case where the capital surcharges equally concern all banks. The SIBs remain still more stable in both cases, so that the additional capital requirements for them do not increase the stability of the banking system, while the more vulnerable banks become more unstable because of the lower capital.

High risk appetite / idiosyncratic shock: Risk sensitivity of bank capitalization to the individual risk (IRS) lowers the default rate of banks while systemic risk sensitivity (SRS) produces a negative impact on the resilience of the banking system in general. Furthermore, the negative effect of SRS can outweigh the positive impact of the IRS (*d* -(SRS&IRS) above *a*-flat-rate capital adequacy) for sufficiently small levels of the initial shock. Moreover, the positive effect of the individual risk adjusted capital (IRS) clearly predominates the negative one related to the systemic risk sensitive capital requirements (SRS) see Fig. 8.5 the bottom ((b)-(SRS) above (a)-flat-rate capital adequacy, but (d)-(SRS&IRS) below (a)), which can be considered for both cases, with and without the liquidity risk. Here we can observe the positive influence of the (individual) risk adjusted capital requirements, characterized by a higher capital base of the banking system in the case of an above-average risk content of the banking investments compared to the flat capital requirements. The above-average risk weights are connected to the investments of banks in highly risky tranches, see section 2.3, implying the higher capital requirements for banks. The IRS-predomination for moderate shocks can be explained by a relatively large impact of the equity in the centre range of the shocks, which can be seen exemplary in Fig. 8.6. The negative effect of the SRS shows its independence against the risk appetite of banks and has been already explained above.

High risk appetite / systematic shock: As with the idiosyncratic shock, we can see a pos-

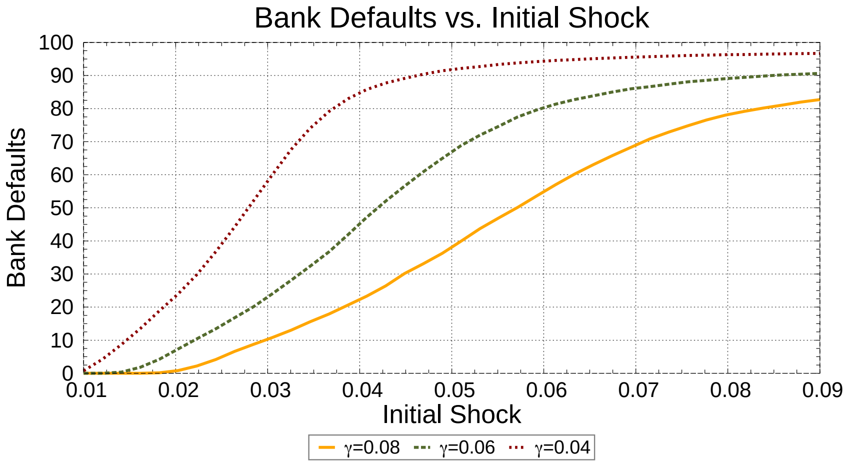


Figure 8.6: Impact of the equity rate on the banking system stability (default rate) in relation to the magnitude of the idiosyncratic shocks (high risk appetite of banks and absence of liquidity risk ($\tau = 0$).
Parameter setting: $\zeta = 0.1$; $\tilde{\gamma} = 0$; $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.2$; For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix. Note, that the example is only for illustration of the equity impact. The parameters deviate from the examples above.

itive effect of IRS and a negative impact of SRS again, which are even more pronounced than in the scenarios discussed above. As already indicated, the negative effect of the SRS is able to outweigh the positive impact of the IRS for small and moderate levels of shock. For sufficiently large shocks, the positive impact of IRS predominates again, which can be considered for both cases, with and without the liquidity risk.

Bank losses

Fig. 8.7 and Fig. 8.8 show the impact of risk adjusted capital rules on cumulated bank losses summarized in Tab. 8.4. Thereby the aggregated bank losses are displayed in relation to the equity rate γ or the magnitude of the initial shock λ for a number of experiments and 100 runs for each of them. For the detailed analysis of the curve slopes we refer to section 5 and chapter 4. Here we examine the differences between the curves to show and explain the effects of the risk sensitive capital requirements. The results of the comparative analysis are summarized in Tab. 8.4 and described below.

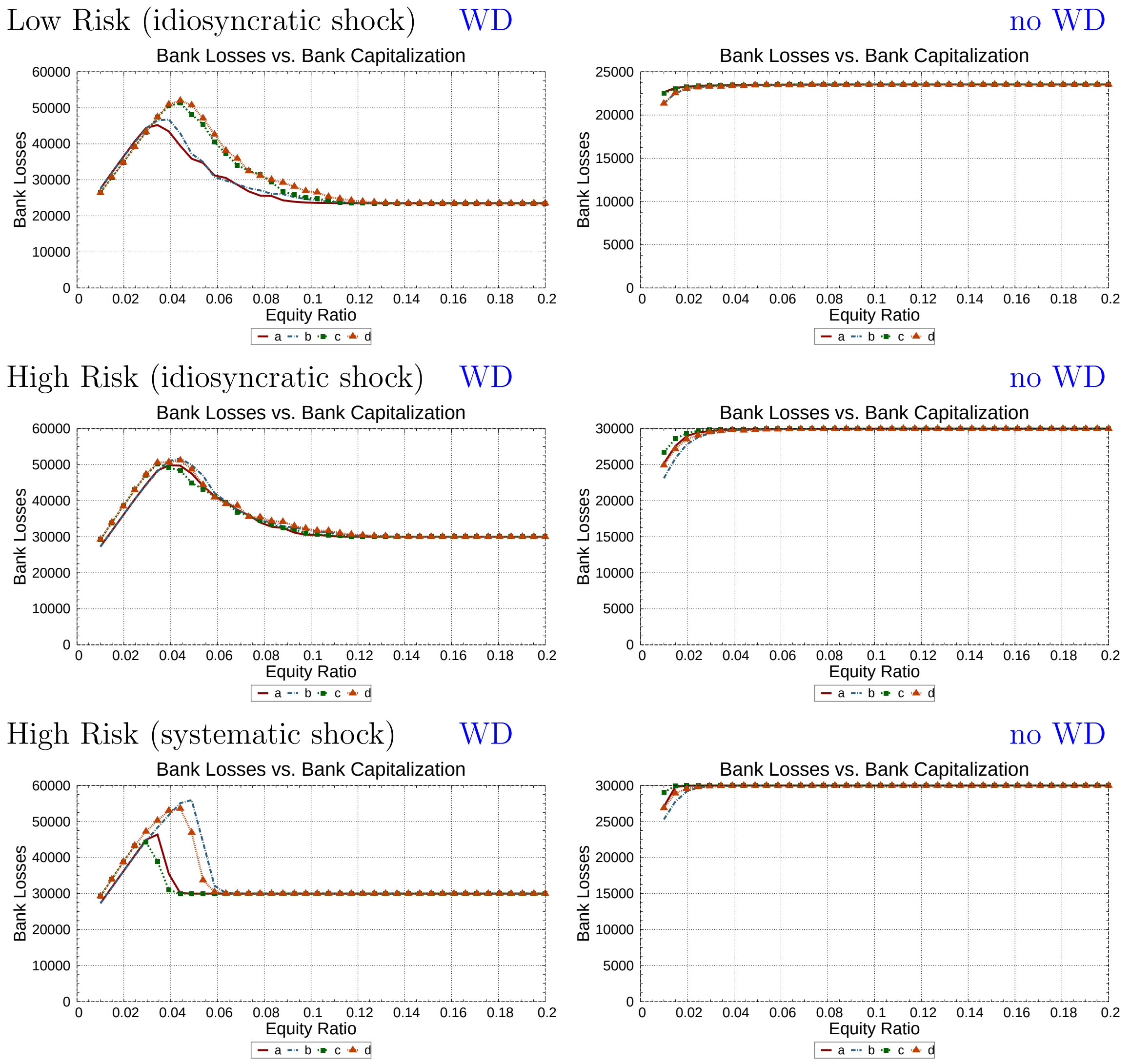


Figure 8.7: Bank losses for LR (idiosyncratic shock), HR (idiosyncratic shock), HR (systematic shock) for scenarios (a) - lumpsum capital adequacy; (b) - SRS; (c) - IRS; (d) - SRS&IRS; liquidity risk (left); no liquidity risk (right).
The nomenclature of scenarios is presented in appendix A.1.3. For a detailed explanation of the curve shapes please refer to section 5.1. *Parameter setting*: see Fig. 8.4.

Low risk appetite / idiosyncratic shock: The simulation experiments demonstrate the only small (negative) effect of the sensitivity of bank capitalization to the systemic risk (SRS) for total bank losses. Simultaneously, substantially higher losses to banks can be seen in the case of individual risk sensitivity of bank capitalization (IRS), if liquidity risk exists. Furthermore, this difference increases with decreasing bank capitalization for sufficiently

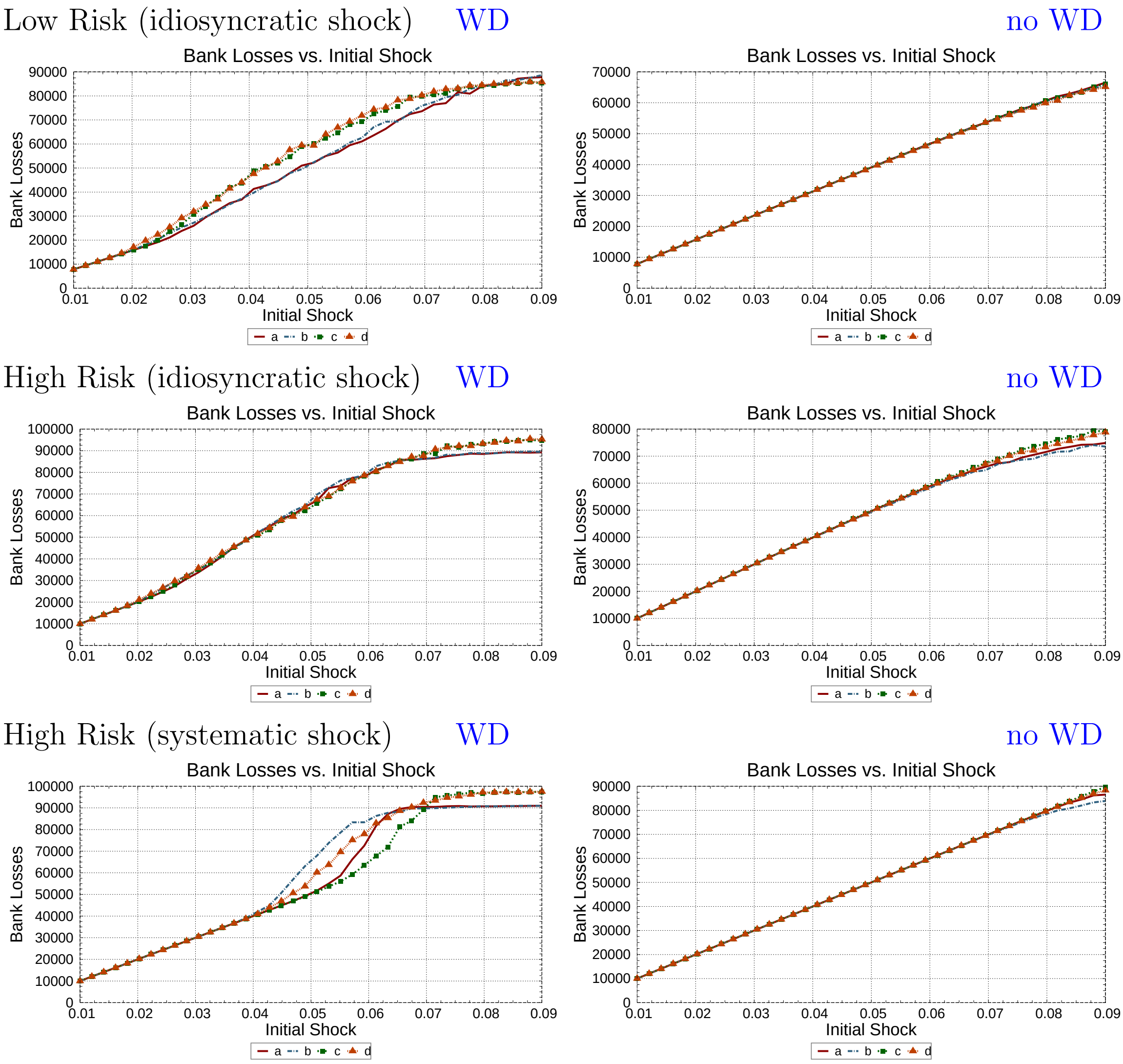


Figure 8.8: Bank losses for LR (idiosyncratic shock), HR (idiosyncratic shock), HR (systematic shock) for scenarios (a) - lumpsum capital adequacy; (b) - SRS; (c) - IRS; (d) - SRS&IRS; liquidity risk (left); no liquidity risk (right).
The nomenclature of scenarios is presented in appendix A.1.3. For a detailed explanation of the curve shapes please refer to chapter 4. *Parameter setting*: see Fig. 8.4.

high capital levels and decreases once again. The same trend can be observed for the increasing initial shocks: at very little or quite high shocks there is a slight impact and even conversion of the negative impact of IRS (lower losses with IRS if shocks are high) become visible. For high levels of the shock, the initial shock can be observed without it triggering withdrawal of deposits. No effects of the risk sensitivity of the capital re-

Changes in the bank losses through the risk sensitivity of bank capital to the

	individual risk		**systemic risk**	
	withdrawal	no withdrawal	withdrawal	no withdrawal
Low Risk Idiosyncratic Shock	↑	()	()	()
High Risk Idiosyncratic Shock	↑	↑	()	()
High Risk Systematic Shock	↓	()	↑	()
Hints: association between results here and Fig. 8.9 - 8.5.	$\uparrow\equiv c$ above a and d above b *and vice versa*		$\uparrow\equiv b$ above a and d above c *and vice versa*	

Table 8.4: General Impact of risk-sensitive bank capitalization in relation to the non-risk-sensitive capitalization on bank losses in the banking system (↓ and ↑ mean higher or lower bank losses respectively, while () implies that no clear or significant impact has been observed).

quirements for bank losses could be observed. Similarly, no impact can be seen for low capital of banks, which has to be explained by the total collapse of the banking system and limiting of the cumulated bank losses by the available equity. The higher losses to banks in the case of the individual risk sensitivity of bank capitalization (IRS) relate to the higher vulnerability of the banking system against the idiosyncratic shock and has been addressed in the part of this section relating to resilience of the banking systems (see above).

High risk appetite / idiosyncratic shock: No clear effect of the IRS can be obtained here if shocks are relatively low or capital high, otherwise slightly higher losses for IRS can be seen if shocks are high or bank capitalization low. This has to be explained by a higher shock absorption capacity of the banking system if the requirements are sensitive to the individual risk of the banks' assets (see reasoning above). There is no substantial effect of the SRS here, because of its neutrality regarding the total equity of the system and relatively small (negative) effect on the stability of the banking system.

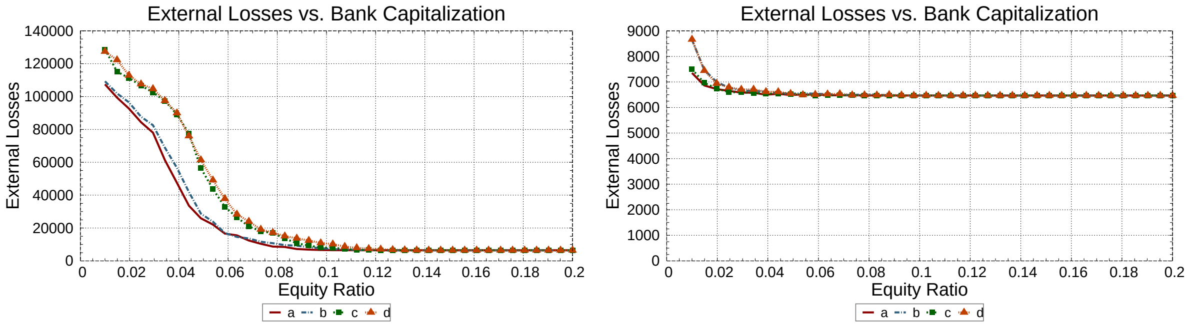
High risk appetite / systematic shock: The IRS seems to reduce the total losses to banks substantially because of its positive effect on systemic stability, while the SRS can lead to significantly higher bank losses, in particular in the somewhat moderate range of the initial shock or banks' capital, especially if withdrawals occur. The latter corresponds to the large negative effect of SRS on the banking system resilience expressed by substantially higher default rates of banks, which we have seen above. At a higher initial shock (lower capitalization) we can see the opposite result regarding IRS, which means that during a serious crisis the individual risk sensitivity of bank capitalization raises the total losses to banks, because higher bank capitalization enables more loss coverage, but defaults can not be reduced. The SRS effects seem to be negligible for higher shocks. These findings are consistent with the observations regarding the resilience of the banking system above. The individual risk sensitive capital requirements are much more effective if banking systems are hit by a wide-spread shock, at least to a certain level of the shock. For very high shocks, a banking system collapses regardless of the capital requirements. In such a case the bank losses with the IRS are higher than with the lumpsum capital requirements because of the higher capital in total.

We can summarize that the capital sensitivity to the individual risk could have significant effects on the total bank losses, especially if liquidity risk exists. But the effects are ambiguous and depend on the risk appetite of banks and the intensity and diversification of the initial shock or common bank capitalization level. In the middle range of shocks, if a systematic shock affects a high risk banking system, bank losses seem to be lower for sensitive capitalization (individual risk), while higher bank losses can be seen for idiosyncratic shocks, generally. For the less risky banks higher bank losses for IRS can be observed in general. Sensitivity to the systemic risk does not show significant effects for total bank losses but seems to be rather negative (higher losses).

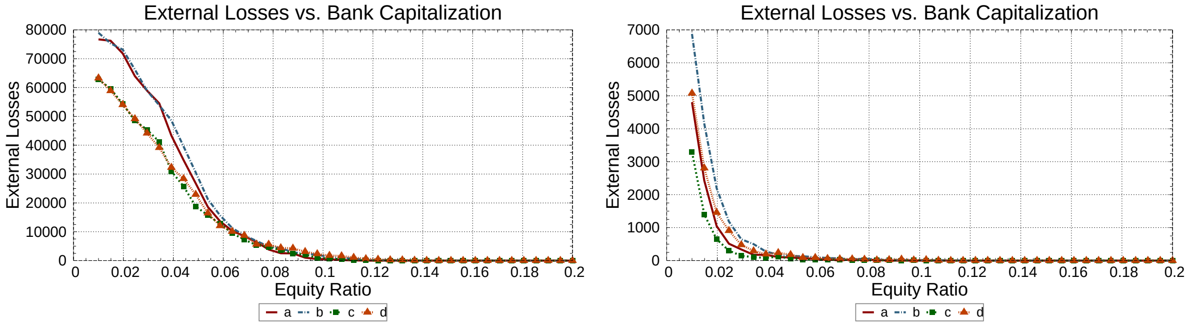
External losses

Fig. 8.9 and 8.10 illustrate the simulated external losses for the scenarios mentioned above, and Tab. 8.5 summarizes the results. The diversity of the results can be seen here again. We describe the general findings given the different characteristics of the shock and risk propensity of banks as follows:

Low Risk (idiosyncratic shock) WD no WD



High Risk (idiosyncratic shock) WD no WD



High Risk (systematic shock) WD no WD

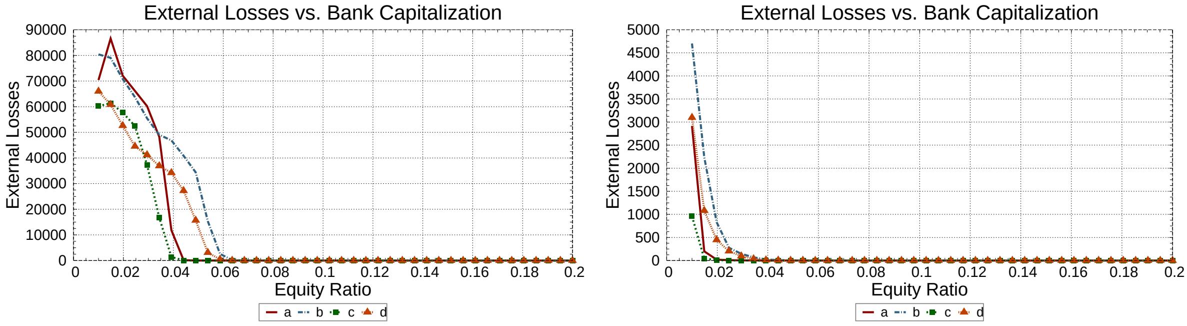
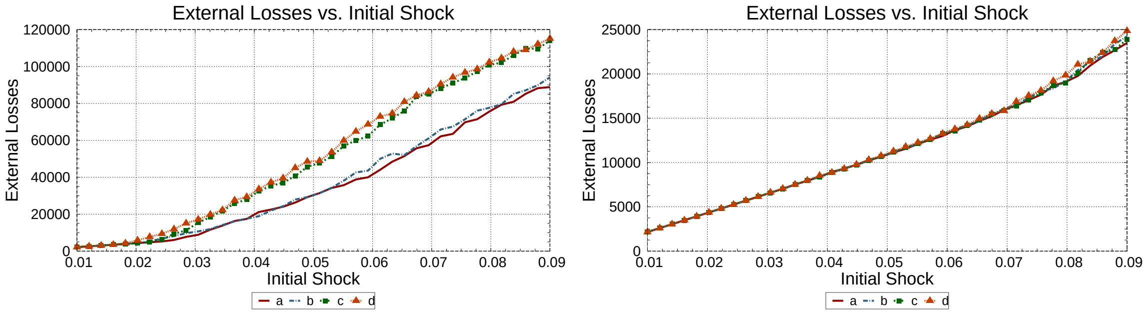


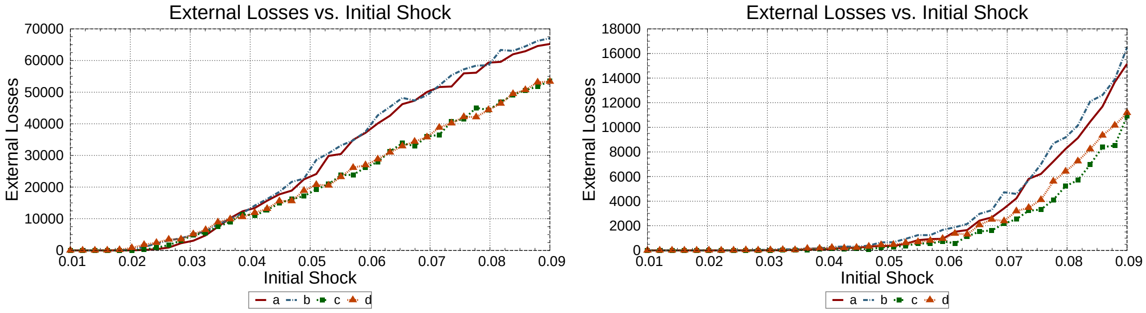
Figure 8.9: (top-down) External losses for LR (idiosyncratic shock), HR (idiosyncratic shock), HR (systematic shock) for scenarios (a) - lumpsum capital adequacy; (b) - SRS; (c) - IRS; (d) - SRS&IRS; liquidity risk (left); no liquidity risk (right).
The nomenclature of scenarios is presented in appendix A.1.3. For a detailed explanation of the curve shapes please refer to section 5.1. *Parameter setting*: see Fig. 8.4.

Low risk appetite / idiosyncratic shock: Individual risk sensitivity of bank capitalization (IRS) raises external losses, especially if withdrawal of deposits is allowed (c above a and d above b). This effect becomes more pronounced with decreasing bank capitalization or

Low Risk (idiosyncratic shock) WD no WD



High Risk (idiosyncratic shock) WD no WD



High Risk (systematic shock) WD no WD

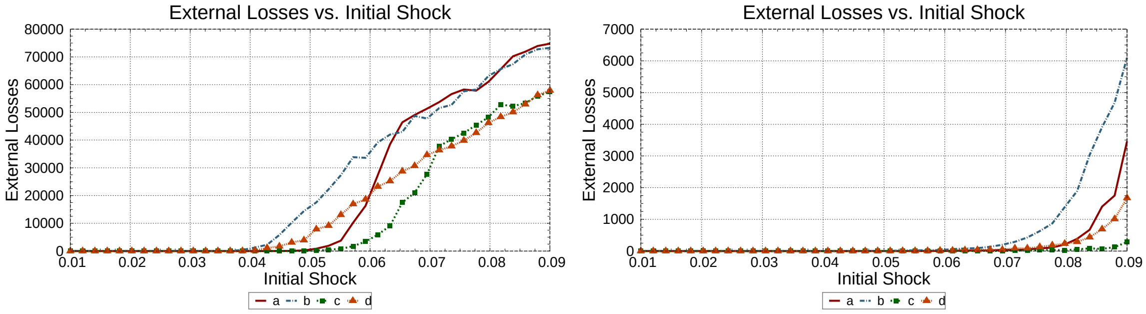


Figure 8.10: External losses for LR (idiosyncratic shock), HR (idiosyncratic shock), HR (systematic shock) for scenarios (a) - lumpsum capital adequacy; (b) - SRS; (c) - IRS; (d) - SRS&IRS; liquidity risk (left); no liquidity risk (right).
The nomenclature of scenarios is presented in appendix A.1.3. For a detailed explanation of the curve shapes please refer to section 4. *Parameter setting*: see Fig. 8.4.

increasing external shocks, respectively. This impact relates to the higher vulnerability of banking systems if risk adjusted capital is sensitive to the individual (a-priori) risk of the assets, leading to higher contagion and transfer of bank losses to externals, see above. The impact of the sensitivity of bank capitalization to the systemic risk (SRS) is rather negative too, but very small.

Changes in the external losses through the risk sensitivity of bank capital to the

	individual risk		**systemic risk**	
	withdrawal	no withdrawal	withdrawal	no withdrawal
Low Risk Idiosyncratic Shock	↑	()	()	()
High Risk Idiosyncratic Shock	↓	↓	()	()
High Risk Systematic Shock	↓	↓	↑ *	↑
Hints: association between results here and Fig. 8.9 - 8.5.	↑≡ c above a and d above b *and vice versa*		↑≡ b above a and d above c *and vice versa*	

* - only for middle ranges of capitalization or shocks.

Table 8.5: General impact of risk-sensitive bank capitalization in relation to the non-risk-sensitive capitalization on external losses in the banking system (↓ and ↑ mean higher or lower default rates respectively, while () implies that no clear or significant impact has been observed).

High risk appetite / idiosyncratic shock: A positive effect for the IRS can be obtained. The impact of the SRS remains slightly negative (higher external losses). The positive impact of the IRS is connected to the higher equity base of the system in total, leading to the higher shock absorption by banks but also to the reduction of contagion within the banking system. For details please refer to the part of this section, where the impact on the banking system resilience is addressed.

High risk appetite / systematic shock: The positive effect of the IRS is obvious and relates to the positive impact on the stability of the banking system, as discussed above, and the higher shock absorption by banks because of the higher banking capital in total. Coincidently, the negative impact of SRS can also be substantial for moderate values of the shock or the banking capital, especially if withdrawals are possible. This negative impact relates to the substantially higher vulnerability of the banking system with capital requirements being sensitive to the systemic risk of banks and thus higher loss transfer from banks to externals in comparison to the equal treatment of all banks.

It can be summarized that external losses are higher if the initial bank capitalization is sensitive to systemic risk, even though this effect is mostly relatively small. Sensitivity to the individual risk is positive for the externals, at least if banks exhibit a high risk appetite. But if banks are rather risk-averse, externals seem to face more losses which will be transmitted to them from banks, because of the lower capitalization of banks in absolute terms.

Conclusion:

We analyzed the impact of additional capital requirements for systemically important banks, using the three-tiered core-periphery network concept. Thereby we studied the impact of equity capital surcharges for selected, 'systemically important', banks and compared the validness of such additional charges with an equal increase of the capital requirements for all banks to the same overall extent. We observed that the equal rise in the equity ratio for all banks tends to stabilize the banking system more effectively than the capital surcharges for systemically important financial institutions only, even if the total increase of the banking capital in the system is the same. We can summarize that diversified capital requirements would lead to a higher systemic risk in comparison to uniform regulations. This finding is confirmed by the experiments discussed above regardless of the type or magnitude of the initial shock and the initial level of capitalization of banks.

Further we looked at the impact of risk adjusted capital requirements (individual risk-sensitive bank capitalization) compared to flat capital adequacy. However, individual risk-sensitive bank capitalization can be stabilizing or destabilizing. The total volume of banking capital in the system seems to play an essential role here. Capital requirements leading to a lower level of capital of the financial system as a whole tend to destabilize the banking system in general. But even if the total capital in the system remains the same, risk adjusted capital requirements can cause higher vulnerability of banks, affected by a strong idiosyncratic shock. 'A-priori' low-risk banks have less risk weighted assets as riskier banks with the same total amount of assets, and possess thus absolutely less equity capital as a-priori riskier banks. Risk adjusted capital requirements could make the banking system more vulnerable to "unexpected" shocks compared to 'flat' capital requirements if banks underestimate the risk, so that the capital reduction effect, caused by the risk sensitive requirements, is larger than the real advantages of the a-priori less risky banks in terms of affectedness by an unexpected shock.

These results are in line with Krug et al. (2014) who studied the special treatment of SIBs in context with the analysis of the impact of the Basel III accord on the financial stability in [41]. The authors found that surcharges on SIBs make the regulatory framework more complex but have a modest stabilizing impact when considered in isolation and even a destabilizing multi-dimensional impact, see [41].

By contrast, Cont and Moussa (2010) in [13] studied the impact of capital requirements in limiting the extent of systemic risk and default contagion in a network context. The authors discussed targeted capital requirements and showed that targeting the creditors of the most contagious institutions is a more effective procedure than increasing capital ratios for all institutions in the network equally.

Chapter 9

Liquidity management

Bank liquidity and arrangement of the funding design and processes are important objects in the international standards of the banking supervision and regulation framework. Their importance has grown significantly in recent years. Following the collapse of the US investment bank Lehman Brothers in 2008, the loss of confidence in banks and the banking system as a whole caused the precautionary hoarding of liquidity. In this phase of the financial crisis, panic fire-sales of assets made interbank market liquidity disappear. It became virtually impossible to obtain short-term refinancing: the interbank market effectively came to a standstill, and the run on money market deposits tightened the already strained liquidity situation. Genuine repurchase agreements (repo deals) and securities-lending business as well as true sale securitization transactions became increasingly difficult as a result of higher margin calls or even by lack of demand. Intervention of central banks and governments around the world was necessary to solve the acute liquidity problem of banks and to reduce the risk of domino effects. Governments offered generous financial guarantees and injected fresh capital into the system. Central banks increased their lending to replace the withdrawal of private lending improving the lending capability and financial stability, e.g. Jean-Claude Trichet (2009) [1].

Furthermore, the crisis made clear that idiosyncratic and systematic liquidity shocks require different policy responses. Because the traditional liquidity facilities available to central banks prior to the crisis were not designed to deal with system-wide disruptions, but with liquidity problems faced by individual institutions, central banks had to adapt their measures to inject liquidity into the global financial system and introduced new facilities, e.g. Lavoie et al. (2011) in [43].

Throughout the last financial crisis the role of the central bank and governmental intervening actions was intensively debated and even reaches into the current times and therefore leaves many questions still unanswered. Several studies suggest that the provision of liquidity by central banks during the crisis was successful and helped to reduce funding pressures on financial institutions. But the actions by central banks also raise a number of questions concerning the impact of the measures, central bank risks, their governance structure as well as their withdrawal from the measures taken, e.g. Pikkarainen (2010) in [57].

Central banks or other supporting institutions who play an important role for the intensity and the pricing of fire sale market activities. In particular, the arrangements of the central bank for providing the suddenly lacking liquidity and buying the excess assets may have significant implications. Not least for this reason, the central bank is an integral part of the asset-based network model used here and presented in chapter 2.

Effects of liquidity losses have been already analyzed in chapter 7. The focus here is on the impact of the initial endowment of liquidity and of the liquidity provided by the central bank in the event of a systemic distortion. This chapter is organized as follows. In section 9.1 we analyze the impact of the initial liquidity endowment of the banking

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[1] Clare Distinguished Lecture in Economics and Public Policy, organized by the Clare College, University of Cambridge in Cambridge

system on its stability and dynamics. Thereafter we take a closer look at the role of the central bank in section 9.2.

9.1 Liquidity endowment

As before, we are using the ABN-Model for the analysis. There are two opportunities to manage liquid funds as a liquidity reserve or a buffer in the stylized banking network system.

The first one is a (minimum) liquidity reserve determined by the required reserve rate ν, as presented in section 2.3.1 and given by

$$m_i = \nu(d_i^b + d_i^e) \qquad \forall i \in \{1, \ldots, N\},$$

where d_i^b, d_i^e denote the deposits of other banks and externals, respectively.

The second is represented through the investments of banks in liquid external assets i_i^e determined by an exogenous parameter ζ denoting a ratio between liquid external assets and external loans for each bank, see 2.2.5,

$$i_i^e = \zeta c_i^e \qquad \forall i \in \{1, \ldots, N\}.$$

We suppose ζ to be equal for all banks for simplicity.

Remember that both kinds of liquid funds can be used for the short-term liquidity management because of the ability to be liquidated at any time without loss of value by definition. However, while the liquidity reserve is linked to customer deposits, the external liquid assets correspond to the external credit volume of banks. Thus, banks with relative high volume of external credit assets would face a higher absolute increase in the liquidity buffer at increasing ζ. This effect will be further intensified by the fact that additional external assets should be refinanced. However, the refinancing of the additional liquid assets is based on the external deposits in the model. Thus the increase of ζ would also cause a modest rise in liquidity reserve but also in amount of external deposits, which can be potentially withdrawn.

In this chapter we analyze the impact of both mentioned instruments of liquidity management. For this purpose we create a set of simulation experiments with various levels of liquidity reserve rate ν and liquid assets to external debts ratio ζ.

To keep the effects of the central bank support and the initial liquidity endowment apart, we assume that the injection of the additional capital by the central bank is not possible ($\delta = 0$, see 2.3.4). However, we will consider this additional effect separately in section 9.2.

We conducted some experiments with high risk appetite of banks and high concentration of the initial shock. In this context, we show the impact of the liquidity reserve rate ν and liquid assets to external debts ratio ζ for various levels of the initial shock and capitalization of banks.[2] The results of the mentioned experiments are pictured in figures 9.1 and 9.2.

Fig. 9.1 demonstrates how the liquidity buffer related to ζ (left) and the liquidity reserve rate ν (right) affect the resilience of the banking system (on the top), the total losses to banks (second from the top) and the external losses (second from the bottom) depending on the initial equity rate of banks. We focus here on the impact of ν and ζ on the results. The curve shapes are explained in Section 5. Additionally, the curves of external deposit withdrawals are illustrated in the bottom charts.

Similarly, Fig. 9.2 shows the effects of ν and ζ depending on the magnitude of the initial

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[2] In the base line scenario the following parameters are used $\nu = 0.01$, $\zeta = 0.1$. The red line on the left is then identical to the blue line on the right.

shock, whose impacts and curve progressions are discussed in Section 4. The figures picture quite clear but not self-explanatory results. Contrary to the common expectation of a stabilizing effect of increasing liquidity in the banking system we obtain higher default rates within the banking system, which are accompanied by more external and bank losses, in general. Moreover, increasing liquidity reserves and growing liquid assets lead to very similar effects. So, the losses seem to be always higher when more liquid funds in the system initially exist, provided that shocks are high enough to destabilize the banking system. Furthermore, the simulation results clearly demonstrate the more intensive withdrawal of external deposits for higher levels of ζ or ν, pictured in figures 9.1 and 9.2 at the bottom. Let us explain the destabilizing effect of the liquidity buffer. For that purpose we focus on the simulation results with various bank capitalization (see 9.1) described above. Additionally we take a look at the development of the total assets and liquidity structure, pictured in Fig. 9.3 (final results) and Fig. 9.4 (initial states) for two cases: with a low liquidity buffer ($\zeta = 0.1$) left and a high liquidity buffer ($\zeta = 0.3$) right.[3]

Note, that the balance sheet positions pictured in Fig. 9.3 and 9.4 correspond to the results of the simulations plotted by blue dashed lines and red lines with triangles in Fig. 9.1 left. Both cases only differ in the amount of liquid assets and external deposits at the beginning of the simulations, which is subsequently reflected in the different initial balance sheet totals, see Fig. 9.4. All other items stay fixed. For both cases, however, decreasing external deposits with an increasing equity rate of banks should be noted here. This is obvious because of the increasing capital and simultaneously sinking refinancing needs of banks and thus their borrowed capital. The difference in the initial liquidity in the system is reflected by the difference in the amounts of (liquid) external assets and external deposits to the same extent. The latter because of the assumption, that liquid assets are refinanced via external customer deposits. The positive correlation between liquid funds, external deposits and withdrawal of them is thus not surprising. However,

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[3] Please refer to Chapter 4 for the details on asset/liability structure and their graphical representation.

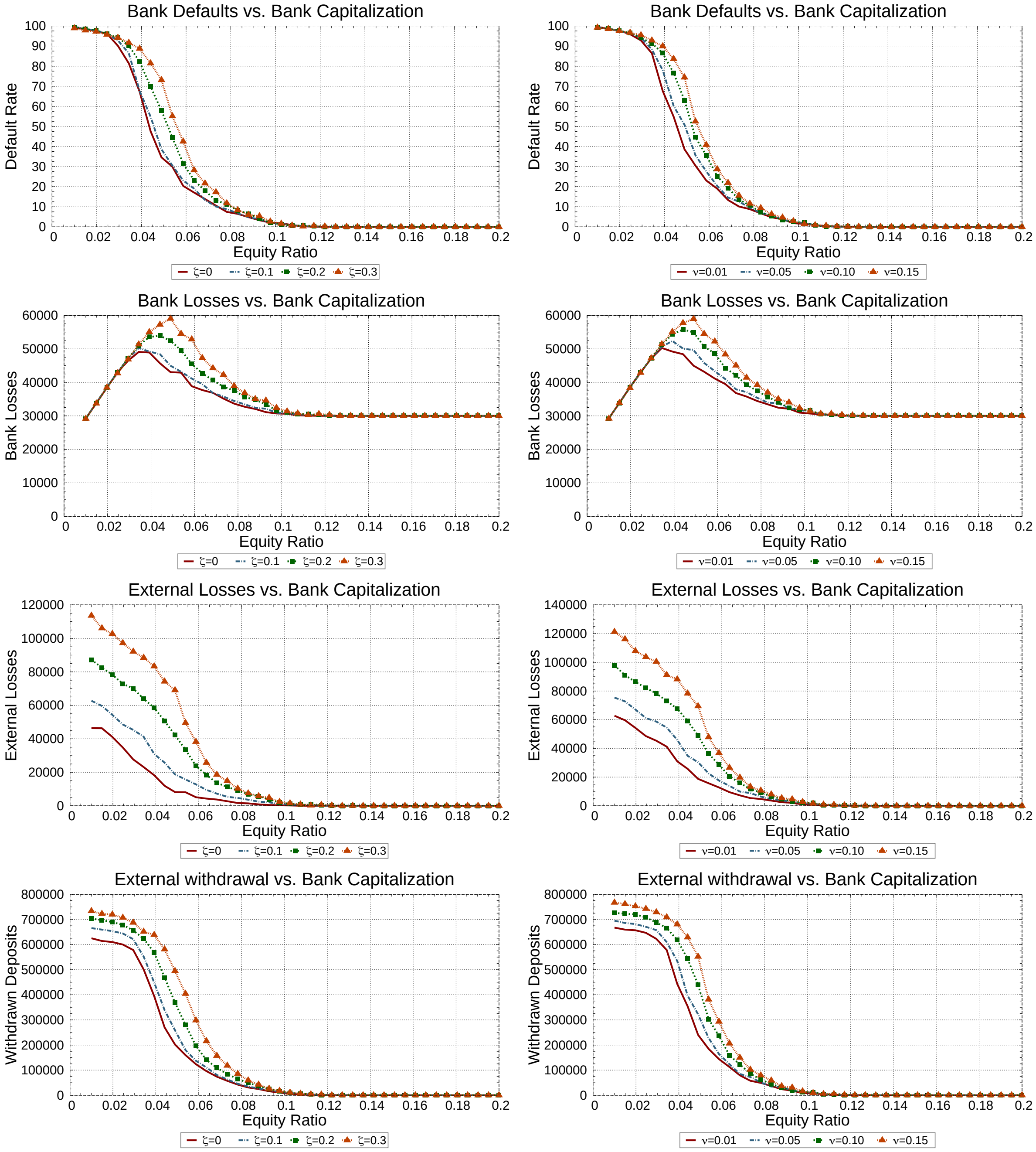


Figure 9.1: Impact of changes in liquidity buffer depending on bank capitalization γ for different levels of liquid investments ζ (left) and liquidity reserve ν (right) for high concentration of the shock and high risk appetite of banks.
Parameter setting: $\tau = 0.1$; $\zeta = 0.1$ (right); $\tilde{\gamma} = 0.02$ (determines additional capital, see (8.8) in 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

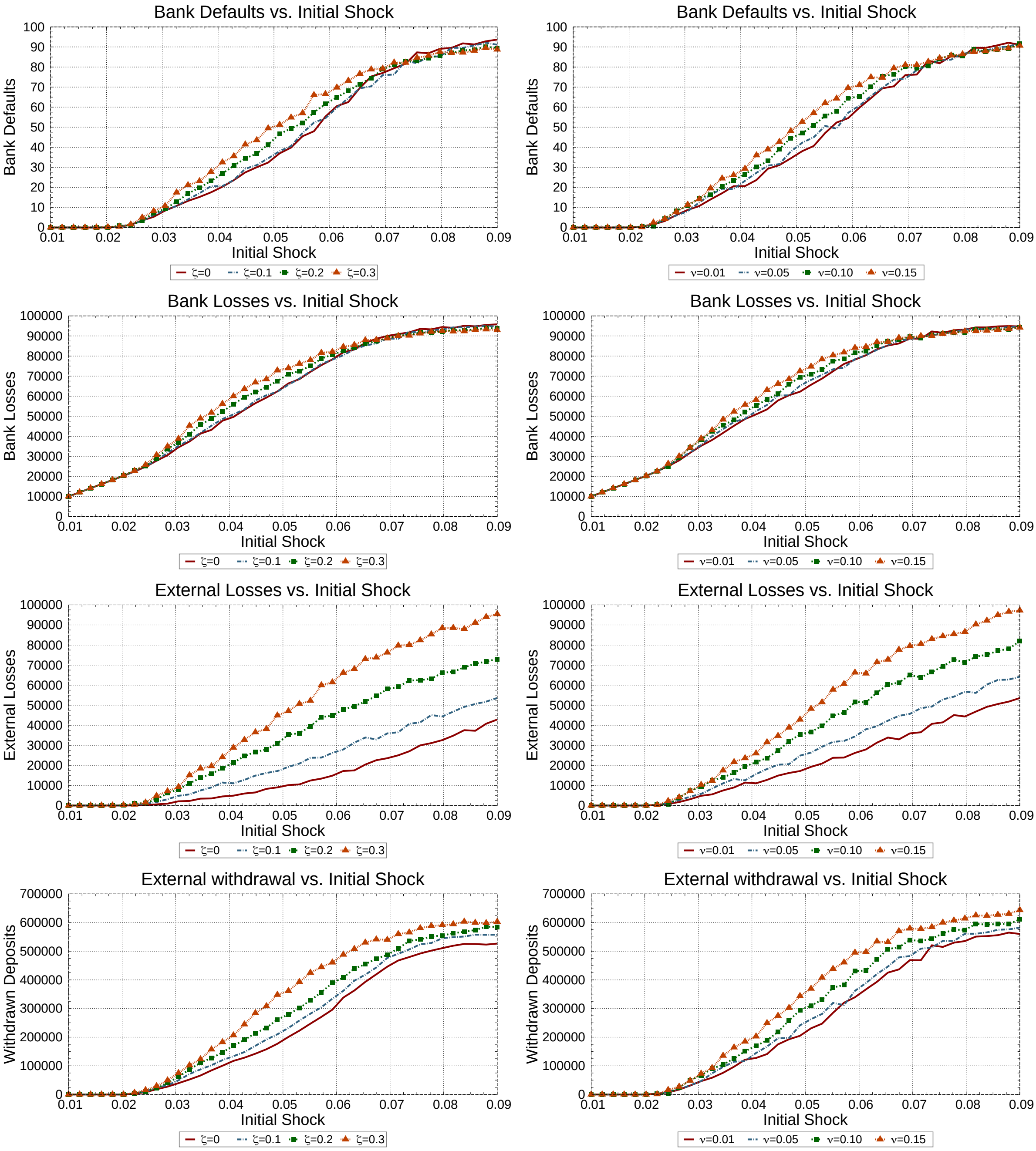


Figure 9.2: Impact of changes in liquidity buffer depending on the intensity of the initial shock λ for different levels of liquid investments ζ (left) and liquidity reserve ν (right) for high concentration of the shock and high risk appetite of banks.

Parameter setting: see Fig. 9.1.

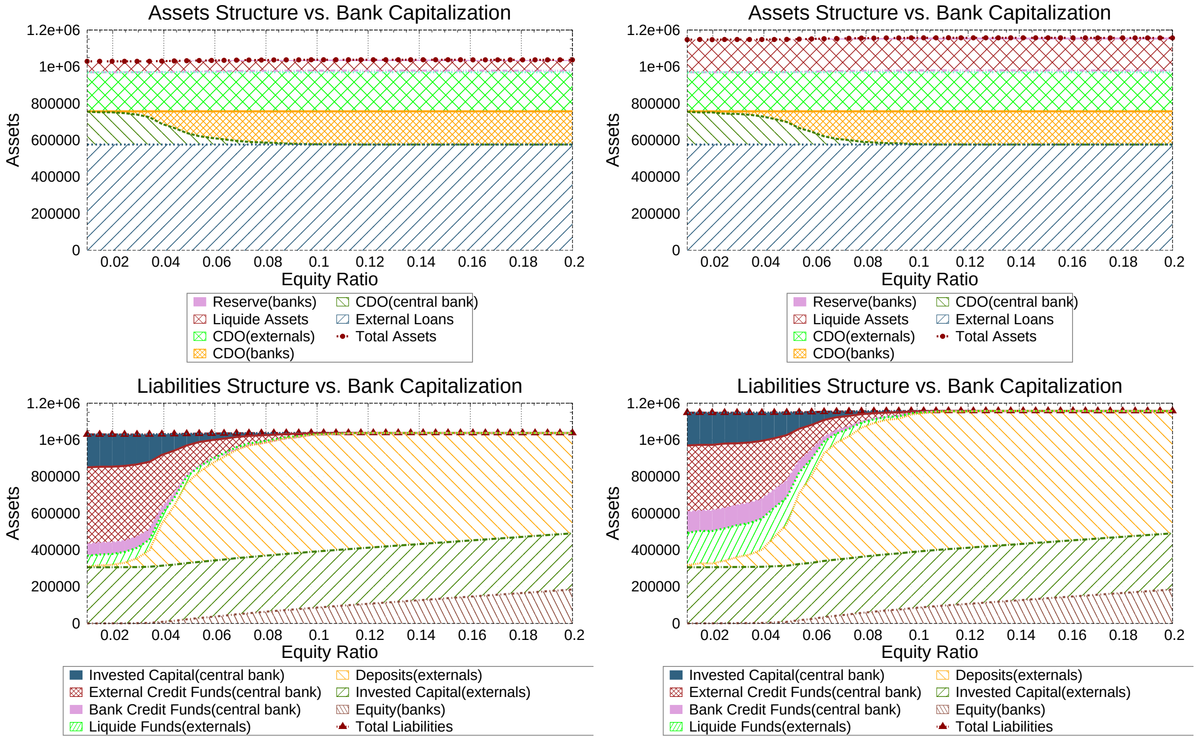


Figure 9.3: Total asset and liquidity structure for scenarios with a low level (left, $\zeta = 0.1$) and with a high level of liquid assets (right, $\zeta = 0.3$) for high risk appetite of banks.
Parameter setting: For the remaining parameters see Fig. 9.1.

such additional external deposits should not be an explanation for more losses and less resistance of the system against the shocks, since the acquired liquid assets can be sold by banks at any time at a guaranteed nominal price without loss of value by definition.

Contagion and further dynamics in the model affect the final asset/liability structure. Thus, it is reasonable to consider it here. As you can see on the right graph in Fig. 9.3 in the case of a higher liquidity buffer, the direct financing of banks through the central bank in the form of loans (pink line or area) is higher compared to the left graph related to the lower liquidity buffer. Taking into account that zero liquidity gap covered by the central bank immediately ($\delta = 0$, see 2.3.4) is supposed in the simulations discussed here, increasing central bank financing provides an indication that banks are becoming more active as a buyer in the fire-sale process, financing their purchases by funds from the

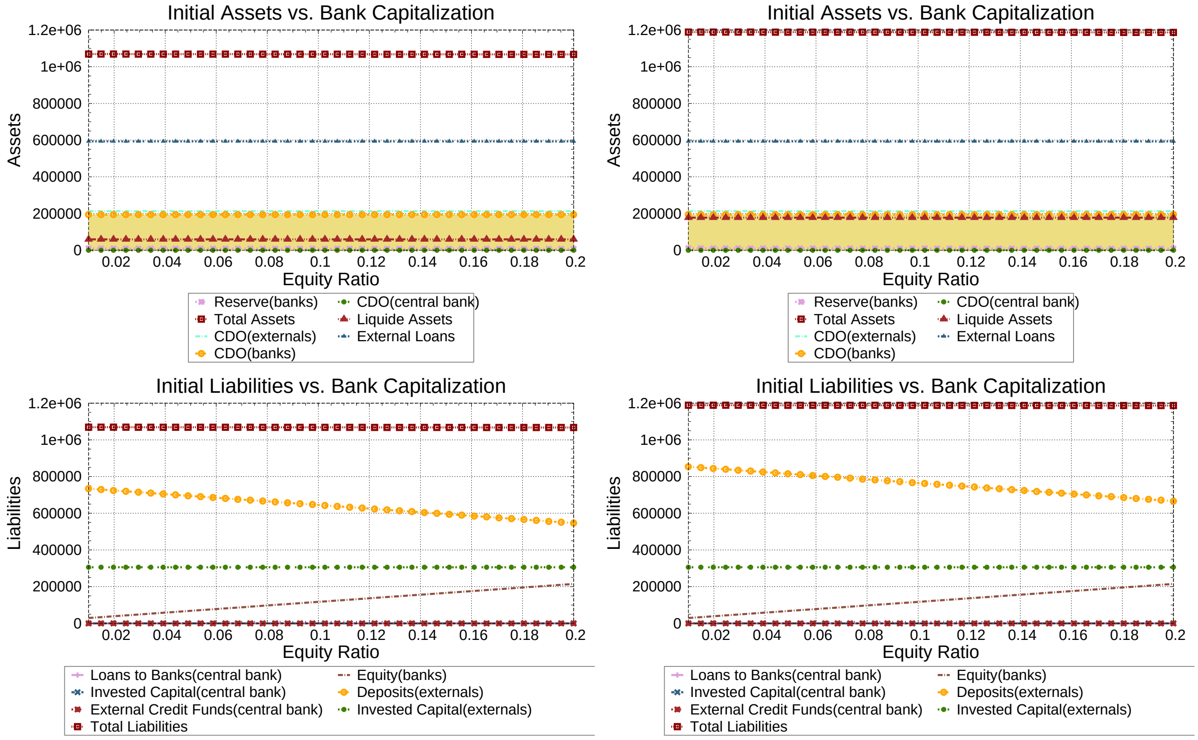


Figure 9.4: Initial total asset and liquidity structure for scenarios with a low level (left, $\zeta = 0.1$) and with a high level of liquid assets (right, $\zeta = 0.3$) for high risk appetite of banks.
Parameter setting: For the remaining parameters see Fig. 9.1.

central bank as assumed in the model. The reason for this is the larger time line of the dynamics if more liquidity in the market exists. Banks will be forced to sell smaller parts of their risky assets at the beginning. So it is more likely that the capital endowment of other banks allows them to buy risky assets offered for sale. Even if buyer banks could make some profit because of low purchase prices at the beginning of the turmoil, the acquisition of risk assets during the crisis can exacerbate the vulnerability of them to become victims of withdrawals because of the smaller equity ratio after purchase of additional credit risk assets. Remember, that fire-sale asset prices depend positively on the (free) capital available in the banking system and negatively on the amount of the offered assets at the point of sale, see section 2.3.4.The weakening of banks' capital can be enforced additionally by the transmission of losses from insolvent banks. Thereafter, the amount of fire-sale assets could explode dramatically and eventually force the central bank to intervene. Hence, the high liquidity buffer of banks could extend the withdrawal process and increase the total volume of withdrawn deposits.

On the contrary, a smaller initial liquidity buffer would lead to more intensive fire-sales at the beginning of the dynamics. In consequence, the higher amount of fire-sales quickly exceeds the capital capacity of the banking system restricted by capital requirements. The intervention of the central bank, in terms of purchasing fire sale assets, will be triggered earlier. Banks do not purchase fire sale assets but keep the capital buffer to absorb the potential losses and remain more resistant to withdrawals then. Thus, the earlier intervention of the central bank seems to be able to reduce withdrawals, even if weak banks would face more losses from the fire sales in the earlier phase of the dynamics (fire sale price of the central bank β is at a minimum).

Remember that liquidity withdrawals in the model are solvency risk related and would be triggered by the capital gap of banks, which obviously cannot be reduced if banks sell their liquid risk-free assets to close the liquidity gap without reducing their risky assets. Note that the spreading liquidity crisis, widening gradually, poses problems for any bank, which firstly, begin to sell their risk assets after the liquidity buffer is depleted. If the capital capacity of the banking system is sufficiently ample to buy the offered fire sale assets, the banking system would not lose money as a whole: the losses to sellers would be compensated by gains of buyers. Thereby the total loss/gain depends on the price correlated with the 'free equity' in the banking system in relation to the fire-sale exposure. Such friction losses as transaction costs were not taken into account in the model. The capital erosion of the banking system as a whole occurs if banks are not able to buy the excess assets at appropriate prices. Hence, the volume of assets purchased by the central bank is finally correlated to the total loss to banks and externals (the latter because of the possible transmission of losses from banks to externals).

The described results are very stable for medium levels of bank capitalization and intensity of the initial shock. For a sufficiently high magnitude of the shock, increase of the liquid funds may display a smaller impact on banks, corresponding to the smaller increase of deposit withdrawals than for the more moderate shock intensities. The explanation is related to the absence of the extension of the fire sale process discussed above, because of a very quick initial capital depletion during the absorption of very strong initial shocks.

Conclusion

If withdrawals of deposits are solvency-based, i.e. connected to the deterioration of the capital compared to the risk profile of banks, the high liquidity reserve or buffer do not only not assist the stabilization process but could actually significantly complicate it and increase losses to both: banks and externals. Withdrawal of liquidity would not be stopped in particular, if appropriate actions to ensure adequate capitalization of banks have not been undertaken. Furthermore, a large liquidity buffer can cause an explosion in withdrawals, even if no impairment of liquid assets takes place and no further defaults of commercial loans occur. Higher losses to banks as well as of the external segment are connected to the higher fire-sale of assets, which could not be held within the banking system (here purchased by the central bank). Evidence of this is to be seen in the growing funds raised by the central bank to buy the new assets.

A similar argumentation applies to the impact of the liquidity reserve presented above in Fig. 9.2, which can be skipped here.

9.2 Support by the central bank

In this section we scrutinize the role of the willingness of the central bank to support banks that fall victim to the loss of depositor confidence and to analyze if such a 'lender of last resort' intervention would always produce satisfactory results. Demonstrating results of simulation experiments we will focus on only one case, including withdrawal risk. The effects for other simulation scenarios show a similar trend and are therefore redundant here. We begin with the analysis of the losses to the external counterparts.

Remember that the liquidity supporting role of the central bank has been implemented in the ABM in two respects as described in section 2.3.4. One of two supporting activities of the central bank in the model focuses on providing the liquidity to banks to close a part of the individual liquidity gaps, determined as a percentage of the liquidity gap δ. The second activity includes the intervention of the central bank in the "fire-sale market" by buying the excess credit assets at a specified price β.

9.2.1 Injection of liquidity

We focus on the first support activity of the central bank, providing additional liquidity. Thereby we vary the percentage of the liquidity gap δ which will be immediately covered by central bank money. This parameter determines the level of the central bank support in the following analysis.

Resilience of the bank system

Fig. 9.5 provides a visual representation of some of the simulation results in three-dimensional graphics. On the left side, the failure rate of banks is displayed in relation to the percentage of the liquidity gap δ and the equity rate γ. On the right side, the banks' default rate is plotted in relation to the central bank support related to δ in conjunction with the level of the intolerance of depositors against undercapitalization of banks τ. We have seen before that decreasing capital as well as increasing loss of confidence in the banking system contribute to destroying its resistance against shocks. The provided simulation results demonstrate that the intervention of the central bank can create a barrier effect against loss of confidence in the banking system related to the increasing intolerance of depositors τ. We can see this effect in Fig. 9.5 on the right. Increasing τ and so the upward movement for withdrawal of deposits corresponds to the growing default rate of banks. This negative development can be substantially diminished in the case of the central bank intervention. Moreover, central bank support can eliminate the negative impacts of withdrawals, which can be seen in Fig. 9.5 for large values of τ. Remember that withdrawals start earlier if intolerance for undercapitalization of banks τ increases. At high levels of τ capital level of banks is quite high at the begin of the deposit withdrawal processes. The intervention of the central bank by closing liquidity gaps of banks prevents the further withdrawal of deposits and defaults of banks.

Considering the development of bank bankruptcies in relation to their equity, we can say that the intervention of the central bank can weaken or even prevent contagion, generally. The greater support of the central bank related to the larger values of δ corresponds to the lower equity rates at which bank defaults start to rise rapidly or the total banking system collapses, see Fig. 9.5 (left). Increasing resistance of the banking system with increasing central bank support is also displayed by example in Fig. 9.6 (right) for relatively high capital. For sufficiently low equity rates we do not observe any substantial effects, see Fig. 9.5 (left). We can summarize that the number of bank bankruptcies decreases with increasing central bank support in general. However, the central bank support may only achieve a significant effect if the banking system is sufficiently capitalized after the initial shock absorption. Because otherwise, withdrawal of deposits which focus on creditworthiness of banks still take place and lead to further losses to banks and the total collapse of the financial system.

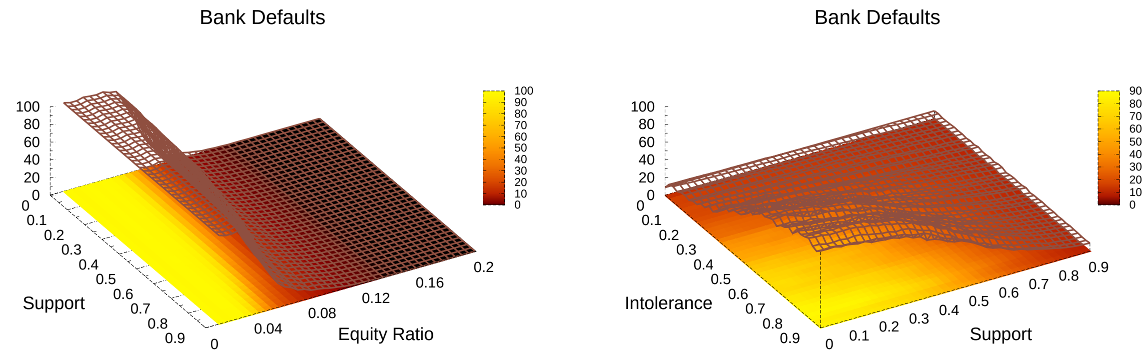


Figure 9.5: Resilience of the banking system depending on support of the central bank δ, bank capitalization and intolerance for high concentration of the shock and high risk appetite of banks.
Parameter setting: see Tables A.1 to A.3 in the appendix A.1.1.

Bank losses

Fig. 9.7 provides the simulation results regarding total losses to banks in accordance with the presentation of bank defaults in 9.5. Increasing central bank support leads to decreasing bank losses in total, as long as it is able to reduce the negative impact of deposit withdrawals or even to prevent them, as can be seen in Fig. 9.7. Banks would face less necessity for fire-sales and achieve higher asset prices. Thus, solvency risk tends to decrease, stopping or limiting further withdrawals. This positive effect can be observed for the capital rate level from 4% to 8% in the example. However, the providing of additional

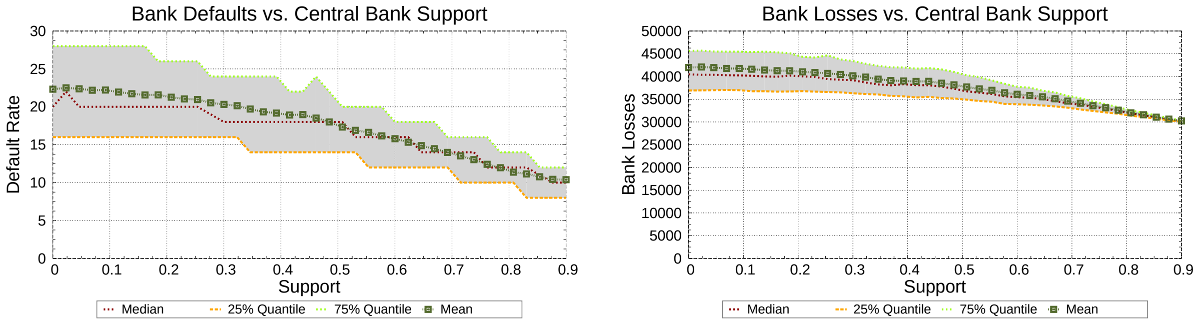


Figure 9.6: Resilience and losses within the banking system depending on support of the central bank δ in relation to the bank capitalization for high concentration of the shock and high risk appetite of banks.
Parameter setting: $\tau = 0.1$; $\zeta = 0.1$ (right); $\tilde{\gamma} = 0$ (see section 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

liquidity does not necessarily always help. Such support of the central bank will be less useful for seriously undercapitalized banks after a shock because withdrawals of deposits may occur repeatedly until banks' capital has reached an appropriate level which can restore the confidence of the depositors again (see more in section 2.3.4).

In better capitalized systems the intervention of the central bank could be more helpful, especially for such banks which are less affected initially but suddenly lose a big part of their liquidity, because weak banks have to recover their funds to close their own liquidity gap. Further withdrawal of deposits can be prevented by the central bank in this way, because less assets have to be sold then, which would reduce losses to banks and rescue their own capital. Decreasing losses within the banking system with increasing central bank support is also displayed by example in Fig. 9.6 (right) for relatively high capital. For very well capitalized systems no effect of the willingness of the central bank to inject liquidity can be observed in 9.7, because no withdrawals take place and the central bank has no reason to intervene.

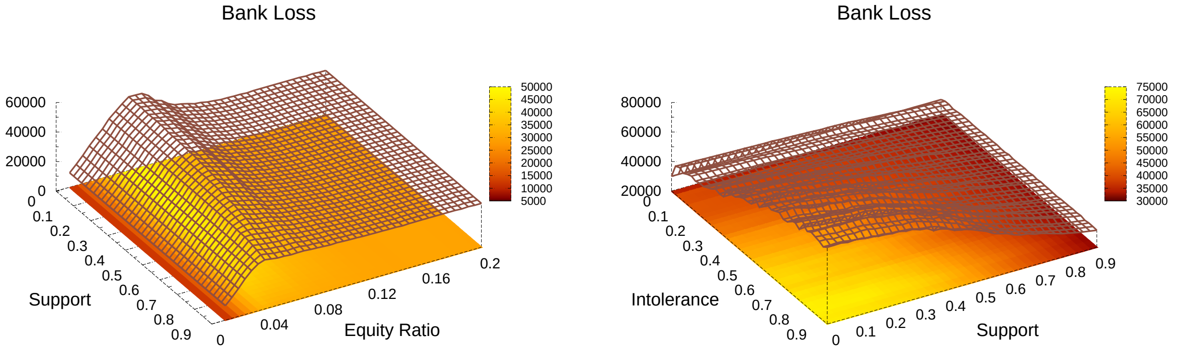


Figure 9.7: Cumulated bank losses depending on support of the central bank δ, bank capitalization and intolerance for high concentration of the shock and high risk appetite of banks. For a detailed explanation of the non-monotone relation between capitalization and losses within a banking system we refer to section 5.1.
Parameter setting: see Fig. 9.5.

External losses

Let us look at Fig. 9.8 showing that external losses decrease with increasing central bank support. These dynamics are greatly assisted by the effects of decreasing intolerance or increasing initial capitalization of banks, which is straightforward to understand considering our analysis of both these factors in the previous sections: both mentioned dynamics lead to decreasing external losses, in general. It is even possible that central bank support does not have any impact on external losses, if all losses are completely covered by banks or withdrawal of deposits is not triggered. The positive effect of the central bank support for externals will also nearly disappear, if banks have very low capitalization compared to the initial shock they have been facing. Non-monotonic association between capitalization of banks and losses to externals has been explained in 5.1.

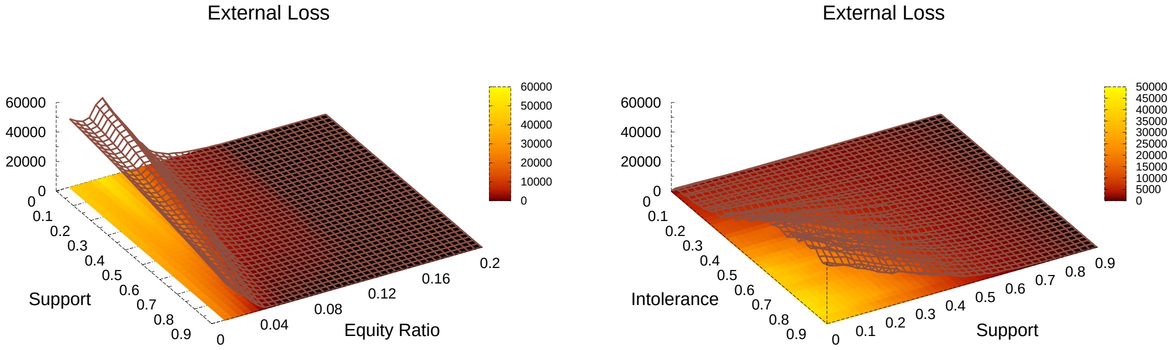


Figure 9.8: External losses depending on support of the central bank δ, bank capitalization (left) and intolerance (right) for high concentration of the shock and high risk appetite of banks. For a detailed explanation of the non-monotone relation between capitalization of banks and losses to externals we refer to section 5.1.
Parameter setting: see Fig. 9.5.

Additional details

At this point it may be interesting to give a deeper insight into the discussed impacts of the central bank support on the stability of the banking system and losses to banks and externals. In addition, we will look at the effects of the initial liquidity endowment discussed in section 9.1 under the influence of the central bank support now. Fig. 9.9 shows the results of the experiments, where central bank support is varied for different levels of liquidity buffers related to liquid investments ζ (left) and liquidity reserves ν (right).

It can be seen, that support of the central bank works against the negative effects of withdrawals, reducing the sudden lack of liquidity: decreasing bank default rates and losses to externals and banks can be observed with increasing central bank support for all levels of the liquidity buffers, see Fig. 9.9. Moreover, the impact of the support is higher in the case of higher liquidity endowment compared to its lower levels, which can be seen by the steeper curves for larger values of ζ (left) and ν (right).

The interesting point here is the change of the impact of the initial liquidity endowment, analyzed in the previous section, that is caused by the central bank. It can be seen that the negative impact of the large liquidity endowment can be neutralized by the central bank if its support is intensive enough (compare results for $\zeta = 0$ and $\zeta = 0.3$ for example). The impact of the high level of liquidity can become even positive (see red line with triangles below other lines in Fig. 9.9 at sufficiently high levels of δ). But, the possible positive effect of the liquidity endowment in such a case is significantly smaller than the negative impact of the excess liquidity combined with a meager support of the central bank.

The explanation of this phenomenon may be provided as follows. The destabilizing effect

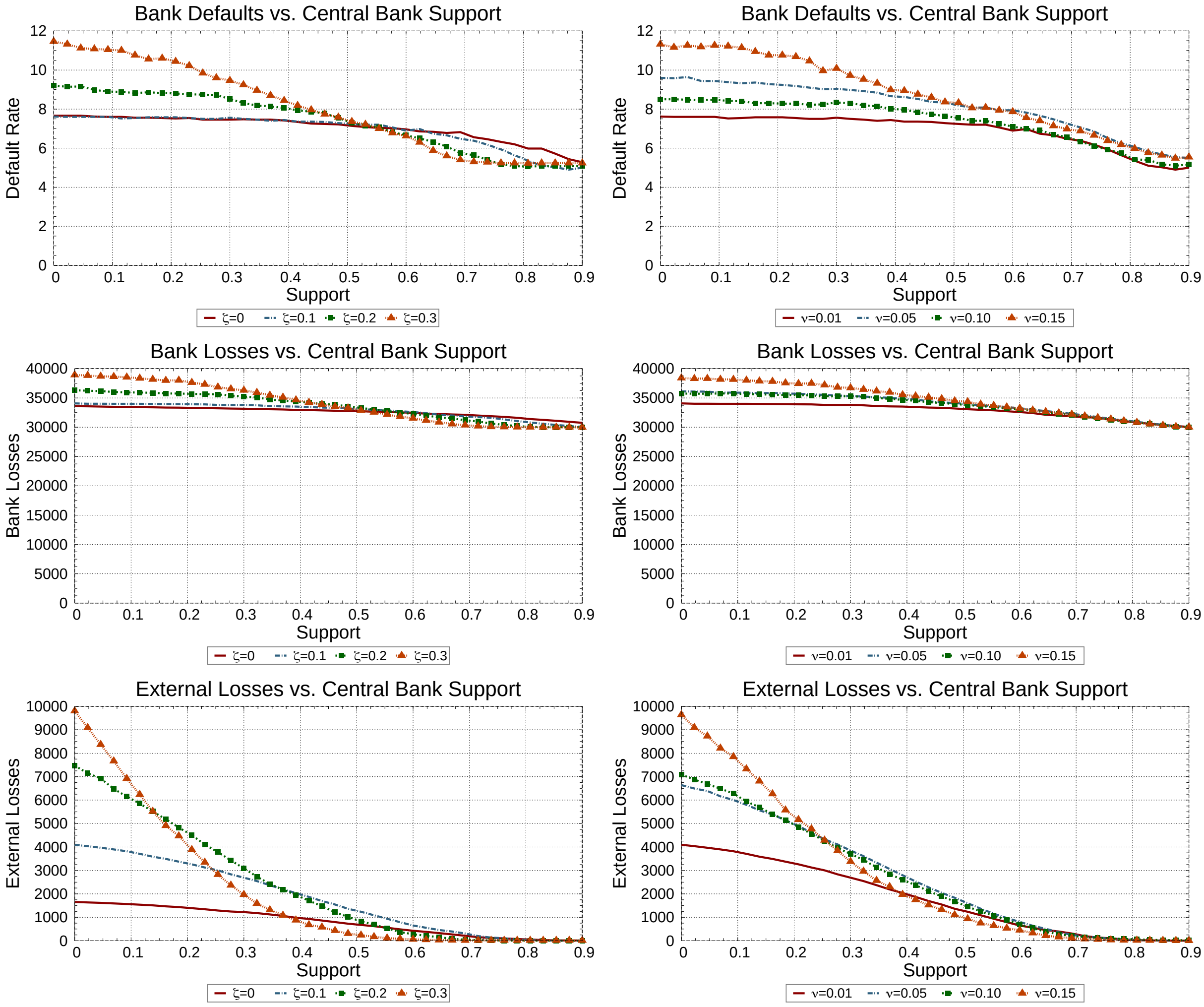


Figure 9.9: Impact of changes in liquidity buffer depending on central bank support δ (liquidity injection) for different levels of liquid investments ζ (left) and liquidity reserve ν (right) for high concentration of the shock and high risk appetite of banks.
Parameter setting: $\tau = 0.1$; $\zeta = 0.1$ (right); $\tilde{\gamma} = 0.02$ (determines additional capital, see (8.8) in 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

of the initial liquidity endowment was argued with the escalation of withdrawals after the purchase of fire sale assets by other banks, see section 9.1. The intensive liquidity support of the central bank acts against this escalation by covering the liquidity gap and reducing the fire-sales substantially. Withdrawals from weak banks can not be stopped by the described central bank activity, but losses from the liquidation of assets and contagion of the rest of the banking system can be substantially reduced.

Conclusion

We can summarize that in contrast to strengthening the regulatory regime, central bank support in the sense of providing liquidity to close the sudden gaps in the banking system acts against intolerance to the benefit of the banking systems and the external segment. While stricter capital requirements and higher initial liquidity endowment of banks tend to intensify withdrawal of deposits and, thus, to destabilize the system, support of the central bank works against it, generally, but does make sense only if the banking system has been sufficiently capitalized to withstand the initial shock. Furthermore, injection of liquidity into the banking system during the crisis may reduce or even eliminate the negative externalities connected to a significant expansion of the fire-sale activities within the banking system, in particular in the case of excess liquidity buffers of banks. The main difference between central bank support and liquidity endowment of banks is probably the neutral impact of the first on the leverage ratio of banks, while the increase of liquidity endowment of banks raises the level of external deposits and thus the banks' leverage. The latter enhances the potential for deposit withdrawals, while the central bank liquidity injection sustainably reduces the resultant liquidity gaps and, thus, the amount of fire-sale assets and counteracts the price pressure on the fire-sale market.

9.2.2 Purchase of assets

Now we would like to take a look at the second supporting activity of the central bank, focussing on the intervention of the central bank in the 'fire-sale market' purchasing the excess credit assets. The central bank will intervene if the price of assets deteriorates below a threshold value β. For the purpose of the analysis presented in this section we create a number of simulation experiments with $\beta \in \{0.3, 0.5, 0.7, 0.95\}$ and a variety of other factors to underpin the stability of the results. For the presentation and discussion of results we focus on a selection of them without loss of generality.

The results of the mentioned experiments are pictured in figures 9.10 - 9.12. The focus of the graphical demonstration is on the case with high risk appetite of banks and high concentration of the initial shock and the impact of the changes of the following parameters depending on the level of β: initial shock, bank capitalization, intolerance of depositors to the bank undercapitalization causing withdrawals, support of the central bank injecting additional liquidity into the banking system and interbank connectivity via credit and investment links. The figures picture quite clear and self-explanatory results, which have to be shortly described here.

The increase of the threshold price for fire-sale assets, at which the central bank would purchase the assets have a positive stabilizing effect on the whole system, reducing the losses to banks and accordingly the losses to externals transmitted from banks which are unable to cover their losses with existing reserves. The reduction of the losses lead to a lower default rate within the banking system and thus higher resilience of the system against shocks and consequences of the after-shock dynamics. The positive effect of the intervention of the central bank purchasing assets during the fire-sale period seems to be very stable and can be observed for a very broad range of the parameters, which can be seen in Fig. 9.10 to Fig. 9.12. In some cases with relatively low hazard for liquidity withdrawal, the effect of β is very small and could even be negative. The last point is explained by the lower profits of some banks in well capitalized systems not being able to purchase cheep fire-sale assets, because of the earlier intervention of the central bank. This effect is very small and can be ignored.

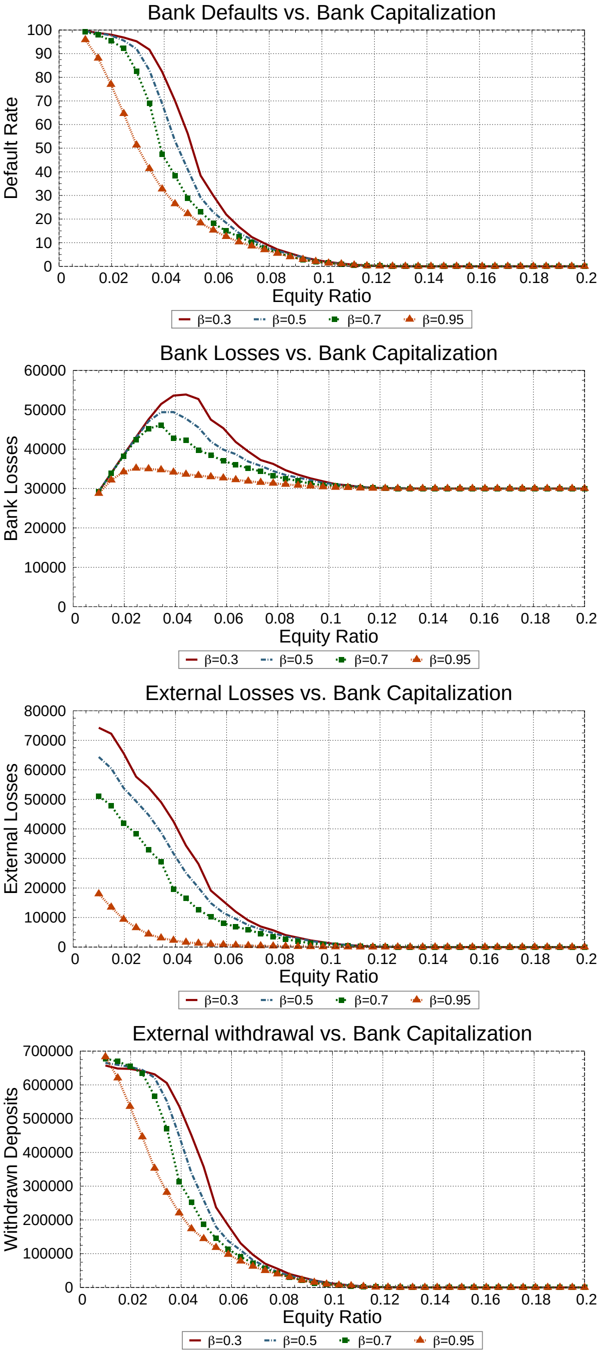


Figure 9.10: Impact of changes in the central bank price for fire-sale assets β, depending on bank capitalization γ (left) and intensity of the initial shock λ (right) for high concentration of the shock and high risk appetite of banks.

Parameter setting: see Tables A.1 to A.3 in the appendix A.1.1.

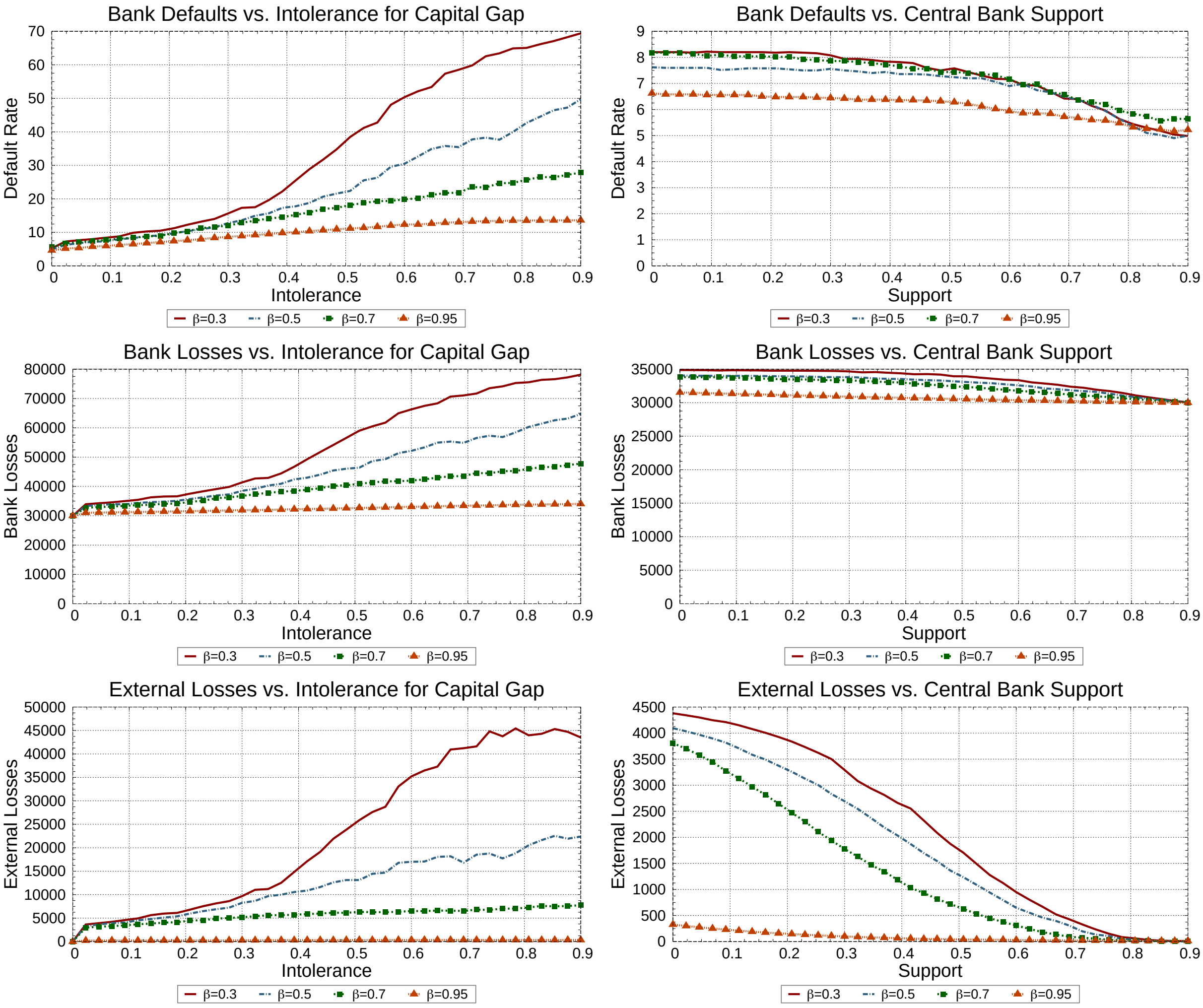


Figure 9.11: Impact of changes in the central bank price for fire-sale assets β, depending on intolerance for undercapitalization τ (left) and liquidity support of the central bank δ (right) for high concentration of the shock and high risk appetite of banks.
Parameter setting: see Tables A.1 to A.3 in the appendix A.1.1.

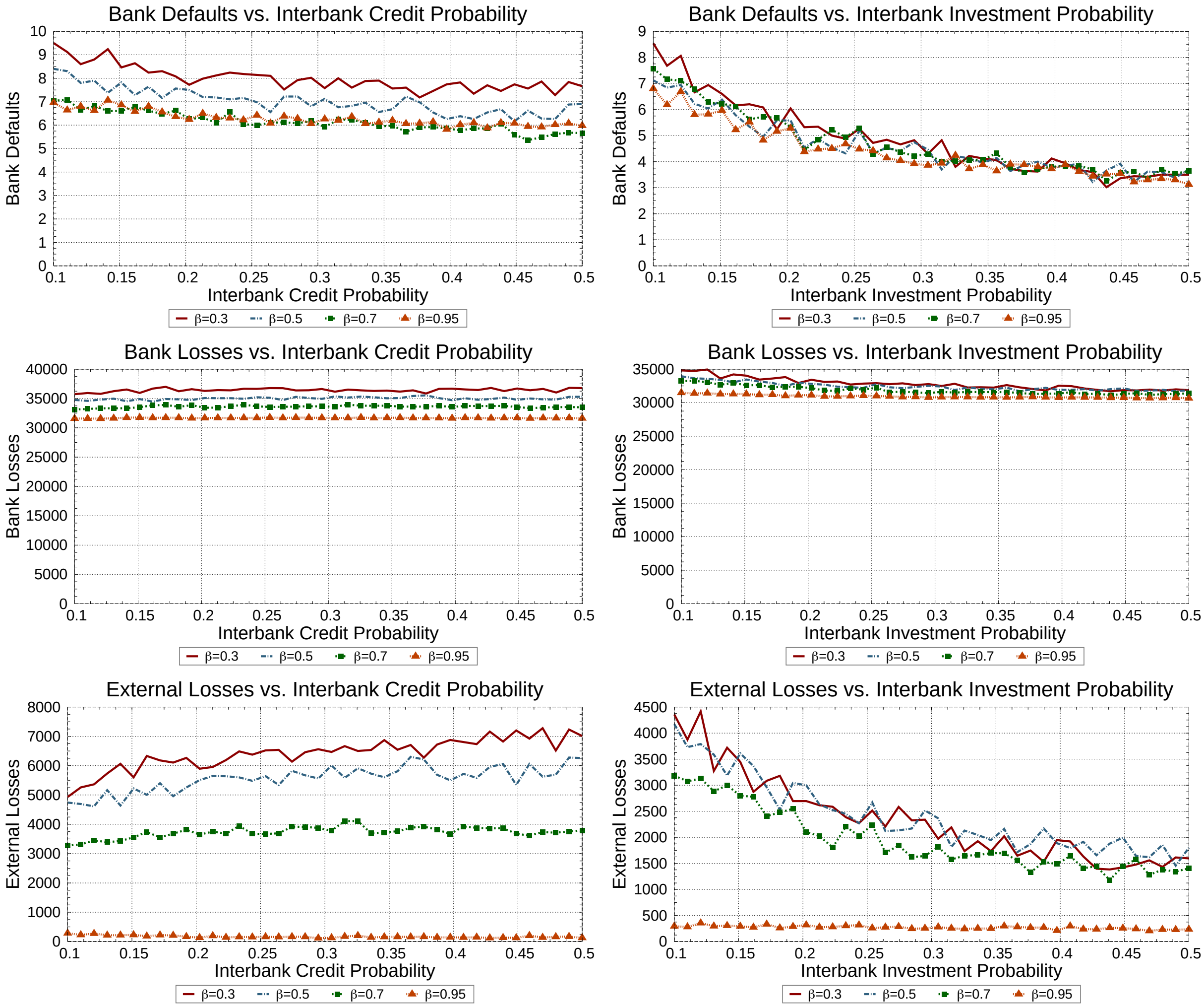


Figure 9.12: Impact of changes in the central bank price for fire-sale assets β, depending on interbank interconnectivity via credit (left) p^c and investment links p^i (right) for high concentration of the shock and high risk appetite of banks.

Parameter setting: see Tables A.1 to A.3 in the appendix A.1.1.

Chapter 10

Conclusion and Outlook

In the present thesis an asset based financial network model has been developed and presented to reproduce and analyze the interaction between banks, different economic sectors and the central bank, whereas the stylized financial system is characterized by the inclusion of strong idiosyncratic or systematic external shocks. The distinctive character of the presented model is that banks are affected by the initial distress depending on their individual asset structure. This forward-looking network model is simulation-based and consists of three groups of nodes: banks, real economy segments and the central bank, which are connected by various credit and investment links building a multi-layer network structure. Furthermore, the model includes the securitization of debts distinguishing between covered bonds and collateralized debt obligations. The latter are characterized by a number of tranches with various risk degrees and subordination. Moreover, the model takes account of the regulatory capital and minimum liquidity requirements, as well as the risk of deposit withdrawals and possible supportive activities by the central bank.

Applying the asset based financial network model, a number of bank and network properties have been analyzed here. It could be shown that the resilience of the financial system and the erosion of the banks' capital base, as well the allocation of losses between the banking sector and the external players greatly depend on the network characteristics and shock properties, such as the magnitude and the concentration of the initial event.

In particular, it could be shown that a high capitalization level of banks has positive effects for the stability of the system as well as for the external sector. However, in the case of a relatively low capitalization level compared to the initial event, a moderate increase in the equity rate may lead to higher losses for both, banks and externals, which is connected to the deposit withdrawal risk and implies that a moderate increase of the capital base has little stabilizing effect and is even able to increase contagion. Much more effective recapitalization of banks is necessary in such a case to stabilize the banking system.

Further, we analyzed the impact of risk appetite of banks in terms of risk preferences of the banking sector with respect to initial credit investments. Our analyses discovered that, even if the willingness of banks to assume higher risk from the granted credit would be positive for the external segment and negative for banks with respect to their participation in the initial losses in general, the negative impact of higher risk on both is also possible, especially if liquidity risk exists.

In view of the initial shock, we focused on two of its main properties – intensity and concentration. We showed that the resistance of the banking system is related to two opposite effects: the positive effect by sharing losses across banks, and the negative one caused by contagion effects. Liquidity risk aggravates the crisis and may rapidly trigger a crash of the whole system, causing significantly higher losses. In general, the banking system is more resistant against systemic initial events than against the idiosyncratic shocks with the same magnitude if shocks are relatively small. At a high magnitude of the initial shock, the banking system may be more resilient against idiosyncratic events than against broader distributed shocks with the same intensity in total, transmitting more losses to externals, especially if banks have low connectivity degrees. Furthermore, the underestimation of the systemic risk at the start of the crisis may cause significantly higher losses for depositors. Especially fire-sale trading within the banking system is able to deepen the banking crisis and raise its costs.

We looked at the impact of the following network properties on the financial stability: degree of connectivity and heterogeneity of the banking system. We emphasized the following effects: Increasing interconnectedness of the banking system increases the shock absorption and implicates the higher systemic stability of the system, provided that the banking system is well capitalized in relation to the systemic event that has taken place. Higher absorption means higher losses within the banking system and lower losses to externals. However, increasing interconnectedness may increase contagion, causing the lower systemic stability connected to more bank failures. The extent of contagion depends on the bank capitalization level and of the system's ability to prevent bank runs. We can conclude then that higher connectivity can be positive or negative for the systemic resilience, depending on which of both mentioned effects predominates: In well-capitalized networks increasing connectivity tends to strengthen the system's resistance. For low capitalized systems increasing connectivity would have rather more negative implications, particularly when liquidity risk exists.

Furthermore, we analyzed the effect of size of the interbank networks. It could be shown that the size of the banking system, just like the connectivity degree, could also play a significant role for the systemic stability. Moreover, the capitalization of the banking system highly determines the way in which an increasing number of banks acts on the system stability and on the loss distribution between banks and external segments. In this way, an increasing number of banks does not induce a clear effect. Further, we observed a combined effect of the increasing network size. The first part of the effect is similar to the impact of the increasing connectivity, playing a negative role for the resistance of banking systems in low capitalized banking systems, and stabilizing well capitalized systems by the broader distribution of losses. The second part is based on the increasing network granularity due to the decrease of the average balance sheet total with an increasing number of banks, leading to higher losses to externals due to higher shock transmission, if banks have low levels of capitalization and interconnectivity. The total effect depends on the network structure as well as further risk drivers like degrees of connectivity and capitalization of banks.

Focusing on the network structure effects, we introduced the extended core periphery concept including the semi-periphery in addition to the common core and periphery network areas and analyzed the impact of this heterogeneity on the stability of the system, in general, but also on the vulnerability of the single network areas, in particular. The core-periphery structure studied here has two major structural differences compared to the random network. Firstly, the external credit exposure is more concentrated: core banks do more or larger lending deals. Secondly, the interbank lending is more heterogeneous in structure. Thereby, the concentration of the interbank lending decreases with increasing exposure differences between core and periphery, if structural differences with regard to the interbank relationships exist, and increase otherwise. We showed that these properties have different effects on system stability and on the resilience of the single bank groups. Generally, core banks tend to be more stable, while periphery banks are more prone to shocks in core-periphery networks if significant differences between the core and periphery exist. Furthermore, more heterogeneity in banking systems has stabilizing effects on low capitalized systems and may have a negative effect on the banking stability, if banks have better capitalization or shocks are sufficiently small.

We analyzed the effects of the loss of confidence in the banking system, defined by an increase of creditor and depositor intolerance for undercapitalization of banks. We showed that, when banks are still well capitalized after the shock, withdrawals would not occur, whatever the level of intolerance is. Otherwise, at some sufficiently high level of the intolerance, in other words if confidence has been already considerably damaged, the negative impact of withdrawals would increase disproportionately strongly compared to the further increase of the intolerance, which means that a marginal loss of confidence would lead to heavily growing losses to banks and externals and destabilize the banking system substantially. One interesting aspect here is, that the more rigorous the capital regulations are, the stronger this negative effect is. In contrast, central bank support could positively counteract this effect, stabilizing the banking system. Furthermore, the effects of deposit withdrawal risk can be influenced not only by capital regulations, willingness of the central bank to support the banking system or initial bank capitalization, but also by network structure, intensity and distribution of shocks and, not least, by risk appetite of banks and externals, inter alia.

Further, we analyzed the influence of some properties connected to the regulatory framework. We looked at the impact of tightening of the regulatory capital restrictions followed by two short-term consequences: deceleration of new business and, thus, pressure on the demand and prices for fire sale assets, firstly, and maintaining uncertainty about appropriate capitalization of the banking system among depositors, secondly, using the regulatory capital requirements as an orientation marker with regard to the safety of the deposits. We can summarize that tighter capital requirements may increase the vulnerability of the banking system from the short term perspective and, even more, the losses to both, banks and externals due to increasing liquidity risk. Nevertheless, we recognized that at least in the medium term, banks would react by increasing their equity base or reducing their (risk) assets, strengthening systemic stability as a result.

Moreover, we analyzed the impact of the additional capital requirements. Thereby we considered the case that all banks are treated equally, and the case of different allocation of the additional capital assuming that only systemically important banks faced the capital surcharge. We observed that the equal rise in the equity ratio for all banks tends to stabilize the banking system more effectively than the capital surcharges for systemically important financial institutions only, even if the total increase of the banking capital in the system is the same. We can summarize that the diversified capital requirements may lead to a higher systemic risk in comparison with uniform regulations.

Furthermore we looked at the risk adjusted capital requirements compared to the 'flat' capital adequacy. We demonstrated that individual risk-sensitive bank capitalization can be stabilizing or destabilizing. Risk adjusted capital requirements could make a banking system more vulnerable to 'unexpected' shocks, compared to 'flat' capital requirements, if the capital reduction effect, caused by the risk sensitive requirements, is larger than the advantages of the 'a-priori' low risk banks in terms of affectedness by an unexpected shock.

Analyzing liquidity effects, we focused on the impact of the initial liquidity endowment and of the liquidity provided by the central bank during the crisis. We observed that, if withdrawals of deposits are solvency-based, a high liquidity reserve or buffer do not only not assist the stabilization process but could actually significantly complicate it and raise losses to both: banks and externals. Withdrawal of liquidity could not be stopped in particular, if little or no activity has been undertaken to ensure adequate capitalization of banks. Furthermore, a large liquidity buffer can cause an explosion in withdrawals, even if no impairment of liquid assets takes place and no further defaults of commercial loans occur. A similar impact and reasoning can be observed for additional liquidity reserves in such a case.

We underlined the role of the willingness of the central bank to support banks falling victim to the loss of depositor confidence. The first of two supporting activities of the central bank implemented in the model focuses on providing the liquidity to banks to fill part of the individual liquidity gaps. The second activity includes the intervention of the central bank in the fire-sale market by buying the excess credit assets.

We showed that support by the central bank providing the additional liquidity during the crisis can reduce the bank losses and defaults and even the losses transmitted from banks to externals. However, the effectiveness of such activities seems to depend on depositor confidence in the banking system as well as on the banks' solvency. The main difference between central bank support and the liquidity endowment of banks is likely to be the neutral impact of the first on the leverage ratio of banks, while the increase of liquidity endowment of banks raises the level of external deposits and thus the banks leverage. The latter enhances the potential for deposit withdrawals, while central bank liquidity injection sustainably reduces the resultant liquidity gaps and, thus, the amount of fire-sale assets and counteracts the price pressure on the fire-sale market. The increase in the threshold price for fire-sale assets, at which the central bank would purchase the assets, tends to have a positive stabilizing effect on the whole system, reducing the losses to banks and, accordingly, the losses to externals transmitted from banks. The reduction of the losses causes a lower default rate within the banking system, diminishing negative consequences from the after-shock dynamics.

The simulation experiments and results discussed here have shown several times, how diverse characteristics of the network itself and its environment, as well as the properties of the systemic event, exert influence on the dynamics within the network and thus on systemic risk. As demonstrated, the tangible results often depend on a broad spectrum of factors. Therefore, data quality and completeness play an important role for the empirical research of systemic risk. But this is the problem that we are facing. Unfortunately, data of bilateral exposures in the interbank market is scarce, incomplete and often of limited quality. In addition, it must be underlined here that even if good quality data were available, special care always has to be taken to avoid false conclusions, because of the multiplicity and diversity of the financial systems combined with the rarity of systemic events.

In global financial markets a solvency crisis of certain economic sectors can very quickly turn into a solvency and liquidity crisis for many financial institutions and sovereign countries. Economic implications of the last financial crisis and of the associated monetary policies are still not very clear. As stated previously, network structures play an important role in analyzing financial system stability and withstanding external shocks and not least in supporting and evaluating economical and political approaches to regulate the financial sector. Dynamic processes in the real system can be effected through the changes in the market state and mostly by the implementation of regulatory policies. Such changes may be implemented and used in a simulation engine as presented here, creating more meaningful results. We are convinced that an effective monitoring and regulating of banking systems should be based on a deep understanding of financial products and of current developments in the financial markets, transparency of bank books to the greatest possible extent and a continuous development of sophisticated models using this knowledge and data.

Appendix A

A.1 Parameters

A.1.1 Baseline scenarios

In Tables A.1, A.2 and A.3 we list the benchmark parameters and ranges that are used for the simulation experiments which are based on the baseline scenarios. These scenarios and methodology of simulation experiments are described in section 3.2. Table A.1 contains the general network parameters, that mainly determine the network structure and are unique (the same for each related node in the network). For a number of experiments which are discussed in this work we parameterized the simulation engine by benchmark values and vary the parameters presented in Tab. A.1 in the specified range. In Table A.2, segment specific parameter are listed, which are separately defined for each external segment and determine the heterogeneity of the external sector. Parameters which are related to securitization of external loans and separately defined for CBs and each tranche of CDOs are listed in Fig. A.3. For the description of the parameters and their incorporation in the model we refer to chapter 2.

Parameter		Value	Range
C^e	total amount of external loans	1.000.000	fixed
N	number of banks	25	5 to 100
p^c	interbank lending probability	25%	10% to 50%
p^i	interbank investment probability	25%	10% to 50%
γ	initial equity ratio of banks	8%	0% to 20%
γ^r	regulatory equity ratio of banks	5%	0% to 8%
η	proportion of external loans, refinanced by interbank deposits	50%	0% to 100%
ζ	proportion of liquid assets as percentage of external loans	0%	0% to 100%
λ	external credit default rate (magnitude of the initial shock)	3%	0.5% to 10%
β	threshold price for fire-sale assets	0.5	0 to 1
ν	minimum reserve rate	1%	0% to 10%
τ	intolerance for capital gap of banks *(with liquidity risk)*	10%	0% to 90%
τ	intolerance for capital gap of banks *(without liquidity risk)*	0%	
σ	support by the central bank	0%	0% to 90%

Table A.1: General network parameters with benchmark values and ranges (baseline scenarios).

Parameter		Sec 1	Sec 2	Sec 3	Sec 4	Sec 5	Sec 6
α_s	Alpha-parameter for the risk-distributions	1.1	1.2	1.4	1.6	1.8	2
β_s	Beta-parameter for the risk-distributions	10	10	10	10	10	10
w_s^c	Credit weight	0.1	0.1	0.1	0.2	0.2	0.3
p_s^b	Percentage of connected banks	1	0.8	0.5	0.3	0.2	0.1
q_s	Securitization ratio	0.5	0.5	0.5	0.5	0.5	0.5
δ_s	Distribution of the initial shock *(high concentration)*	0	0	0	0	1	0
δ_s	Distribution of the initial shock *(low concentration)*	1	1	1	1	1	1

Table A.2: Segment-specific parameters (baseline scenarios).

Parameter		CB	Tranche A	Tranche B	Tranche C
u	Upper risk threshold	0.05	0.15	0.25	1
β^{CB}, β_t^{CDO} $(t \in T)$	Bank shares of investments	0	0	1	1

Table A.3: Tranche-specific (CB and CDO) parameters (baseline scenarios).

A.1.2 Modified scenarios (connectivity experiments)

In Tables A.4, A.5 and A.6 we list the benchmark parameters and ranges that are used for analyzing the impact of connectivity within banking systems. The basics of scenarios and methodology of simulation experiments are similar to the baseline scenarios and are described in section 3.2.

Table A.4 contains the general network parameters. In Tab. A.5 segment specific parameter are listed, which are separately defined for each external segment. Parameters which are related to securitization of external loans and separately defined for CBs and each tranche of CDOs are listed in Fig. A.6. For the description of the parameters and their incorporation in the model we refer to chapter 2.

The scenarios are similar to the baseline scenarios (see section A.1.1). Their modification consists of only a few parameters. It is used to eliminate the possible side effects or to see the effects of connectivity more clearly. The smaller interbank lending and investment probabilities p^c, p^i are chosen to generate more heterogeneous networks. A higher number of banks N helps to stress p^c (Tab. A.4) and obtain sensible results even for quite small values of p^c. The percentage of connected banks p^b_s for the external sector which will be stressed to simulate a strong idiosyncratic shock, $s = 5$, is chosen at a very low level to induce a high concentrated initial shock, $p^b_5 = 0.02$. The contagion effects could play a more important role then. Loans given to this sector should not be securitized $q_5 = 0$, which is sensible in order to eliminate the effects of the contagion via investments (Tab. A.5). The banking and the external sector have the same risk preferences: $\beta^{CB} = 0.5$ and $\beta^{CDO}_t = 0.5 \quad \forall t \in T$ (Tab. A.6) for simplicity.

Parameter		**Value**	**Range**
C^e	total amount of external loans	1.000.000	fixed
N	number of banks	50	5 to 100
p^c	interbank lending probability	0.1%	10% to 50%
p^i	interbank investment probability	0.1%	10% to 50%
γ	initial equity ratio of banks	8%	0% to 20%
γ^r	regulatory equity ratio of banks	5%	0% to 8%
η	proportion of external loans, refinanced by interbank deposits	50%	0% to 100%
ζ	proportion of liquid assets as percentage of external loans	0%	0% to 100%
λ	external credit default rate (magnitude of the initial shock)	3%	0.5% to 10%
β	threshold price for fire-sale assets	0.5	0 to 1
ν	minimum reserve rate	1%	0% to 10%
τ	intolerance for capital gap of banks *(with liquidity risk)*	10%	0% to 90%
τ	intolerance for capital gap of banks *(without liquidity risk)*	0%	
σ	support by the central bank	0%	0% to 90%

Table A.4: General network parameters with benchmark values and ranges (connectivity experiments).

Parameter		**Sec 1**	**Sec 2**	**Sec 3**	**Sec 4**	**Sec 5**	**Sec 6**
α_s	Alpha-parameter for the risk-distributions	1.1	1.2	1.4	1.6	1.8	2
β_s	Beta-parameter for the risk-distributions	10	10	10	10	10	10
w_s^c	Credit weight	0.1	0.1	0.1	0.2	0.2	0.3
p_s^b	Percentage of connected banks	1	0.8	0.5	0.3	0.02	0.1
q_s	Securitization ratio	0.5	0.5	0.5	0.5	0.	0.5
δ_s	Distribution of the initial shock *(high concentration)*	0	0	0	0	1	0

Table A.5: Segment-specific parameters (connectivity experiments).

Parameter		**CB**	**Tranche A**	**Tranche B**	**Tranche C**
u	Upper risk threshold	0.05	0.15	0.25	1
β^{CB}, β_t^{CDO} $(t \in T)$	Bank shares of investments	0.5	0.5	0.5	0.5

Table A.6: Tranche-specific (CB and CDO) parameters (connectivity experiments).

A.1.3 Nomenclature for scenarios

scenario (mode)	Asset Risk Adjusted Capital	Core-Periphery Structure	Redistribution of External Debts	Systemic Risk Adjusted Capital (Special Treatment) (of SIBs)
1	no	no	no	no
2	no	no	no	**yes**
3	no	no	**yes**	no
4	no	no	**yes**	**yes**
5	no	**yes**	no	no
6	no	**yes**	no	**yes**
7	no	**yes**	**yes**	no
8	no	**yes**	**yes**	**yes**
9	**yes**	no	no	no
10	**yes**	no	no	**yes**
11	**yes**	no	**yes**	no
12	**yes**	no	**yes**	**yes**
13	**yes**	**yes**	no	no
14	**yes**	**yes**	no	**yes**
15	**yes**	**yes**	**yes**	no
16	**yes**	**yes**	**yes**	**yes**

Table A.7: Structure of the scenarios, used for the analysis dealing with sensitivity of capital requirements in chapter 8.

A.2 Further supportive illustrations

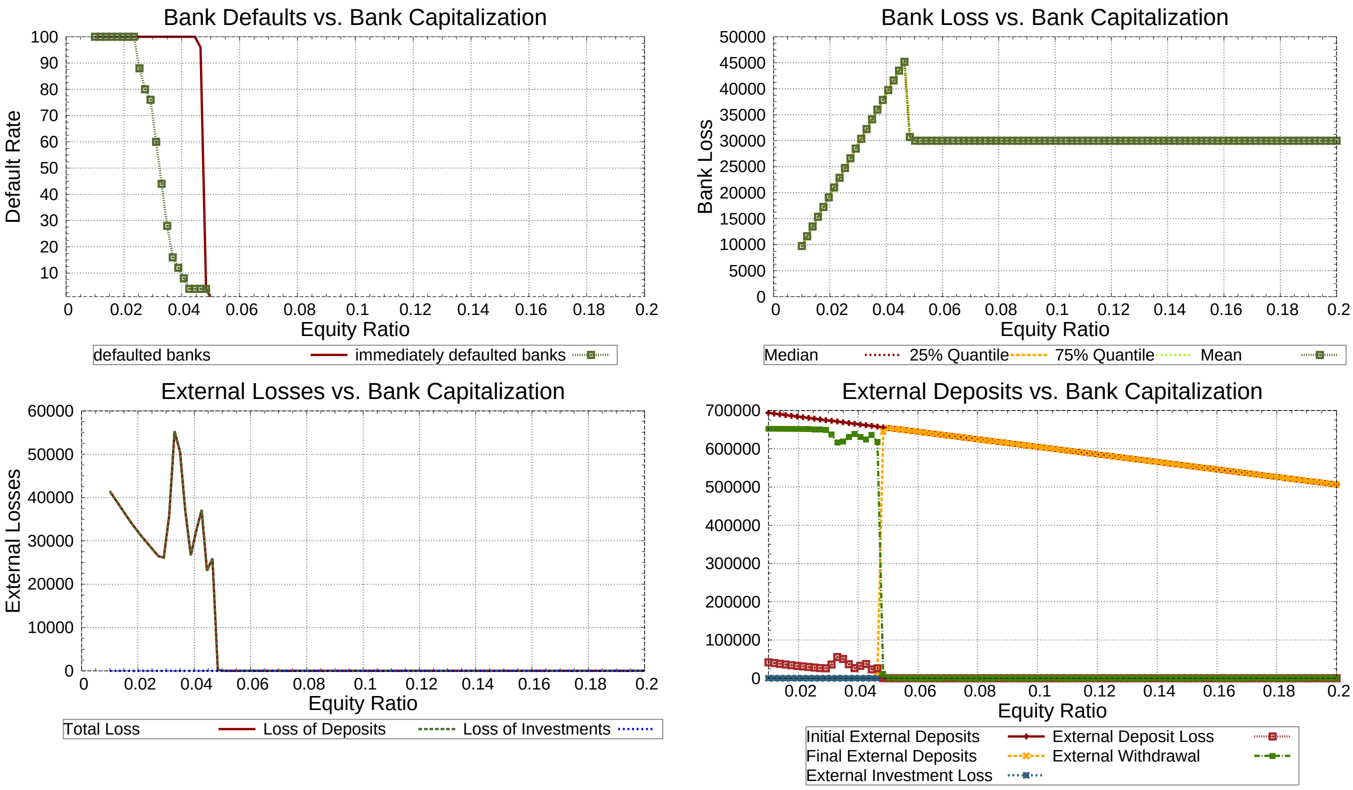
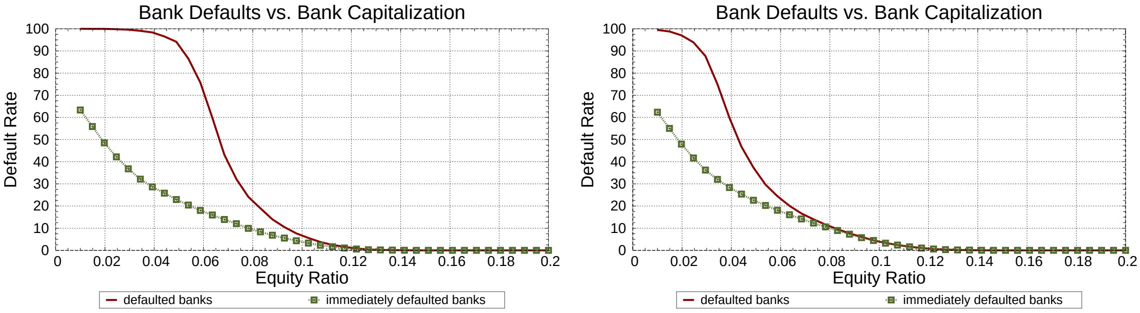
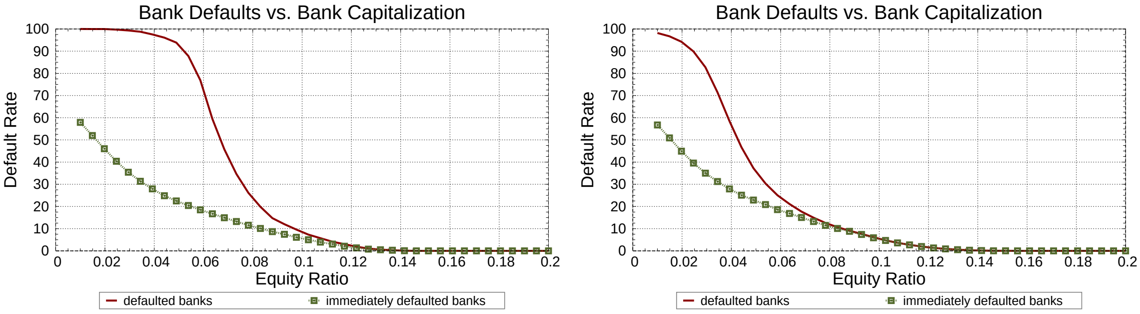


Figure A.1: Example: Development of losses and bank defaults at increasing capitalization of banks with low concentration of the shock and deposit withdrawal risk(NW03).

exposure difference WD no WD



structural difference WD no WD



exposure and structural difference WD no WD

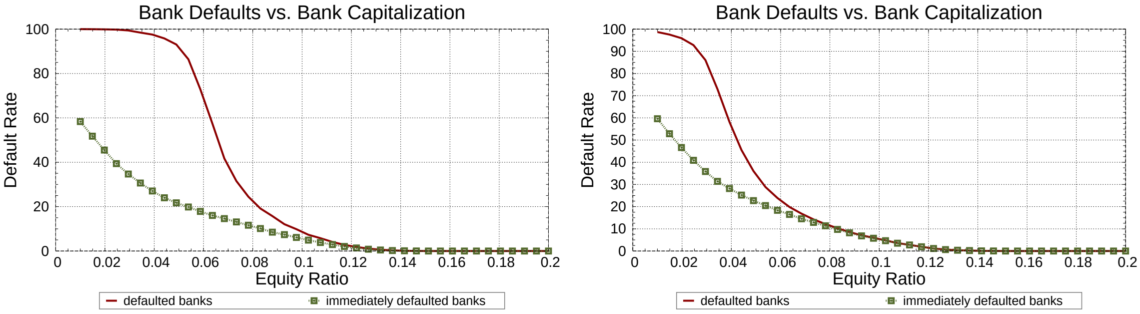
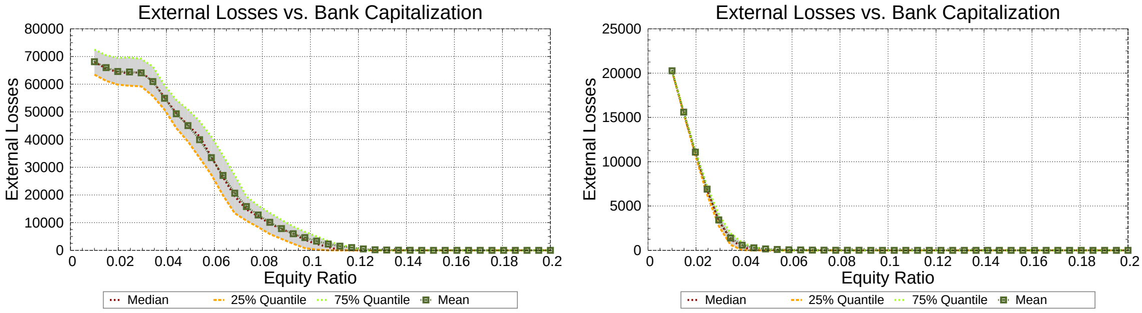
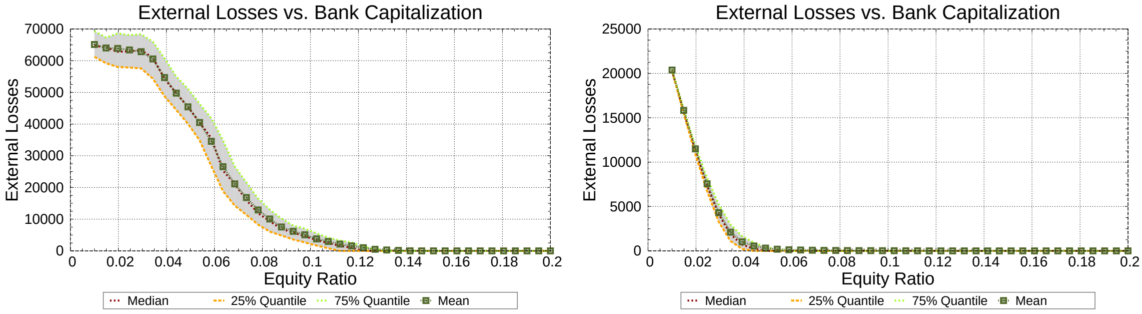


Figure A.2: External losses in CP-networks with different properties in the case of idiosyncratic shocks, high risk appetite of banks with or without liquidity risk related to withdrawal of deposits (WD with $\tau = 0.1$ (left) or no WD with $\tau = 0$ (right)).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.2$ if exposure difference exists and $\xi = 0$ otherwise, $\zeta = 0.1$. $\tilde{\gamma} = 0.02$ (determines additional capital, see (8.8) in 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

exposure difference WD no WD



structural difference WD no WD



exposure and structural difference WD no WD

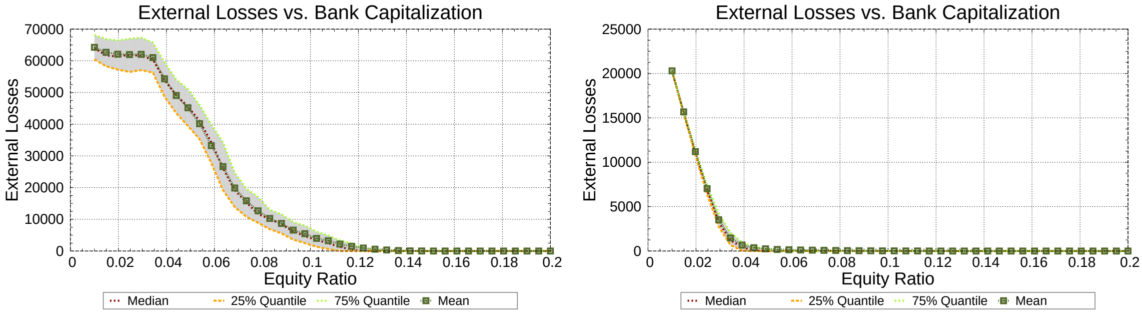
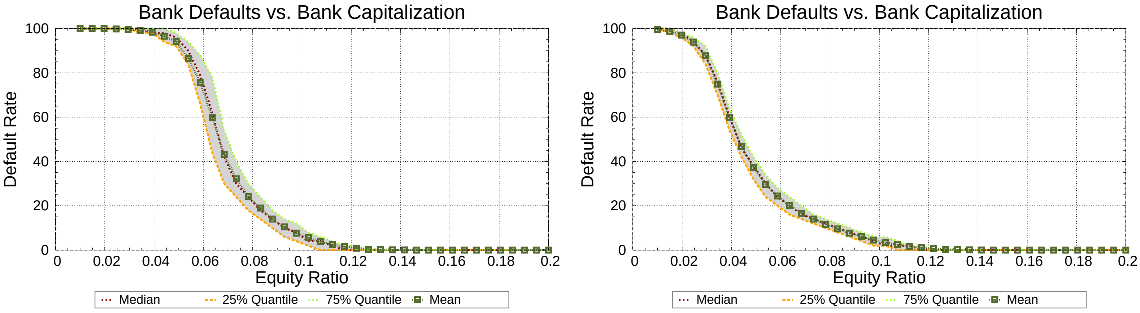
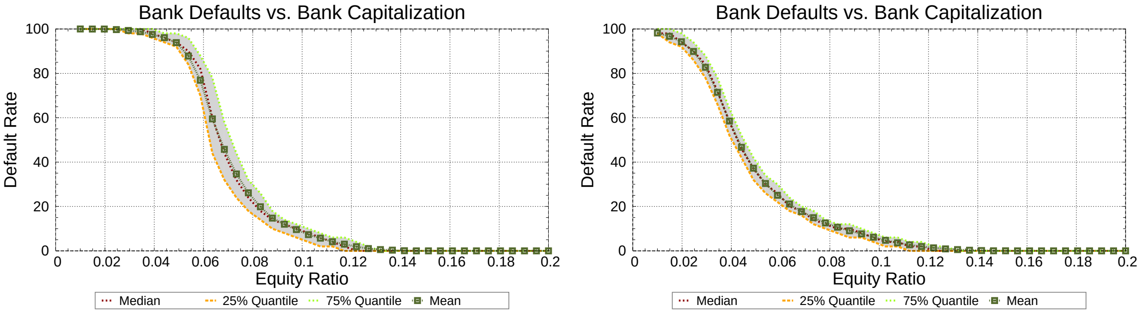


Figure A.3: Bank defaults in CP-networks with different properties in the case of idiosyncratic shocks, high risk appetite of banks with or without liquidity risk related to withdrawal of deposits (WD with $\tau = 0.1$ (left) or no WD with $\tau = 0$ (right)).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.2$ if exposure difference exists and $\xi = 0$ otherwise, $\zeta = 0.1$. $\tilde{\gamma} = 0.02$ (determines additional capital, see (8.8) in 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

exposure difference WD no WD



structural difference WD no WD



exposure and structural difference WD no WD

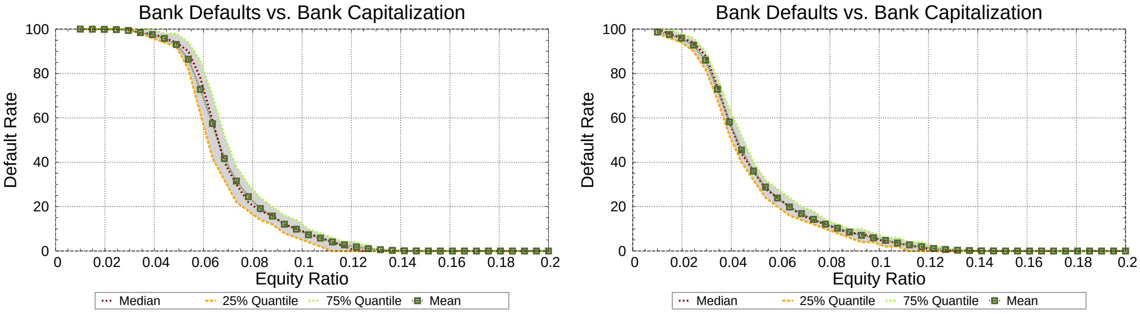
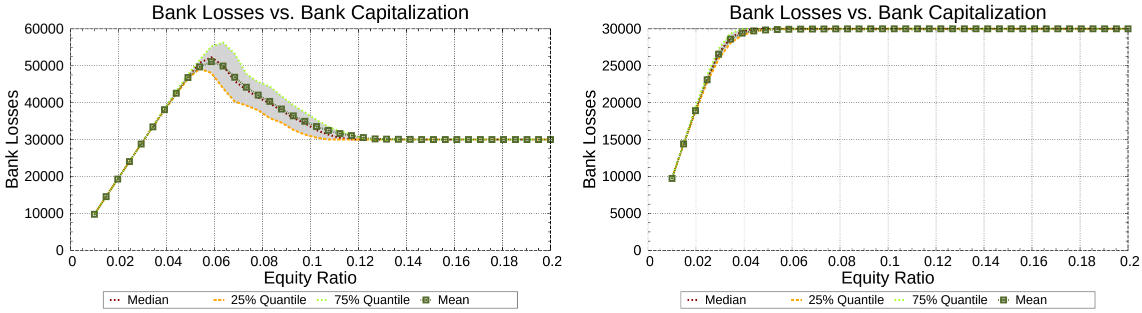
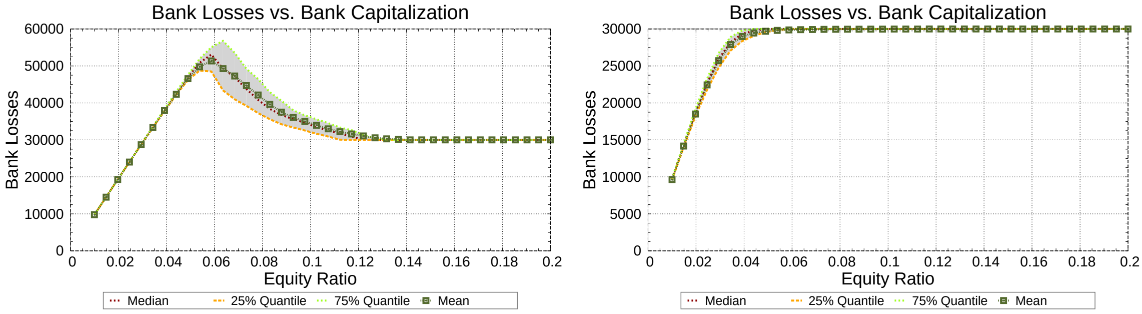


Figure A.4: Bank defaults in CP-networks with different properties in the case of idiosyncratic shocks, high risk appetite of banks with or without liquidity risk related to withdrawal of deposits (WD with $\tau = 0.1$ (left) or no WD with $\tau = 0$ (right)).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.2$ if exposure difference exists and $\xi = 0$ otherwise, $\zeta = 0.1$. $\tilde{\gamma} = 0.02$ (determines additional capital, see (8.8) in 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

exposure difference WD no WD



structural difference WD no WD



exposure and structural difference WD no WD

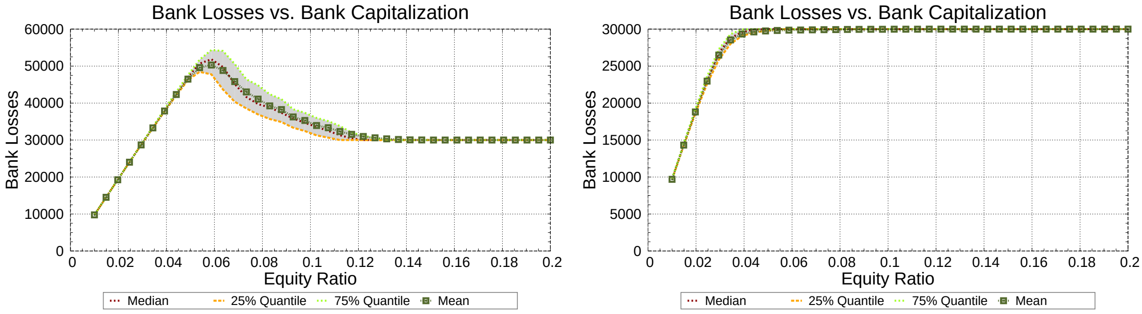


Figure A.5: Total bank losses in CP-networks with different properties in the case of idiosyncratic shocks, high risk appetite of banks with or without liquidity risk related to withdrawal of deposits (WD with $\tau = 0.1$ (left) or no WD with $\tau = 0$ (right)).
Parameter setting: $\psi_1 = 0.1$, $\psi_2 = 0.5$, $\xi = 0.2$ if exposure difference exists and $\xi = 0$ otherwise, $\zeta = 0.1$. $\tilde{\gamma} = 0.02$ (determines additional capital, see (8.8) in 8.2.2). For the remaining parameters please refer to Tables A.2, A.3 and A.4 in the appendix.

A.3 Source code

Here we present the most important parts of the source code of the simulation engine. The following source listing shows the main steps of the typical simulation used for the analyses in this thesis. The comments on the separate steps are highlighted in green. The terminology and names of variables are closely linked to the model description. There is no need to explain these here. For this reason we refer at this point to chapter 2, where the description of the model is given.

The main program structure is presented in Listing A.1. The Individual program steps like creation of a financial system as a random network, unbalancing the system by wiping out external credits and the subsequent dynamics in order to maintain the balance of the system again are annotated in detail in Listings A.2 to A.4. The remaining listings expound the dynamics which are included in Listing A.4. The solvency chain reaction related to the absorption of banks' losses and contagion dynamics is presented in A.5. For the according process description refer to section 2.2.5. Withdrawal of deposits is implemented in the source code listed in A.6. The liquidity chain reaction is shown in A.7. The last two processes are described in section 2.3.4. The mentioned sections of the source code are presented in a sufficiently clear and complete manner. Exceptions to this are solely error- and self-consistency checking macros and functions, which are excluded for the sake of simplicity.

Listing A.1: Running a simulation

```
void Szenario::Run(ofstream& file)
{
// read out the parameter file, determine the core and periphery banks
    ParamFile pf("network.param");
    int ng = ExtLost.size();  //number of iterations
    int i_b_max=(int)max(n*psi_big,1); //upper core bank index
    int i_s_min=(int)min(n*(1-psi_small),(n-1));//lower periphery bank index
// begin of the simulation
    for (int i=0; i<m; i++) //for each of m runs
    {
// generate random matrices
        RandomMatrix RSB(n,s,psb);
```

```
        RandomMatrix R  (n,p);
        RandomMatrix RI (n,ip);
// begin of the iteration
        for (int g=0; g<ng; g++) // for each of ng iterations
        {
// calculate varying parameters (depending on the scenario definition)
            Stress(g,R,RI);
// initialize network parameters
            Network N(n,s,pf);
// initialize the network
            N.Init(R,RI,RSB,gamma,nu,xi,psi_big,psi_small,zeta,
            delta_cap,gamma_srfi,rgamma_srfi,mode);//see List. A.2
// trigger the shock
            for (int ds=0; ds<s; ds++)
            {
                double def=wsd[ds]/wsd.sum();
                N.ExternalDefault(ds,lambda,def);//see List. A.3
            }
// trigger a chain reaction and clean the system
            N.ChainReaction(phi,tau,rgamma,delta,nu);//see List. A.4
// calculate and save results
            N.Analyse(i_b_max, i_s_min);
        }
// end of the iteration
    }
// end of the simulation
}
```

Listing A.2: Creating a network

```
void Network::Init(const BoolMatrix& R, const BoolMatrix& RI,
                const BoolMatrix& RSB, double gamma, double nu,
                double xi, double psi_big, double psi_small,
                double zeta, double delta_cap, double gamma_srfi,
                double rgamma_srfi, int mode)
{
//initialize initial interbank network structure
    IntVector srfi(0);
    ND.W().equ(1.,R.Get());
    for (int i=1; i<ND.WIS().size(); i++)
    {
        ND.WIS()[i].equ(1.,RI.Get());
    }
//build core periphery network structure (depending on the mode)
    BuildCoreNewStep1(xi, psi_big, psi_small, FunctionB(mode));
    BuildCoreNewStep2(xi, psi_big, psi_small, FunctionB(mode));
```

```
//determine initial linking between the external segments and banks
    ND.ExtW().equ(1.,RSB.Get());//debts
    for (int i=1; i<(ND.ExtWIS().size()-1); i++)//securitized debts
    {
        ND.ExtWIS()[i].equ(1.,RSB.Get());
    }
//determine external debts
    for (int i=0; i<s;i++)
    {
        double creditbanknum = max(ND.ExtW().ColumnSum(i),1.);
        double w = E*SegmentWeight[i]/SegmentWeight.sum()/creditbanknum;
        ND.ExtW().ScaleColumn(i,w);
    }
//redistribute external credits (depending on the mode)
    RedistributeExternalCredits(xi, psi_big, psi_small, FunctionC(mode));
//realize securitization of external debts
    ND.MatrixCB().equ(1.,ND.ExtW());
    for (int i=0; i<ND.NumberOfTranches(); i++)
    {
        ND.Tranche(i).equ(1.,ND.ExtW());
    }
    InitCBandCDO();
    for (int i=0; i<ND.NumberOfTranches(); i++)
    {
        ND.ExtW().Substract(ND.Tranche(i));
    }
    for (int i=0; i<n; i++)
    {
        double creditsum =  B[i].ExternCredit()-
                            B[i].ExternShareholderInterest()-
                            B[i].BankShareholderInterest();
        double creditbanknum = max(ND.W().ColumnSum(i),1.);
        double w = 0.;
        if (creditbanknum>0.)
        {
            w = creditsum*eta/creditbanknum; ND.W().ScaleColumn(i,w);
        }
    }
//determine risk weights using the segment-specific beta functions
    BetaRiskWeights();
//apply risk weights (depending on the mode)
    AdjustRiskWeight(FunctionA(mode));
//determine liquidity buffer (external assets) and equity
    for (int i=0; i<n; i++)
    {
    B[i].InitExternInvestment(gamma, zeta);
```

```
    }
//determine systemically relevant banks
    double minscore=0.;
    minscore=SRFIminscore();
    srfi=SRFIBanks(minscore);
//adjust initial bank capital (depending on the mode)
    AdjustInitialCapital(gamma, delta_cap, srfi, FunctionD(mode));
//determine initial external deposits and minimum liquidity reserves
    for (int i=0; i<n; i++)
    {
        B[i].InitExternDeposit(nu);
    }
//calculate and save initial values (for further analyses)
    for (int i=0; i<n; i++)
    {
        B[i].CalculateInitials();
    }
    for (int i=0; i<s; i++)
    {
        Ext[i].CalculateInitialInvestment();
    }
}
```

Listing A.3: Unbalancing the network by an external shock (relating to a certain external segment)

```
void Network::ExternalDefault(  int segment, double extdef,
                                double weightsegdef)
{
// determine proportion of non-performing loans
    double defaultquote=extdef*weightsegmentdef/SegmentWeight[segment];
// reduce (performing) external credit assets
    ND.ExtW().ScaleColumn(segment,1.-defaultquote);
// transfer the losses to CDOs and CB
// (depending on degrees of subordination)
    double cdosum = 0.;
    for (int i=0; i<ND.NumberOfTranches(); i++)
    {
        cdosum += ND.Tranche(i).ColumnSum(segment);
    }
    double def = cdosum*defaultquote;
    for (int i=ND.NumberOfTranches()-1; i>-1; i--)
    {
        double cs = ND.Tranche(i).ColumnSum(segment);
        double deff = min(def,cs);
        if (deff>0.)
```

```
            {
                 def -= deff;
                 double scalefactor = 1.-deff/cs;
                 ND.Tranche(i).ScaleColumn(segment,scalefactor);
            }
       }
// calculate direct losses of externals and banks
// (before contagion takes place)
ComputeInitialLoss();
}
```

Listing A.4: Chain reactions and rebalancing of the system

```
void Network::ChainReaction(double tau, double rgamma,
                                        double delta, double nu)
{
// create and initialize vectors containing insolvent or
// considerably weakened banks
     IntVector badbanks = BadBanks();
     IntVector weakbanks = WeakBanks(tau,rgamma);
// trigger chain reaction once at least one bank bankrupts
// continuing until the bank losses are fully absorbed or transmitted
// and deposit withdrawals do not happen
     while (BadBanks().size()>0)
     {
          badbanks = BadBanks();
// transmit (uncovered) losses from insolvent banks via lending links
// continuing until bank losses are fully absorbed or transmitted
          while (badbanks.size()>0)
          {
               ChainCreditLoss(badbanks,phi);//see List. A.5
               weakbanks = WeakBanks(rgamma,tau);
               badbanks = BadBanks();
          }
// trigger withdrawal of deposits and liquidity chain reaction if possible
// once at least one considerably weakened bank exists;
          if (weakbanks.size()>0 && (Deposits(weakbanks)!=0))
          {
               ChainWithdrawDeposits(weakbanks,tau,rgamma);//see List. A.6
               ChainLiquidity(delta,nu,rgamma); //see List. A.7
          }
     }
}
```

Listing A.5: Absorption of losses

```cpp
void Network::ChainCreditLoss(IntVector badbanks)
{
    for (int j=0; j<badbanks.size(); j++)
    {
        B[badbanks[j]].ChainReaction();
    }
}

void Bank::ChainReaction()
{
    double defaultsum    = -Capital();
    double defaultbank   = min( defaultsum,BankDeposit());
    double defaultextern = min( ExternDeposit(),defaultsum-defaultbank);
    double defaultcbank  = min( CentralBankDeposit(),
                                defaultsum-defaultbank-defaultextern);
    ReduceBankDeposits(defaultbank);
    ReduceExternalDeposits(defaultextern);
    ReduceCBankDeposits(defaultcbank);
}
```

Listing A.6: Withdrawal of deposits

```cpp
void Network::ChainWithdrawDeposits(     IntVector weakbanks, double tau,
                                         double rgamma)
{
    for (int i=0; i<weakbanks.size(); i++)
    {
        IntVector creditorbanks = B[weakbanks[i]].CreditorBanks();
        double withdraw = B[weakbanks[i]].WithdrawingDeposits(tau,rgamma);
        double withdrawrate = B[weakbanks[i]].WithdrawDeposits(withdraw);
        if (withdrawrate>0.)
        {
            for (int k=0; k<creditorbanks.size(); k++)
            {
                B[creditorbanks[k]].Deficit() -=
                B[creditorbanks[k]].BankCredit(weakbanks[i])*(1-withdrawrate)/
                 withdrawrate;
            }
        }
    }
}
```

Listing A.7: Liquidity Chain Reaction

```
void Network::ChainLiquidity(double delta, double nu, double rgamma)
{
    IntVector deficitbanks = DeficitBanks();
    while (deficitbanks.size()>0)
    {
        double price    = 0.;
// managing all banks' accounts with the central bank:
// (a) in case of liquidity gap, close the liquidity gap by withdraw
// the bank's deposits from the central bank (if available);
// (b) in case of excess liquidity, return the loans provided by the
// central bank or superfluous deposit funds with the central bank.
        CBNetting();
        for (int i=0; i<deficitbanks.size(); i++)
// use liquidity reserves to close the gaps
        {
            B[deficitbanks[i]].FirstReactionLiquidity(delta,nu);
        }
// manage banks' accounts with the central bank (as above)
        CBNetting();
// sell liquid assets
        for (int i=0; i<deficitbanks.size(); i++)
        {
            if (B[deficitbanks[i]].Deficit()>0.)
            {
                SellExternInvestments(deficitbanks[i]);
            }
// withdraw banks' own deposits to close liquidity gaps
            if ((B[deficitbanks[i]].Deficit()>0.)&&
                (B[deficitbanks[i]].BankCredit()>1.)
            {
                AdjustBankCredits(deficitbanks[i]);
            }
        }
// manage banks' accounts with the central bank (as above)
        CBNetting();
// sell covered bonds, CDOs and then the external credits (if necessary)
        for (int i=0; i<deficitbanks.size(); i++)
        {
            if ((B[deficitbanks[i]].Deficit()>0.) &&
                (B[deficitbanks[i]].BankInvestmentCB())>0.)
            {
                price = PotentialBanks(deficitbanks[i],rgamma).sum()/
                        B[deficitbanks[i]].Deficit();
                if (price>beta)
```

```
                {
                    SellBankInvestmentCB (deficitbanks[i],price,rgamma);
                }
                else
                {
                    SellBankInvestmentCB2CBank(deficitbanks[i],beta);
                }
            }
            if ((B[deficitbanks[i]].Deficit()>0.)&&
                (B[deficitbanks[i]].BankInvestment()-
                 B[deficitbanks[i]].BankInvestmentCB()>0.))
            {
                price = PotentialBanks(deficitbanks[i],rgamma).sum() /
                B[deficitbanks[i]].Deficit();
                if (price>beta)
                {
                    SellBankInvestmentCDO(deficitbanks[i],price,rgamma);
                }
                else
                {
                    SellBankInvestmentCDO2CBank(deficitbanks[i],beta);
                }
            }
            if ((B[deficitbanks[i]].Deficit()>0.) &&
                ((  B[deficitbanks[i]].ExternCredit()-
                    B[deficitbanks[i]].BankShareholderInterest()-
                    B[deficitbanks[i]].ExternShareholderInterest())>0.))
            {
                price = PotentialBanks(deficitbanks[i],rgamma).sum() /
                        B[deficitbanks[i]].Deficit();
                if (price>beta)
                {
                    SellExternCredits(deficitbanks[i],price,rgamma);
                }
                else
                {
                    SellExternCredits2CBank(deficitbanks[i],beta);
                }
            }
// manage banks' accounts with the central bank (as above)
            CBNetting();
            deficitbanks = DeficitBanks();
        }
    }
}
```

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