A Soft Bail-Out Concept to Reduce Contagion in Financial Systems

Wolfgang Aussenegg[(a)] and Bernhard Kronfellner[(b)]

[(a)] Department of Finance and Corporate Control, Vienna University of Technology,
Address: Theresianumgasse 27, A-1040 Vienna, Austria;
E-mail: waussen@pop.tuwien.ac.at, Phone: +43 1 58801 33082;
Fax: +43 1 58801 33098; Corresponding author

[(b)] Consultant at The Boston Consulting Group
E-mail: kronfellner.bernhard@bcg.com, Phone: +43 676 5797379

First Draft

December 2011

Abstract

Problem: The financial crisis of 2007-2009 has shown that regional problems in the financial industry can quickly spread over to the complete financial system and can even affect the worldwide economy. Thus, current financial systems are characterized by a high degree of interconnections and consequently a high amount of system risk. *Objective:* To reduce systemic risks, regulators and governments have to understand their main drivers. Upon this understanding, they need concepts of how to use most efficiently funds of new bank taxes. *Method:* By modeling the financial system with its interactions as stochastic processes we are able simulate the two main reasons for systemic risks – macroeconomic shocks and contagion – at the same time. *Results:* Based on our model of the financial system we propose the new concept of ´soft-bail-outs´. Compared to the current best practice of bank bail-outs, soft-bail-outs tend to reduce the probability of default of the whole financial system, lower the bail-out costs, and decrease the bail-out cost volatility. *Application:* This new concept of soft-bail-outs and the understanding of sensitivities to systemic risk can help regulators and governments to strengthen the financial system with fewer costs. In particular, we derive three suggestions to regulators of how to adapt the current regulatory regime.

JEL classification: G21, G28, G33

Keywords: Systemic Risk, Contagion, Bail-Out, Bank Tax, Financial Crisis, Bank Fragility, Bank Failure, Financial Stability

1 Introduction

Contagious diseases are normally treated by isolating the patient. However, in the interlinked financial system, isolation is not (always) possible. The financial crisis of the years 2007-2009 has proven that already the default of one large financial institution (Lehman Brothers) can infect and almost destroy the whole system. Therefore, regulators and governments raise concerns about the increasing degree of systemic risk in the financial sector. We contribute to the systemic risk literature by proposing a new governmental bail-out approach that lowers the risk of a system-wide collapse and reduces bail-out costs imposed on the economy.

Systemic risk is defined as risk that affects the industry as a whole[1]. In particular, it refers to the spillover effect that one event (default of a major company, macroeconomic shock, …) causes a cascade of failures throughout the system and, thus, triggers substantial losses. Furthermore, a crisis can even spill over from the financial to the real economy. According to Freixas and Rochet (2008), ´… systemic crisis may develop either as a result of a macroeconomic shock or as a result of contagion.´ Thus, in a realistic simulation both effects need to be considered in order to develop a model of the financial system and its interdependencies.

Over the last decade, the financial industry has experienced a vast increase in systemic risk. Indicators for system-wide risk extensions are (i) increasing stock return correlations[2], (ii) rising prices of insurance against losses of large financial institutions (i.e. CDS spreads)[3], and (iii) the influence of loss given default (LGD) rates on contagion in the banking system[4].

But what are the reasons for this recent increase of independencies within the financial system and the corresponding rise in systemic risk? Many research contributions relate the extent of systemic risk to the on-going trend of consolidation and conglomeration of

---

[1] *See* Freixas and Rochet (2008).
[2] *See* Nicolo and Kwast (2002).
[3] *See* Huang et al (2009).
[4] *See* Memmel et al (2011).

financial institutions.[5] Over the last decade, two causes underpin this increase in consolidation and conglomeration in the banking sector: (i) the internationalization of markets due to improvements in information technologies, and (ii) the relaxation of the conglomeration interdiction (Glass–Steagall Act[6] of 1933) by the Gramm-Leach-Bliley Act[7] of 1999 in the US.[8]

After the great depression banks in the United States were split by the Glass-Steagall Act of 1933 in investment and commercial banks. Consequently, financial institutions then tend to be smaller, as they were forced by law to stay specialized and as building conglomerations were prohibited. In 1998, the Citigroup merger firstly violated this law. Citigroup took advantage of the Bank Holding Company Act temporary granting consolidations[9]. In 1999, the US Congress passed the Gramm-Leach-Bliley Act that finally permitted the merger. As stated by Broome and Markham (2001), the Gramm-Leach-Bliley Act can also be referred as the ´Citigroup-Relief-Act´. This act not only allows banks with customer deposits to invest in trading activities, but also reduces the barriers for financial conglomeration. Even though the act allows a higher diversification in business activities, the deregulation fosters a trend[10] towards concentration and conglomeration that increases systemic risk (which can be shown empirically[11]). The larger banks are, the more harm an insolvency can cause to the financial system, which is the downside of market liberalization. This fact reminds one to the recent metaphor of Georg Soros who compared systemic risk with an oil tanker boat.[12] To reduce the risk of losing all transported oil (at once), an oil tanker typically consists of many oil compartments. Based on this metaphor, deregulation would be to construct oil tankers without separating walls, directly enhancing the risk of losing the whole oil cargo. With this

---

[5] E.g. Nicolo et al (2003).

[6] Refers to the Banking Act of 1933, ch. 89,48 Stat. 62 (codified as amended in scattered section of 12 U.S.C.).

[7] Also known as the Financial Services Modernization (FSM) Act of the U.S. Public Law No. 106-102, signed into law November 12, 1999.

[8] E.g. Nicolo and Kwast (2002) or Nicolo et al. (2003) investigate the impact of conglomeration on financial stability.

[9] *See* Broome and Markham (2001).

[10] Haldane and May (2011) outline the ´recent rise in the size and concentration of the US financial system´. They show that between the years 1933 (right after Glass-Steagall Act) and 1998 (right before the Glamm-Leagall-Bliley Act) the 3 top US banks only held between 10 and 20 % of all commercial banking sector assets. After passing the Glamm-Leagall-Bliley Act, this percentage increased to nearly 40% in 2008.

[11] *See* Neale et al (2010).

[12] Interview of Georg Soros in 2010, published in the documentary ´Inside Job´.

metaphor, George Soros aims to explain why financial institution conglomeration and consolidation do not lead to a safer financial network.

By combining four different research areas (Financial Networks, Contagion, Concentration/Conglomeration, and Bail-Outs) we build a model of the financial system and explore the interplay between banking network structure, governmental bail-out strategy, and financial stability. In particular, firstly, we contribute by analyzing the contagion effect on a stand-alone basis using various interconnections between banks. Secondly, we study how the network structure (degree of conglomeration, amount of banks, interlinkage between institutions, borrowing rates, …) determines the stability of the system. To elaborate the main drivers of system stability the system is stressed by both macroeconomic shocks and write-offs due to contagion. The aim is to show and rank the main drivers of system stability.

Finally, the results based on various drivers in the banking network are used to make the system more resilient to macroeconomic shocks and contagion by implementing a new ´soft-bail-out´ concept. This 'soft-bail-out' concept is compared with the current best practice ´Too-Big-To-Fail (TBTF)-bail-out´ approach, where only too-big-to-fail banks are bailed-out by the state. The numerical results suggest that our new approach tends to enhance the financial stability of the system and lowers the costs for the state. In this concept, the state uses a bank tax to inject liquidity into the system far before a bank gets insolvent. Additionally, in the new approach the bank tax is structured in a way to optimize system stability.

The reminder of this paper is organized as follows: In the next section, we provide an overview of the related literature. The network of a financial market with stochastic processes for each node, interlinkages of the nodes, macroeconomic shocks, and bank tax payments is modeled in section 3. In section 4 we describe the current concept of bail-outs of too-big-to-fail banks and the new soft-bail-out concept. Based on our network model, section 5 presents numerical results of the reduction in economic costs and added financial stability. Finally, section 6 concludes and derives suggestions for regulators.

2 Literature Review

The related literature can be clustered in four different areas: Financial Networks, Contagion, Concentration/Conglomeration, and Bail-Outs.

Research on the Financial Network Approach: Many researchers apply network techniques from theoretical physics and mathematics to explain systemic risk. Eisenberg and Noe (2001) consider banks as nodes of the system and develop an algorithm that measures systemic risk by incorporating small shocks. Empirical work on the network structure of the Austrian interbank market is provided by Boss et al. (2004). The authors ´… focus on the question of how this structure affects the stability of the network (the banking system) with respect to the elimination of a node in the network (the default of a single bank).´ Their main finding about the Austrian banking market is that ´… there are very few banks with many interbank linkages whereas there are many with only a few links.´ They called this effect ´tiering´. Hanel et al. (2003) examine the potential positive effect of additional ´buffer capital´. They document that additional free capital has no impact on bank behavior. Eboli (2007) uses graph theory and introduces a new ´propagation function´ to model the system of diffusion of losses and insolvencies across the industry. He investigates the relation between characteristics of the network system, e.g. the degree of capitalization, connectivity, and interbank exposures. As a result, he designs a network structure that reduces default contagion. Nier et al. (2008) build a banking network simulation tool to investigate default dynamics and random shock transmission with respect to different capitalizations, interbank exposures, connectivity and concentrations (incl. ´tiered networks´). However, as stated by Allen and Babus (2008), ´the literature of financial networks is still at an early stage´. So far, most academic contributions study financial stability, such as network effects caused by the failure of one bank, i.e. the drop of a node within the network, but seldom focus on the development of new mechanism to increase the stability as a whole.

Research on the Contagion Approach: Besides macroeconomic shocks, contagion is, according to Freixas and Rochet (2008), the second reason for a systemic crisis. Thus, besides macroeconomic shocks we also consider contagion in our model. Many authors focus on informational contagion and analyze the behaviour of banks and depositors. The famous contribution of Diamond and Dybvig (1983) focuses on insurances to avoid bank runs in case of liquidity shocks that arise due to self-fulfilling depositors´ expectations. For the first time, their model addresses the system of contagion. Allen and Gale contribute two important models (Allen and Gale (1998, 2000)). In their 1998 paper, they expand the Diamond-Dybvig model by implementing random returns and earlier access to return information. In their 2000 paper, they explore the response of the financial system to contagion if banks are related in different structures. Against intuition, they show that the more connections within a financial system exist, the more resilient it is since losses are transferred to other banks and, thus, shared within the whole industry. To prevent systemic crisis, they advise regulators to inject liquidity globally (by forcing repos or open market operations).

Freixas et al. (2000) construct a model that captures individual bank risks of random funds withdrawings by customers. Their main question is whether a liquidity shock of one bank can spill over to other banks. In contrast to Allen and Gale (2000), they advise regulators to provide liquidity to specific financial intermediaries instead of flooding the market with liquidity. However, both papers agree on the fact that more connections increase the resilience of the whole banking system. On the other hand, Castiglionesi and Navarro (2007) address a decentralized banking system from the perspective of a social planner that only wants to optimize the structure. A decentralized system is the best solution if the probability of default of the banks throughout the system is low. Problems arise when undercapitalized banks start to gamble.

The main findings in this area of research are summarized by Freixas and Rochet (2008): ´(i) The level of buffers each bank has ... is a key determinant of contagion. (ii) The way in which the failure of a bank is resolved has an impact on the propagation of the crisis. (iii) The system of cross-holdings of assets and liabilities … is essential in triggering systemic crisis. (iv) The specific architecture of this system of cross-holdings matters. A system where each bank borrows only from one bank is more fragile than a system where the sources of funds are more diversified.´

Research on Conglomeration and Concentration: This research area tries to answer the question whether deregulation of markets and allowance of concentration yields to systemic risk and, thus, to a more fragile banking system. Neale et al (2010) examine the impact of the Gramm-Leach-Bliley Act on different sectors of the financial service industry in the US. However, their results about the conglomeration and concentration for the US market are applicable to all financial systems. They find that ´… the reduction of regulation may increase systemic risk …´, but is mitigated at the same time as deregulation allows a higher degree of diversification. Additionally, this recent contribution gives a useful overview of the passage of the Gramm-Leach-Bliley Act and the empirical evidence of the impact over the last decade. Likewise, Nicolo et al. (2003) empirically focus on the relationship of conglomerates and systemic risk and also find that more concentrated markets (concentration) with larger institutions (conglomeration) yields a more fragile banking system. The fact that the famous journal Nature has recently published an systemic-risk article by Haldane and May (2011), underlines the current significance of this topic to the world-wide economy system. They use zoological models to explore the interplay of system complexity and stability and point out that both diversity and modularity ´protects the system resilience of both natural and constructed networks´ such as the financial banking network.

Research on Bank Bail-Outs: According to the early ideas of Bagehot (1873)[13], the founding father of regulatory financial research and the TBTF-approach, central banks function as the lender of last resort (LLR) in case of a potential liquidity shortage of a systemically-relevant, i.e. a too-big-to-fail (TBTF), and solvent bank. Even though many authors and governments consider Bagehot´s idea as obsolete and out-dated, Rochet and Vives (2004) review the idea and confirm, more than hundred years later, his view: a solvent bank (i.e. a bank with a viable business model) can indeed become illiquid. This provides the foundation for the necessity of public bail-outs of solvent but illiquid to TBTF banks. Beside many research papers on the moral hazard of bail-outs, Aghion et al. (1999) argue that too restrictive ´… bank (dis-) closure rules have counterproductive effects on bank managers´ incentives to invest and disclosure prudently´. In order to motivate managers to report truthfully, they put forward the idea of soft-bail-outs, where managers are immune from dismissals. Nevertheless, some researchers, such as Stern and Feldman (2004) criticize that the practice of bail-outs of all too-big-to-fail banks generates moral hazard for TBTF-bank towards a higher risk taking.

[13] *See* Freixas and Rochet (2008).

3 Modeling the Financial Market

In order to study the stability of the financial system, we, firstly, need to model the financial institutions as nodes of the network. Since financial institutions do not share all available assets of the banking market equally, we, secondly, take the different sizes of banks in the network into account. To study network resiliencies, we, thirdly, integrate a realistic interlinkage system between the financial institutions. Fourth, as financial markets experience shocks, expressed in loss of equity, we implement idiosyncratic[14] and system-wide shocks.[15] Fifth, we integrate bank taxation payments in modelling our financial market.

3.1 Modeling One Financial Institution

In accordance with network theory (see, e.g. Eboli (2007) or Nier et al. (2008)), we model the financial system as a network with N nodes, where each node represents one financial institution. Our model contains a maximum number of $\overline{N}$ nodes, thus $N \leq \overline{N}$.

Based on the Merton Model[16] (1974) and the model of financial networks by Haldane and May (2011), we assume that the firm value $V_{t,i}$ of node i follows a stochastic process. Each financial institution is financed by equity $E_{t,i}$ and debt $D_{t,i}$. The firm value at time t is the sum of the equity- and debt-process, i.e., $V_{t,i} = E_{t,i} + D_{t,i}$ with $0 \leq t \leq T$. The debt process follows an exponential process $D_t = D e^{r_D t}$, where r_D is the borrowing yield. As equity is the difference between firm value and debt value ($E_{t,i} = V_{t,i} - D_{t,i}$), the equity process changes automatically if the firm value process alters. The firm value process is modeled as a Geometric Brownian Motion:

[14] An idiosyncratic shock hits one participant of the system. According to the interlinkage of participants in the system, one shock imposes a spillover-effect to other participants. Compare the inclusion of idiosyncratic shocks with Nier et al. (2008).

[15] Note that shocks and contagion caused by the default of one large institution is included in modelling nodes, i.e. financial institutions, with stochastic processes.

[16] However, in contrast to the Merton Model, we also consider defaults during and not only at the end of the observation period. Furthermore, we define a default based on a minimum capital requirement framework.

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t \quad (1)$$

with the stochastic drift parameter $\mu_{t,i}$, the stochastic volatility parameter $\sigma_{t,i}$, and a standard Brownian motion B_t. This basic model is further extended below.

Even though it is academically proven that minimum equity levels are crucial to the stability of the financial system (see, e.g. the Diamond-Dybvig model[17]), the excessive leverage by financial institutions is common practice. This risk taking is widely seen as one reason for the financial crisis.[18] Therefore, we implement in our model a capital ratio parameter ($CR_{t,i}$) as an indicator of leverage, in order to test the hypothesis that a too high leverage can induce a financial crisis. The relationship between the starting values of the equity process $E_{0,i}$ and the firm value process $V_{0,i}$ generates the initial capital ratio ($CR_{0,i}$) of financial institution i at the beginning of the observation period, i.e. $CR_{0,i} = E_{0,i} / V_{0,i}$. The higher the capital ratio, the lower the leverage and, in accordance with the Diamond-Dybvig model, the more stable the financial institution should be. A better capitalization implies that more equity can absorb losses, e.g. due to earnings-fluctuations, spillover write-offs, and macroeconomic shocks, earlier.[19] As all financial institutions have to respect the same minimum capital requirements, the initial capital ratio ($CR_{0,i}$) will be similar for all banks in the analyzed financial system (network). Therefore, we use in our simulation for all financial institutions in the system an equal initial capital ratio, i.e. $CR_{0,i} = CR_0 \;\; \forall i \in N$. However, within the simulation, the capital ratio ($CR_{t,i}$) fluctuates differently according to the realization of the equity and firm value processes of institution i, i.e. $CR_{t,i} = E_{t,i} / V_{t,i}$.

Within the whole observation period, a financial institution i defaults or is, at least, in danger of default if the capital ratio ($CR_{t,i}$) is smaller than a specified minimum capital ratio (CR_{Min})[20], for instance *4.5%* (as proposed in the new Basel III Accord; without conversion or countercyclical buffer), thus if $CR_{t,i} = E_{t,i}/V_{t,i} < CR_{Min}$. In this case the

[17] *See* Diamond and Dybvig (1983).
[18] *See* Hulster (2009).
[19] Spillover-write-offs refer to losses caused by the default of other financial institutions.
[20] Normally, capital ratios are calculated as Tier I capital divided by Risk Weighted Assets. For simplicity reasons, we use in our model all kind of equity $E_{t,i}$ instead of Tier I capital and total assets value $V_{t,i}$ instead of Risk Weighted Assets.

bank will be closed or bailed-out by the regulator. If, on the other hand, institution i meets the minimum capital requirements, thus $CR_{t,i} = E_{t,i}/V_{t,i} \geq CR_{Min}$, it is solvent.

Defaults of nodes at time t are expressed in the default vector F_t, which we need for technical reasons. In case node i defaults in period t the respective entry $f_{t,i}$ in the default vector F_t is 1, and it is 0 in case of no default or in case the default occurred in one of the previous time steps. In other words,

$$f_{t,i} = \begin{cases} 1 & \text{if } E_{i,t}/V_{i,t} < CR_{Min} \\ 0 & \text{if } E_{i,t}/V_{i,t} \geq CR_{Min} \text{ or } \sum_{k=1}^{t-1} f_{k,i} \neq 0 \end{cases}$$

3.2 Structure of the Financial System

The structure of the financial system consists in our case of two components. First, the amount N of financial institutions (with $N \leq \overline{N}$), and second, the distribution of all assets in the system, i.e. the initial distribution of the firm value $V_{t,i}$. The amount of financial institutions in a financial system differs across countries and can be influenced by policy makers. Thus, parameter N is kept variable.

The sizes of financial institutions are not always homogeneous in a system. In general, the opposite holds true. The distribution of all available assets in a financial system ($V_0 = \sum_{i \in N} V_{0,i}$) can appear in many shapes. In our model, we consider four different system shapes, i.e. types of initial firm value distributions V_0:

(i) *homogenous*: all institutions have the same initial firm value,

(ii) *heterogeneous (linear)*: the total initial firm value V_0 is distributed linearly,

(iii) *heterogeneous (tiering*[21]*)*: the total initial firm value V_0 is divided into *m* big and *n* small institutions, where $m + n = N$

(iv) *heterogeneous (1/x)*: the total initial firm value V_0 is distributed according to y = 1/x

Figure 1 demonstrates the different types of initial distributions of firm values $V_{o,i}$ along a fixed amount of *N* financial institutions $(N = 30 = \overline{N})$.

Insert Figure 1 about here

3.3 Interlinkage of Financial Institutions

Each financial institution has a fixed proportion I_i of assets that is interlinked with other institutions, and a fraction of $1 - I_i$ of assets that is not interlinked. Each node $i \in N$ can have a link to another node *j* with $i \neq j$. The probability that node *i* has lent assets to node *j* is denoted as p_{ij}, which is named Erdös-Rényi probability. For simplicity reasons and to lower the number of randomly chosen variables in the simulation, we set the entries of the Erdös-Rényi-Matrix to $p_{ij} = 1 \quad \forall i, j \in N \wedge i \neq j$ and $p_{ij} = 0 \ \ \forall i, j \in N \wedge i = j$.

In accordance with Boss et al (2004), we name the *N x N* - dimensional matrix of assets lent from institution *j* to borrowing institution *i* the liability matrix $L_{i,j}$. In contrast to Boss et al. (2004), we do not focus on the structure of the lent assets. Thus, we normalize the amount borrowed by *i* from *j* by the relative size of the initial firm value of the lending institution $V_{0,j}$. In other words, financial institutions borrow more from bigger counterparts than from smaller ones. In our model, the entries of the liability matrix *L* are calculated by using the initial firm value $V_{0,i}$ of *N* different institutions and the Erdös-Rényi probability matrix entries:

[21] E.g. Boss et al. (2004) document a ‘tiering’ structure for the Austrian Banking System: The set of all financial institutions can be divided into some large banks and many small banks. The term 'tiering' furthermore refers to the fact that very few banks have many interbank linkages whereas many banks have only few links.

$$L_{i,j} = \underbrace{\frac{V_{0,i}}{\sum_j (V_{0,j} \cdot p_{i,j})}}_{\substack{Borrow-Lender- \\ Matrix\ (X_{i,j})}} \cdot \underbrace{(I_i \cdot V_{0,i})}_{\substack{Interlinked- \\ Asset-Vector \\ (Y_i)}} .$$

As (by definition from above) the diagonal of the Erdös-Rényi probability matrix is zero, *L*´s diagonal is zero too, i.e. $L_{i,i} = 0 \ \ \forall i \in N$. The entries of the Borrower-Lender-Matrix ($X_{i,j}$) are between *0* and *1* and represent how much money institution *i* borrows from institution *j*. Furthermore, the sum of each row of $X_{i,j}$ equals one, i.e. $\Sigma_j X_{i,j} = 1$, which represents the total borrowed money of institution *i*. The entries of the Inter-linked-Asset-Vector (Y_i) represent the initial amount of assets of institution *i* that is bor-rowed from other banks. The product of the Borrower-Lender-Matrix ($X_{i,j}$) and Inter-linked-Asset-Vector (Y_i) equals the borrowed money $L_{i,j}$ (the amount *i* borrowed from *j*), which is similar to the expression that *j* lends the amount $L_{i,j}$ to *i*. The sum of each row of matrix $L_{i,j}$ equals the total amount of money that institution *i* has borrowed, i.e. $\Sigma_j L_{i,j} = Y_i$, and the sum of each column of matrix $L_{i,j}$ represents the money institution *j* has lent, i.e. $\Sigma_i L_{i,j}$. Thus, the sum of the column is equal to the write-off of the complete financial system if institution *j* is going bankrupt[22].

In order to calculate the write-off matrix $W_{t,i}$ over time, we need to multiply the liability matrix with the default vector F_t in each period *t*.

$$W_{t,j} = L_{i,j} \cdot F_{t,i}$$

These write-offs have to be implemented in the firm value process. Thus, in case of considered write-offs, equation (1) has to be rewritten to

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} \tag{2}$$

[22] We assume a Loss-Given-Default (LGD) rate of 100%, which means that in case of bankruptcy all outstanding asset have to be written off.

3.4 Idiosyncratic and System-wide Macroeconomic Shocks

Since the financial crisis was not only the result of contagion after the default of one bank, but is also related to economic turmoil[23], we additionally implement macroeconomic shocks in our model. A fixed amount *k* of shocks over the whole observation period *T* that hits all banks $i \in N$ with a shock severity of $h \in (0, 1)$ is integrated in the model and indicating losses relative to the initial firm value. The occurrence of *k* different shocks is randomly distributed over the observation period. Each shock lowers directly the firm value process of bank *i* in time-step *t* by $S_{t,i}$. Therefore, the shock term $S_{t,i}$ has to be implemented into equation (2):

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} \tag{3}$$

Shocks are calculated as follows

$$S_{t,i} = \begin{cases} V_{0,i} \cdot h & \textit{if a shock appears at time t} \\ 0 & \textit{otherwise} \end{cases}$$

3.5 Bank Taxation Payments

As a consequence of the financial crisis, regulators are trying to implement new regimes and rules, e.g. Basel III, that set new limitations and requires more capital insurance. However, in contrast to asking for more equity, Freixas and Rochet (2010) argue that banks have to contribute via a bank tax to finance future banking crises and bail-outs. So far, most countries have already established an additional bank tax in their bank legislation. In most bank tax concepts the tax is calculated as a percentage of assets minus equity. [24] We label this *traditional bank tax* concept with $\hat{B}_{t,i}$ and derive it as follows:

[23] E.g. Allen and Gale (1998, 2000) argue that financial crisis tend to arise as consequence of an economic downturn.

[24] Besides an additional tax on bonuses, in most countries the bank tax (or the currently discussed proposals for bank taxes) follows the same principle: It is calculated as a certain percentage number of total assets minus equity. In *Germany*, banks have to pay annually, depending on their size, between 0.02% and 0.04% of total assets minus equity and minus saving deposits. In *Austria*, banks have to pay 0.07%

$$\hat{B}_{t,i} = \hat{b} \cdot \left[V_{0,i} - E_{0,i}\right]$$

where $\hat{b} \in (0,1)$ is the proportion of assets minus equity that has to be paid.

In accordance with Aussenegg and Kronfellner (2011), we design an *alternative bank tax* $\tilde{B}_{t,i}$ as proportion $\tilde{b} \in (0,1)$ of positive changes of firm value $V_{t,i}$.[25] The advantages of this alternative bank tax are: (i) the tax only needs to be paid if earnings are positive, which does not put further pressure on troubled banks suffering from losses over the last periods, and (ii) it lowers the incentive to gamble[26].

Our results will show (see chapter 4) that one of the main drivers of systemic risk is the interlinkage proportion $I_{t,i}$. Consequently, we enhance the concept of this alternative bank tax and punish banks that are highly interconnected[27], but only – to keep the idea from Aussenegg and Kronfellner (2011) – if earnings are positive. The corresponding alternative bank tax institution *i* has to pay for period *t* is defined as:

$$\tilde{B}_{t,i} = \tilde{b} \cdot 2 \cdot I_{t,i} \cdot Max\left[E_{t,i} - E_{t-1,i},\ 0\right].$$

Although this bank tax construction reminds one to an option payoff, there are no options involved. The alternative bank tax is parameterized such that banks have to pay on average the same amount compared to the traditional bank tax[28]. This fact simplifies a

---

of their total assets as bank tax. *Sweden* proposed a national bank tax of 0.018% of total assets minus equity. In the *United States*, the bank tax proposed by the US president (see The White House Page of Fees – Office of Press Secretary: press release, January 14, 2011) is a Financial Crisis Responsibility Fee that ´… would require the largest and most highly levered Wall Street firms to pay back taxpayers for the extraordinary assistance …´. It would amount to 0.15% of total assets minus Tier I capital and minus insured deposits.

[25] This proportion $\tilde{b}$ has to be set by the local regulators and is a tool to regulate the system.

[26] *See* Aussenegg and Kronfellner (2011).

[27] Note that we only take into account interconnections to other banks if they are not secured or hedged. In practice, this would mean that we only need to consider current credit lines to other financial institutions.

[28] The factor 2 in the alternative bank tax equation scales it to the traditional bank tax. In mathematical terms: The expected alternative bank tax payments equals the traditional bank tax payments, i.e. $E(\tilde{B}_{t,i}) = E(\hat{B}_{t,i})\ \forall i$, under the condition that the expected earnings of institution *i* are around zero for all periods *t*, i.e. $E\left[E_{t,i} - E_{t-1,i}\right] \sim 0$.

potential implementation in the banking sector. Under this approach additional money is kept by the government to finance further bail-outs.

Furthermore, in both concepts the bank tax lowers the firm value process in equation (3), resulting in:

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} - B_{t,i} \,, \tag{4}$$

where $B_{t,i}$ can either be the traditional or the alternative bank tax, i.e.

$$B_{t,i} = \begin{cases} \hat{B}_{t,i} = \hat{b} \cdot \left[V_{0,i} - E_{0,i} \right] & \textit{traditional approach} \\ \tilde{B}_{t,i} = \tilde{b} \cdot 2 \cdot I_{t,i} \cdot Max\left[E_{t,i} - E_{t-1,i},\, 0 \right] & \textit{alternative approach} \end{cases}$$

The question remains how the new funds from the bank tax should be used most efficiently to finance future bank bail-outs, as suggested by Freixas and Rochet (2010). The approach in the next section tries to answer this question.

4 Measuring and Modeling Bank Bail Outs

The model of the financial market, developed in the previous chapter, is not complete. Bail-outs by the central bank of too-big-to-fail (TBTF) banks, need to be implemented such that we can compare the current approach to bail-outs with the new concept of a soft-bail-out. However, measuring the efficiency of a concept is not easy. Many ratios and measurements can be applied to capture how much a mechanism is able to ease the systemic risk in the financial industry. Therefore, we, firstly, focus in this chapter on measuring the stability of a financial system, and, secondly, describe the current and the new bail-out approaches.

4.1 Measuring Bank Stability

We decide to use two common measures to show how much a new concept can increase the stability of the financial system: (i) the simulated weighted default rate of the whole system (weighted based on the banks total assets), and (ii) the economic costs for bail-outs.

We design the *weighted default rate* as the proportion of defaulted assets (not numbers of banks) in the system in comparison to the total amount of assets in the system. Since defaults of small banks are not as server as the insolvency of large banks, we weight the default rate with the initial size of the bank $V_{o,i}$. Obviously, the higher the weighted default rate ($\Omega_t \in (0,1)$) at the end of the observation period ($t = T$), the higher the probability of the total collapse of the financial system. Ω_T is calculated as matrix multiplication of the default vector (F_T) at the end of the observation period and the transposed initial firm value vector V_0 in relation to the sum of the initial firm values V_0.

$$\Omega_T = \frac{\left(F_T \cdot (V_0)^T\right)}{\sum_{i=1}^{N} V_{0,i}}$$

The costs for bail-outs are divided into *bail-out costs for the government* (C_G) and *bail-out costs for banks* (C_B). Consequently, the sum of both equals the total costs for the whole economy and is denoted *economical bail-out costs* (C).

The bail-out costs for the government (C_G) are only driven by the need of a bank bail-out. In both approaches, a bank will be bailed-out by the state if it belongs to the group of the too-big-to-fail (TBTF) banks. A bank is a TBTF-bank if its initial firm value $V_{0,i}$ settles above the *TBTF-Borderline* (V_{TBTF}), indicated as a percentage number of assets owned compared to all assets (V_0) in the financial system. We indentify bank i as a TBTF-bank if $(V_{0,i} / V_0) > V_{TBTF}$.

The bail-out costs for banks (C_B) only consist of the bank tax. However, these expenses can be seen as a liquidity reserve collected by the government to finance further necessary[29] future bail-outs.

4.2 Two Bail-Out Concepts

In this section, we describe the two bail-out concepts: *´TBTF-bail-out´* and *´soft-bail-out´* and we will compare them in the next chapter according to the two measures of stability.

(a) The first concept, the *´TBTF-bail-out´*, is the current best practice of governments to bail-out too-big-to-fail banks. If within the observation period the realization of the residual equity process $E_{t,i}$ of a TBTF-bank is lower than the realization of the firm value process $V_{t,i}$ times the minimum capital ratio CR_{Min}, for instance 4.5%, the government bails-out the bank by recapitalizing it via a capital injection to the higher capital ratio CR_I. Consequently, this approach requires the (partial) nationalization of the insolvent bank and, as the firm value almost equals the debt process, we assume that the government pays nothing to shareholders in acquiring the troubled institution. In this TBTF-bail-out concept the traditional bank tax is applied, i.e. $B_{t,i} = \hat{B}_{t,i}$.

Implementing the bail-out of too-big-to-fail banks into the equity process implies:

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} - B_{t,i} + \overline{dE_{t,i}} \tag{5}$$

The additional term $\overline{dE_{t,i}}$ is the bail-out payment by the state. This payment should recapitalize troubled banks up to capital ratio of CR_I, a specific too-big-to-fail capital injection ratio parameter, for instance 9%. It is only paid to ´insolvent´ ($E_{t,i} / V_{t,i} < CR_{Min}$) too-big-to-fail banks ($V_{0,i} / V_0 > V_{TBTF}$):

[29] According to our definition, we consider a bail-out as `necessary` if the bank is big enough, i.e. belongs to the group of TBTF-banks, such that the government – per model construction – needs to bail-out the bank.

$$\overline{dE_{t,i}} = \begin{cases} dE_{t,i} = CR_I \cdot V_{t,i} - E_{t-1,i} & if \ \dfrac{V_{0,i}}{V_0} > V_{TBTF} \ \wedge \ CR_{t,i} < CR_{Min} \\ 0 & otherwise \end{cases}$$

(b) The second concept is a new approach called *´soft-bail-out´*. The government would use the liquidity reserve from the bank tax to boost the firm value $V_{t,i}$ of all troubled banks (and not only the TBTF-banks) far before the insolvency. This liquidity injection – that is already conducted in the area of the bank´s solvency – allows the bank to recover from a downturn on its own[30]. The point of liquidity injection is given by soft-bail-out-capital ratio borderline (CR_{SBO}), of, for instance, 6%. Note that CR_{SBO} is similar for all banks.

However, if the bank could not manage to fight its financial troubles with this early liquidity injection and is still heading towards bankruptcy, the government will – as in the normal bail-out approach – bail-out the crisis-ridden TBTF-bank. Thus, the soft-bail-out concept can be seen as an enriched normal TBTF-bail-out concept, as in case of insolvency a TBTF bank receives a (´normal´) bail-out too.

As the liquidity injection directly increases the equity of the bank, it needs to be added to the equity process function and equation (5) has to be rewritten (again):

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} - B_{t,i} + \underbrace{\overline{dE_{t,i}}}_{\substack{TBTF- \\ Bail-Out}} + \underbrace{\sum_{t=\overline{t_{j-1}}}^{\overline{t_j}} B_{t,i}}_{Soft\ Bail\ Out} \tag{6}$$

$\overline{t_j}$ are dates of liquidity injections with $j \in (1, 2, ...)$, where the realization of the firm value process is smaller than the specified soft-bail-out-capital-ratio (CR_{SBO}). In this concept $B_{t,i}$ refers to the alternative bank tax, i.e. $B_{t,i} = \hat{B}_{t,i}$.

[30] Moreover and as already implemented in the EU restructuring process, we suggest that a liquidity injection via a soft-bail-out requires the submission of a bank-restructuring concept from the bank. This condition should help troubled banks to turnaround the obviously miss-functioning business model.

In times of profit, firms usually boost their business by increasing the leverage, i.e. institutions take more debt. In our model, this means that above a specific maximum capital ratio (CR_{Max}), for instance 12%, banks increase leverage such that the capital ratio equals exactly this maximum capital ratio.

Figure 2 gives an overview of the four different capital ratio boundaries (CR_{Min}, CR_{SBO}, CR_I, and CR_{Max}) for too-big-to-fail and for non-too-big-to-fail institutions. Note that meaningful assumptions of these four different capital ratio boundaries must satisfy the following inequation $CR_{Min} < CR_{SBO} < CR_I < CR_{Max}$.

Insert Figure 2 about here

On the left hand side of the graph, we illustrate the situation for non-too-big-to-fail institutions, which will not be bailed-out by the government in case of insolvency. Below the minimum capital ratio (CR_{Min}) the institution is in our model per definition defaulted. If the new soft-bail-out concept is used, institutions below the soft-bail-out capital ratio (CR_{SBO}) receive soft-bail-out payments from the state, which pushes the capital ratio ($CR_{t,i}$) away from the default area. (The amount of capital that is used for the soft-bail-out of institution i depends on the funds that i has paid to the state in previous periods.) Above the maximum capital ratio (CR_{Max}), institutions are considered to increase leverage by taking more debt, which pushes the capital ratio again at the maximum capital ratio.

On the right hand side Figure 2, we consider the situation for too-big-to-fail institutions. They will be bailed-out by the government if the capital ratio ($CR_{t,i}$) falls below the minimum capital ratio (CR_{Min}). As described above, TBTF bail-out means that the bank is (partial) nationalized and the capital ratio $CR_{t,i}$ is increased by the government till the TBTF capital injection ratio CR_I.

5 Numerical Simulation and Results

Even though the above descript model might remind the reader of the relatively new theory of general stochastic hybrid systems, an analytical solution cannot be achieved due to the complexity of the model. As every time step t of the observation period T can be a hitting time (i.e. where a bank turns insolvent) for the N different realizations of firm value processes, a solution would consists of T different convolutions for all N different institutions, which cannot be calculated properly. Consequently, we use – in analogy to most financial networks- and contagion-research contributions – a numerical Monte Carlo Simulation approach to derive results.

5.1 Simulation Method and Assumptions

We use Monte Carlo Simulation (and the software package Crystal Ball) to demonstrate (i) the effect of contagion (see chapter 5.2), (ii) the main drivers of systemic risk (see chapter 5.3), and (iii) the possibilities to increase system stability with the new soft-bail-out concept, that enriches the current TBTF-bail-out concept (see chapter 5.4).[31]

Steps and Iterations

The overall observation period is divided into 100 different steps. In our simulation we interpret one step as one quarter of a year and parameterize the model upon. Thus, the whole observation period consists of 25 years, which is a long time horizon but a realistic view for systemic risk considerations. However, any other number of steps could be applied and would deliver comparable results. At each step we calculate for all N different banks their profits, firm values, potential defaults, write-offs, bank-taxes, etc. The Monte Carlo Simulation is performed with 10,000 iterations. This means that each of the 100 steps are calculated 10,000 times with $N \leq \overline{N} = 30$ different stochastic processes for the firm value process, as described in the section above.

[31] The software Crystal Ball is used to conduct Monte Carlo Simulations.

Modeling the Banks´ Profit

The increments ΔV_t of the firm value process V_t and, thus, also the equity process E_t are determined by the profit. As the model is designed to capture situations in the financial sector, yearly mean and standard deviation of the profit are simulated based on daily returns of the S&P Banking Index (BIX) over the six year period from 2006 until 2011[32]. This time period ensures that we encounter the situation of a steep decrease in value in an environment of high volatility. Hence, our simulation can be taken as a realistic extreme or stress test scenario.

5.2 Measuring the Contagion Effect

It is commonly known in the academic literature that contagion is *the* critical factor for financial network failures.[33] Our model is built in a way such that the contagion effect can be carved-out from others factors and can be directly measured. To show this effect, we set up the model such that the government never bails-out a bank[34] and simulate the *weighted default rates* for different *interlinkage proportions* (I_i). Recall that the interlinkage proportion indicates the percentage of assets connected to other financial institutions within the system and has, therefore, to be written-off in case of a counterpart default.

Figure 3 represents the relationship between the interlinkage proportion and the weighted default rate in different financial network structures. The graphs reveal a strictly positive relationship between the interlinkage proportion and the average weighted default rate. Note that in all financial network structures, the simulated weighted default rate reaches 100% at a certain interlinkage proportion. In other words, if the financial system is very interlinked (with an interlinkage proportion of 35% to

[32] Both the mean and the standard deviation are calculated based on the BIX by applying a rolling window of one year. The S&P Banking Index (BIX) is a sub-index of the S&P 500 and contains 16 mid- and large-cap financial institutions. The BIX is a commonly used index to model the developments of financial institutions.

[33] This is also demonstrated in the sensitivity analysis of the next chapter.

[34] A governmental bail-out would falsify the contagion effect as banks are then be supported by public money.

45%), then bail-outs are no more an option for the regulator, as the whole financial system will collapse very likely.

Insert Figure 3 about here

This analysis exhibits that the degree of bank interconnections within a system is a crucial driver for contagion.

5.3 Drivers of Instability

In accordance to many research contributions, such as Nier et al (2008), we fixed in the previous chapter all input parameters (except the interlinkage proportion) with a ceteris paribus approach to perform the Monte Carlo Simulation. This allows us to carve out the contagion effect in order to study it stand-alone. However, in the real world, many factors need to be taken into account together. Thus, we try to answer the question of many regulators and governments on which factors of the financial system they need to focus on and what parameter manipulation is most efficient to stabilize the financial system as a whole. The system parameters we focus on are:

- Interlinkage proportion (I_i)
- Amount of shocks (k)
- Initial capital ratio (CR_0)
- Amount of banks (N)
- Severity of shocks (h)
- Costs of debt (r_D)
- Financial structure
- Market Volatility[35]

By using Monte Carlo Simulation, we perform a sensitivity analysis of all model parameters and study how they influence the weighted default rate, which is the objective

[35] Fitted to the S&P Banking Index BIX.

function in this analysis.[36] Figure 4 reveals the results of this sensitivity analysis and indicates the importance of the different factors on the weighted default rate at the end of the observation period (Ω_T) and, thus, on the financial stability. The parameter sensitivities are displayed as percentage numbers. The higher the percentage number and the larger the bar in Figure 4, the bigger is the influence of a specific parameter on the weighted default rate. The interlinkage proportion parameter (I_i = *39.5%*) is the main driver for the weighted default rate and, thus, for the financial network stability. The second most influential parameter is the amount of banks (N = *18.1%*), followed by the market volatility with (σ_i = 16.2%) and the amount of macroeconomic shocks (k = *13.4%*).

Insert Figure 4 about here

Based on these results, regulators and governments can design new regulations and limiting requirements for these parameters to further stabilize the financial system. Normally, some of those parameters are already given by the financial network. For instance, in Austria the tiering-structure is given and cannot be changed (easily) by the regulator. Consequently, for a set of given parameters, regulators can perform optimizations to find the value for the not-given parameters that most efficiently stabilize the system.

[36] The sensitivity analysis is performed by the software package Crystal Ball. While it runs the Monte Carlo simulation, Crystal Ball uses the method of Rank Correlation to dynamically calculate the relationships among the parameters and the results of the simulation.

5.4 Comparing TBTF-Bail-Out with Soft Bail-Out Concept

In this section we compare the traditional TBTF-bail-out concept and the new soft-bail-out concept. To recall, in the traditional *TBTF-bail-out* concept an insolvent bank will be bailed out by the state if it is a too-big-to-fail bank, i.e. $(V_{0,i} / V_0) > V_{TBTF}$. We set a maximum of 50% of banks that are bailed-out.[37] In this traditional approach the bank tax is calculated as a percentage $\hat{b}$ of the difference between asset and equity and needs to be paid in every period. In our simulation $\hat{b}$ = 0.01% per step, i.e. a quarter of a year, which is comparable to the German and Austrian legislation.

In contrast, in the new *soft-bail-out* concept the bank tax is an earnings tax that only needs to be paid if the return per period is positive. Moreover, the bank tax is linked to the amount of interconnections of the bank within the financial system. Thus, the bank tax increases with the amount of interconnections. In addition to the traditional TBTF-bail out, in the new soft-bail-out concept banks already receive funds far before their bankruptcy. This allows banks to recover from financially troubled times on their own. The soft-bail-out payment is injected to troubled banks at an optimal point – according to our Monte Carlo Simulation optimization results[38] – of CR_{SBO} = 6%.

To provide an overview, Table 1 compares the three approaches along the main characteristics: bail-out trigger event, bank tax calculation, and bank tax calculation linked to the interlinkage proportion of the bank.

The three approaches analyzed are:

- **TBTF-bail-out** (with traditional bank tax)
- **Soft-bail-out without** connection between bank tax and the interlinkage proportion (with alternative bank tax)
- **Soft-bail-out with** connection between bank tax and the interlinkage proportion (with alternative bank tax)

[37] On one hand, if the maximum value of banks that are bailed-out is small, too-big-to-fail banks are not considered for governmental bail-out. On the other hand, if the maximum value of bailed-out banks is close to 100%, governments risk to support unsustainable banking systems. In our simulation, we set this value to 50% to avoid both extreme value problems, described above.

[38] This optimization is performed by minimizing the economic costs for a fixed weighted default rate.

Approach	Bail-out trigger event	Bank tax calculation	Bank tax linked to interlinkage proportion
TBTF-bail-out	At insolvency	Asset-Equity	No
Soft-bail-out w/o	Far before insolvency*	Profit	No
Soft-bail-out with	Far before insolvency*	Profit	Yes

* If funds for soft-bail-out are not sufficient, only TBTF banks are completely rescured.

Table 1: Comparison of the three bail-out approaches

We show that the new soft-bail-out concept improves the traditional TBTF-bail-out approach in three dimensions: **(i)** the new approach is *less costly*, **(ii)** the bail-out costs are *less volatile* when credit lines (i.e. interlinkage proportions) change[39], and **(iii)** it is *more stable* (i.e. lowers the weighted default rate).

Ad (i): In a first step we compare the two approaches TBTF-bail-out and soft-bail-out w/o. As the interlinkage proportion (I_0) is the main driver of contagion and system stability, we plot the economic bail-out costs (C) on a *I_0-C-coordinate system*. Figure 5 reveals how the soft-bail-out approach (*without* considering the connection between bank tax and interlinkage proportion) lowers, compared to the traditional TBTF-bail-out concept, economic costs (C) (which are the bail-out costs for the government (C_G) minus the bail-out costs for all banks (C_B)). The area *above* the x-axis represents negative economic costs (C) and can be seen as profit for the economy (the government) that can be used elsewhere. In contrast, the area *below* the x-axis displays positive costs (C), implying that the bank tax does not provide enough funds to cover all bail-out costs. In this case, the economy (the government) needs to finance the bank-bail-outs with other funds. The two lines in Figure 5 are the result of linear regressions on 10,000 data points of Monte Carlo Simulations for the two bail-out approaches.[40] The parallel shift of the two lines, indicated by the arrows in Figure 5, can be interpreted as reduction in government costs (C_G), whereas the costs borne by banks (C_B) are the same in both ap-

[39] Below we display economic cost changes for different (bail-out) approaches as a function of the interlinkage proportion.

[40] Even though the R^2 of the linear regression is lower than for a regression with a higher order, we choose linear regression lines to easier compare the two concepts.

proaches.[41] In other words, under the same circumstances (bank tax and weighted default rate[42]) the new soft-bail-out concept is less costly than the traditional TBTF-bail-out approach. Economically spoken, the increase in system efficiency is caused by the fact that in the soft-bail-out approach banks receive a liquidity injection far before their insolvency and, thus, have the opportunity to (easier) recover on their own.

Insert Figure 5 about here

Ad (ii): In a second step we consider the connection between the alternative bank tax and the interlinkage proportion, as described in equation (4). Figure 6 reveals that the soft-bail-out concept *with* a connection between bank tax and interlinkage proportion generates a flatter slope of the regression line. This implies that in a world where credit lines between banks (i.e. the interlinkage proportions) are changing over time[43], bail-out costs are not as volatile as in approaches where the bank tax is not linked to the interlinkage proportion. This twist of the regression line towards less volatile costs is indicated in Figure 6 by small arrows that compare the soft-bail-out approach without and with interlinkage proportion connection. Note that the soft-bail-out approach with interlinkage proportion connection is less favorable in banking systems with a low degree of interlinkages between banks. The reason for this is that a lower interlinkage level generates less bank tax proceeds when the bank tax is based on the interlinkage level.

Insert Figure 6 about here

Ad (iii): In both, the first and the second step of our simulation, we can show that the weighted default rate decreases in a soft-bail-out concept, implying a *more stable* financial system. This effect is indicated in Figures 4 and 5 by circled numbers. They reveals that the TBTF-bail-out approach generates a weighted default rate of *20%*, whereas the

[41] Note that the alternative bank tax is parameterized according to the traditional bank tax in order to simplify a potential implementation of this new mechanism in the bank sector.
[42] The weighted default rate is even slightly smaller by applying the soft-bail-out concept than it is for the traditional TBTF-bail-out approach.
[43] Eisenberg and Noe (2001) even describe linkages between firms as cyclical and create the term *cyclical interdependence*.

soft-bail-out approaches generates lower rates of *17%* and even *16%*, in case the bank tax is connected to the interlinkage proportion.

5.5 Robustness checks

Having outlined the three dimensions of improvements of the new approach, we finally focus on the question of model sensitivity. In other words, what happens to the results and to the relative positions of the regression lines if we consider other scenarios? Therefore, as shown in Table 2, we define a best-, base-, and worst-case scenario by varying the main model parameters (amount of banks (*N*), amount of shocks (*k*), initial capital ratio (CR_0), severity of shocks (*h*), and debt costs (r_D)). As the interlinkage parameter (*I*) is the most influential driver for financial stability, we vary it in every calculation and illustrate it on the x-axis of the charts in Figures 7 and 8. The two least influential parameters, the financial network structure and the debt costs (r_D) remain fixed. The column ´Sensitivity´ in Table 2 refers to the results of Figure 4, where we outline the degree of influence of the parameters.

		Considered Cases		
Parameters	**Sensitiv**	**Best**	**Base**	**Worst**
Interlinkage (I)	39.5%	-----0-100% (variable)-----		
Amount of Banks (N)	18.1%	10	20	30
Market Volatility	16.2%	-------Fitted to BIX -------		
Amount of Shocks (k)	13.4%	0	1	3
Initial Capital Ratio (CR)	-10.0%	15%	12%	9%
Serverness of Shocks (h)	1.9%	10%	20%	30%
Debt Costs (r_D)	1.0%	0%	2.5%	5%
Financial Network Structure	NA	------Tiering (fixed)-------		

Table 2: Considered cases for model sensitivities

Figure 7 reveals the results of the best-, base-, and worst-case scenario. The new concepts, i.e. the two new *soft-bail-out approaches*, are in any case better than the *TBTF-concept*. In all three scenarios, the soft-bail-out concept *without* connection to the bank tax is (slightly) less costly for the economy when the interlinkage proportions (*I*) is low.

In contrast, the soft-bail-out concept *with* connection to the bank tax should be preferred when banks are highly interlinked with each other. Note that in the best case (see Panel (a) of Figure 7), where no shock appears, banks have a high initial capital ratio of 15%, the costs for debt are zero, and the amount of banks is low, the economy even receives money from the bank tax (for interlinkage values of 40% and lower).

Insert Figure 7 about here

Furthermore, we analyze the effect of changing only one parameter from the base case in Table 2 to the best- or worst-case. Figure 8 reveals that in all cases the relative position of the regression lines for the three approaches, the *soft-bail-out concept with* and *without* a connection to the bank tax and the *TBTF-concept*, are quite similar. The two new soft-bail-out concepts are better and less costly. This analysis shows that the dominance of the two new soft-bail-out concepts does not only hold true for a specific set of parameters, but is valid for many other realistic (and also extreme) parameter combinations. The eight graphs in Figure 8 exhibit the results for the base case plus the variation of one specific parameter (e.g. I.(a) shows the base case with k = 0 as varied parameter).

Insert Figure 8 about here

Moreover, in all cases (see Figure 7) *and* (parameter-wise) variation of the base case (see Figure 8), the weighted default rates (Ω) of the soft-bail-out concepts are better than for the TBTF-concept, the current best practice.

6 Concluding Remarks and Implications

In the run-up to the recent financial crisis, regulators and financial institutions intend to avoid future crisis and, thus, strive to strengthen the financial system for upcoming shocks and bankruptcies. Especially, systemic risk has become an industry-wide concern. So far, new regulatory regimes, new taxations, new limitations of bank´s capital ratios, etc., have been installed to stabilize the system. However, the contagion effect as the main driver of systemic risk has been hardly tackled directly yet. In order to do so, this paper contributes in applying ideas from four different research areas – Financial Networks, Contagion, Concentration/Conglomeration, and Bail-Outs – and proposes a new soft-bail-out concept that can reduce contagion after macroeconomic shocks or bankruptcies.

By including the most important network parameters of the current financial system in our model, we, firstly, show that the interconnectivity between banks is the main driver of contagion. Secondly, we outline the influence of all parameters on the system stability and rank them. Thirdly, we elaborate a new soft-bail-out concept for regulators that lowers the costs for (necessary) bank bail-outs, decreases the fluctuation of bail-out costs, and increases the stability in terms of the system-wide default rate. This soft-bail-out approach refers to the idea that governmental funds are injected far before bank insolvency. To finance these funds an alternative bank tax, connected to the most influential driver of instability, the interconnectivity of banks, is proposed. Thus, the concept suggests that a bank needs to pay more if it is highly connected to other financial market participants. Furthermore, for banks this new bank tax is equally expensive compared to a bank tax that is calculated as a proportion of total assets or total assets minus equity, as it is currently often applied in practice.

Based on our results, we drive three implications for regulators and governments:
(i) Current bank taxes should be changed from a fixed proportion of total assets system to an earnings based system. This would put less pressure on already troubled banks.
(ii) Bank taxes should be related to the interconnectivity of the corresponding bank, as this parameter tends to be the main driver of financial instability.

(iii) Soft-bail-out payments – paid far before an actual insolvency occurs – should be implemented, funded by the proposed alternative bank tax. This would allow troubled banks to recover on their own.

As an outlook to further research based on this paper, we want to mention the following additional ideas: first, a cyclical modeling of the market drift and volatility and, consequently, of capital ratios would even more precisely describe financial markets. Second, the collected funds from an alternative bank tax for future soft-bail-outs could be kept in the banks as liability reserves instead of being transferred to the governmental budget. Third, the asset process could be divided into different asset categories. Upon this separation a more precise asset modeling with stochastic processes and calculation of risk weighted assets would be possible.

Appendix: Notation overview

N … Amount of considered nodes (financial institutions) in the system

$\overline{N}$ … Maximum amount of considered nodes (financial institutions) in the system

T … Amount of time steps in the observation period with time index t

$E_{t,i}$ … Equity process of financial institution i at time t (Geometric Brownian Motion)

$D_{t,i}$ … Debt process of financial institution i at time t (Exponential Process)

$V_{t,i}$ … Firm value of bank i at time t ($V_{t,i} = E_{t,i} + D_{t,i}$) with initial firm value $V_{0,i}$

r_D … Borrowing yield, i.e. costs of debt

$CR_{t,i}$ … Capital ratio of financial institution i at time t ($CR_{t,i} = E_{t,i} / V_{t,i}$)

CR_{Min} … Minimum capital ratio. If $CR_{t,i} < CR_{Min}$ institution i defaults

CR_{Max} … Maximum capital ratio. If $CR_{t,i} > CR_{Max}$ institution i will increase debts $D_{t,i}$

CR_I … TBTF capital injection ratio. If $CR_{t,i} < CR_{Min}$ and if institution i is too-big-to-fail, it receives a governmental bail-out up to this capital ratio

CR_{SBO} … Soft-bail-out capital ratio. If $CR_{t,i} < CR_{SBO}$ institution i receives a soft-bail-out

F_t … N-dimensional default vector with entries $f_{t,i}$ equals 0 (no default or earlier default) and 1 (default in period t)

I_i … Proportion of the initial firm value that is interlinked to other institutions

$p_{i,j}$ … Erdös-Rényi probability that node i has lent a fraction of I_i to node j

$L_{i,j}$ … Liability matrix indicates liabilities that the financial institution j has with institution i (Equals the product of the Borrower-Lender-Matrix ($X_{i,j}$) and the Interlinked-Asset-Vector (Y_i))

$S_{t,i}$ … Equity losses of bank i at time t due to a shock

k … Amount of shocks within the observation period

h … Severity of a shock, indicated as a percentage number of the initial equity $E_{0,i}$

$B_{t,i}$ … Bank tax payment of bank i at time t

$\hat{B}_{t,i}$ … Traditional bank tax of bank i at time t. It is a proportion $\hat{b}$ of $V_{t,i}$ minus $E_{t,i}$

$\tilde{B}_{t,i}$ … Alternative bank tax of bank i at time t. It is a proportion $\tilde{b}$ of the profit and the interlinkage proportion $I_{t,i}$

Ω … Weighted average default rate of the financial system. It indicates the proportion of defaulted banks (measured in initial firm value $V_{0,i}$)

C_G … Bail-out costs for the government

C_B … Bail-out costs for all banks

C … Economic bail-out costs

V_{TBTF} TBTF-Borderline

References

Aghion, P., P. Bolton, and S. Fries, 1999, *Optimal Design of Bank Bailouts: The Case of Transition Economics*, Journal of Institutional and Theoretical Economics, Vol. 55, pp. 51-70.

Allen, F. and A. Babus, 2008, *Networks in Finance*, Wharton Financial Institutions Center Working Paper No. 08-07.

Allen, F. and D. Gale, 1998, *Optimal Financial Crises*, Journal of Finance, Vol. 53 (4), pages 1, pp. 245-284.

Allen, F and D. Gale, 2000, *Financial contagion*, Journal of Political Economy, Vol. 108, pp. 1-33.

Aussenegg, W., and B. Kronfellner, 2011, *Alternative Bank Tax Modelling to Increase Bank Stability*, Vienna University of Technology, Working Paper.

Bagehot, W., 1873, *Lombard Street, a Description of the Money Market*, London: Kegan Paul. Rpt., London: John Murray, 1920.

Boss, M., H. Elsinger, M. Summer, and S. Thurner, 2004, *The network topology of the interbank market*, Quantitative Finance, Vol. 4, pp. 1-8.

Broome, L. L. and J. W. Markham, 2001, *The Gramm-Leach-Bliley Act: An Overview*, Center for Banking and Finance of the University of North Carolina School of Law, Working Paper

Castiglionesi, F., and N. Navarro, 2007, *Optimal Fragile Financial Networks,* CentER Discussion Paper, 2007-100, pp. 1-39.

Diamond, D. and P. Dybvig, 1983, *Bank Runs, Deposit Insurance and Liquidity*, Journal of Political Economy, 91, pp. 401-419.

Eboli, M., 2007, *Systemic risk in financial networks: a graph-theoretic approach*, Università di Chieti Pescara, Working Paper.

Eisenberg, L. and T. Noe, 2001, *Systemic Risk in Financial Systems*, Management Science, 47(2), pp. 236-249.

Feldman, J. R, G. H. Stern, and P. A. Volcker, 2004, *Too Big to Fail: The Hazards of Bank Bailouts*, Brookings Institution, Washington D.C.

Freixas, X., B. Parigi, and J.C. Rochet, 2000, *Systemic Risk, Interbank Relations and Liquidity Provision by the Central Bank*, Journal of Money, Credit and Banking, 32(3), pp. 611-638.

Freixas, X., and J.C. Rochet, 2010, *Taming SIFI (Systemically Important Financial Institutions)*, Universitat Pompeu Fabra, University of Zurich, Working Paper.

Freixas, X., and J.C. Rochet, 2008, *Microeconomics of Banking – Second Edition*, The MIT Press, Cambridge Massachusetts.

Haldane, A. G., and R. M. May, 2011, *Systemic Risk in Banking Ecosystems*, Nature, Vol. 469, pp. 351-355.

Hanel, R., S. Pichler, and S. Thurner, 2003, Risk Trading, Network Topology, and Banking Regulation, Quantitative Finance, Vol. 3, Issue 4, pp. 306-319.

Huang, X., H. Zhou, and H. Zhu, 2009, *A Framework for Assessing the Systemic Risk of Major Financial Institutions*, Finance and Economics Discussion Series Divisions of Research & Statistics and Monetary Affairs Federal Reserve Board, Washington, D.C. 2009-37.

Hulster, D. K., 2009, *The Leverage Ratio*, Worldbank Crisis Response No. 11, Financial Systems Department of the World Bank.

Memmel, C., A. Sachs, and I. Stein, 2011, *Contagion at the interbank market with stochastic LGD*, Discussion Paper Series 2: Banking and Financial Studies No 06/2011.

Merton, R. C., 1974, *On the pricing of corporate debt: the risk structure of interest rates*, Journal of Finance, Vol. 29, pp. 449–470.

Mirchev, L., V. Slavova, and H. Elefteridis, 2010, *Financial System Transformation – a Network Approach*, University of Nice, New Bulgarian University Sofia, Working Paper.

Neale, R. F., P. P. Drake, and S. P. Clark, 2010, *Diversification in the Financial Services Industry: The Effect of the Financial Modernization Act*, The B.E. Journal of Economic Analysis & Policy, Vol. 10, Issue 1, Article 16, pp. 1-28.

Nicolo. D. G., P. Bartholomew, J. Zaman, and M. Zephirin, 2003, *Bank Consolidation, Internationalization, and Conglomeration: Trends and Implication for Financial Risk*, IMF Working Paper WP/03/158.

Nicolo, D. G, and M. L. Kwast, 2002, *Systemic Risk and Financial Consolidation: Are They Related?*, IMF, Journal of Banking and Finance, Vol. 26, Issue 5, pp. 861-880.

Nier, E., J. Yang, T. Yorulmazer, and A. Alentorn, 2008, *Network Models and Financials Stability*, Bank of England, Working Paper No. 346.

Rochet, J. C. and X. Vives, 2004, Coordination Failures and the Lender of Last Resort: Was Bagehot Right After All, Journal of the European Economic Association Vol. 2(6), pp. 1116–1147.

Figure 1: Different types of financial network structures

By varying the initial firm value $V_{0,i}$ of the $N=30$ financial institutions $i \leq N$, we generate different financial structures: in a homogeneous financial structure all N financial institutions have the same initial firm value $V_{0,j} = V_{0,i} \quad \forall i \neq j$, whereas in a heterogeneous world financial institutions are starting from different initial firm values $V_{0,j} \neq V_{0,i} \quad \forall i \neq j$. (i) Homogeneous: all institutions have the same size; (ii) Heterogeneous-linear: the firm value increases from institution to institution by the same amount; (iii) Heterogeneous-tiering: the system consists of m big banks and n small banks (e.g., for N = 30, m = 8 and n = 22); (iv) Heterogeneous - 1/x: the firm value decreases according the function 1/x, i.e., $V_{0,i} = V_0/i$ with $i = 0 \ldots N$. Thus, firm $i = 1$ is the largest and $i = N$ is the smallest institution.

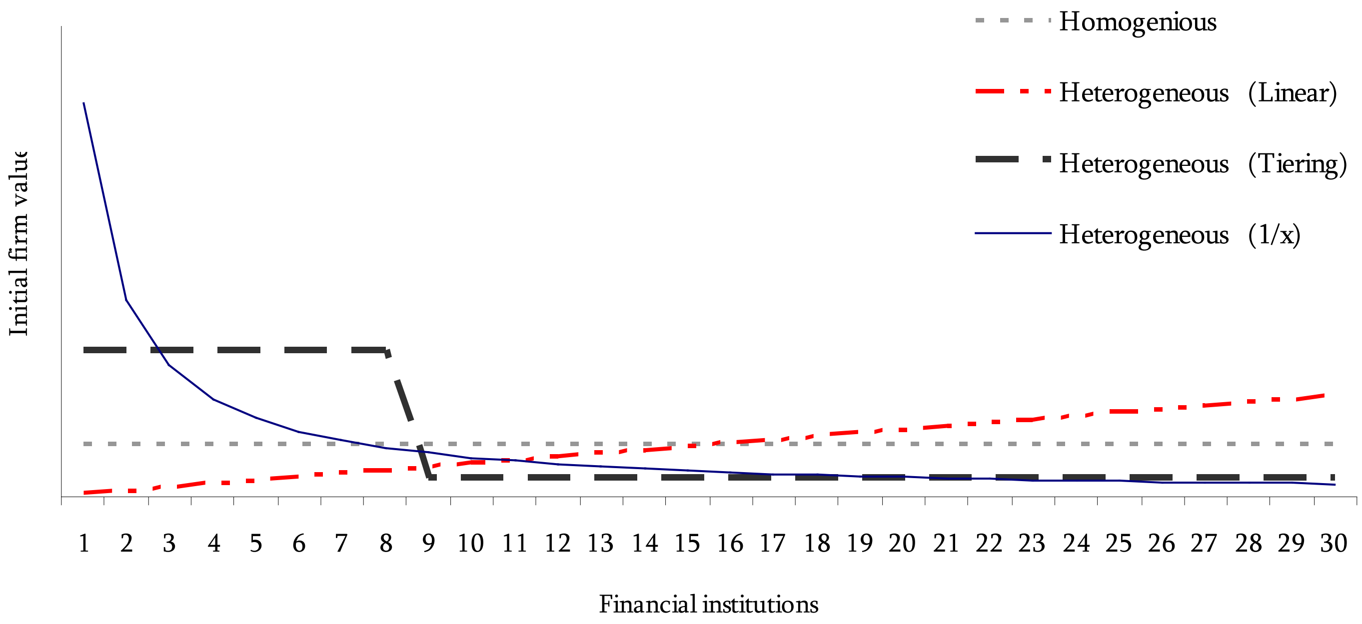


Figure 2: Overview of different capital ratio boundaries used in the model for (a) non-too-big-to-fail banks and (b) too-big-to-fail banks.

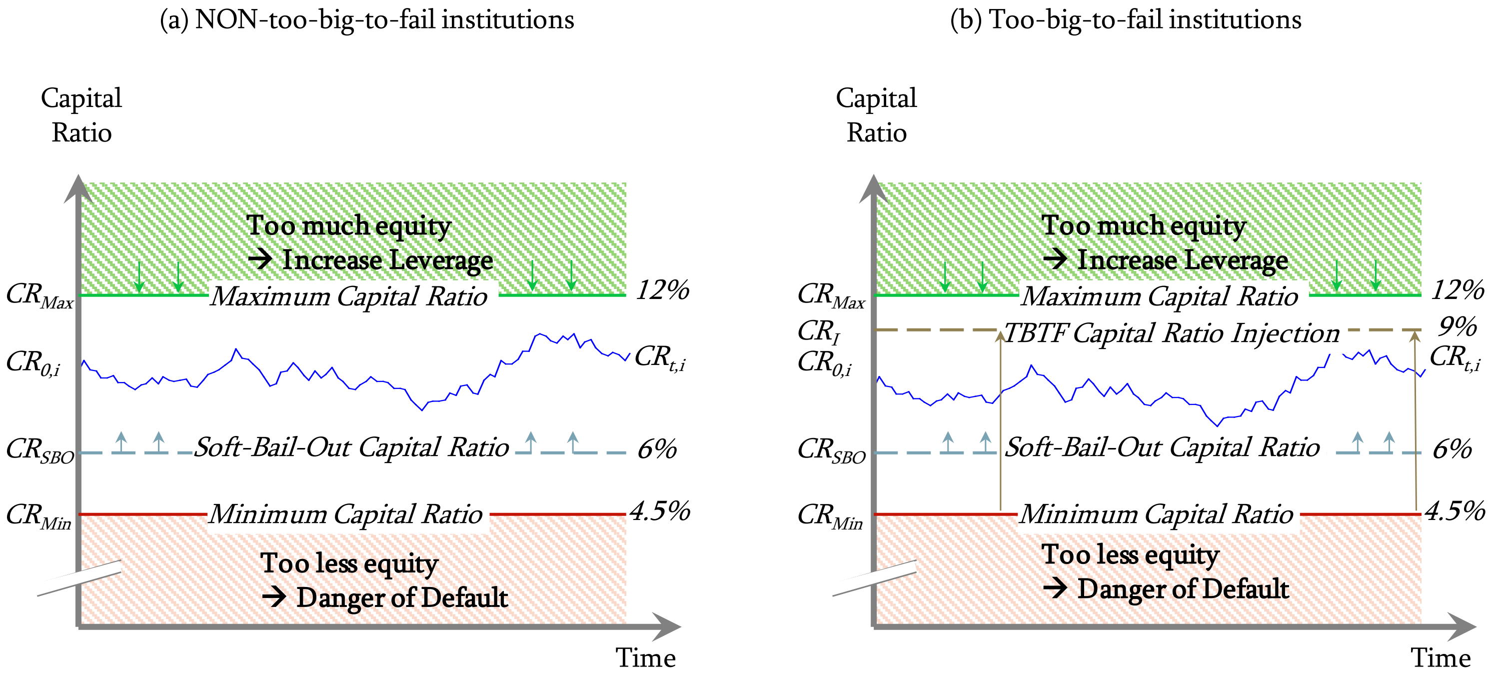


Figure 3: The contagion effect of different financial network structures

The relationship of interlinkage proportion and weighted default rate of the total system is simulated by using N = 30 banks, no macroeconomic shocks, a leverage ratio of $l_i = 10 \ \forall i$, i.e. 10% equity), costs of debt of $r_D = 5\%$ *p.a.* , total asset values standardized to $V_0 = 1{,}000$ currency units, a linear heterogeneous financial structure (the firm value increases from institution to institution by the same amount), and a too-big-to-fail- (TBTF-) bail-out concept. The firm value process is the sum of the equity- and debt-process, where the debt process is an initially fixed movement of the exponential process (see equation (1)) and the equity value is modeled with a stochastic process (with mean and standard deviation parameters based on the BIX (S&P Banking Index) by applying a rolling window of one year).

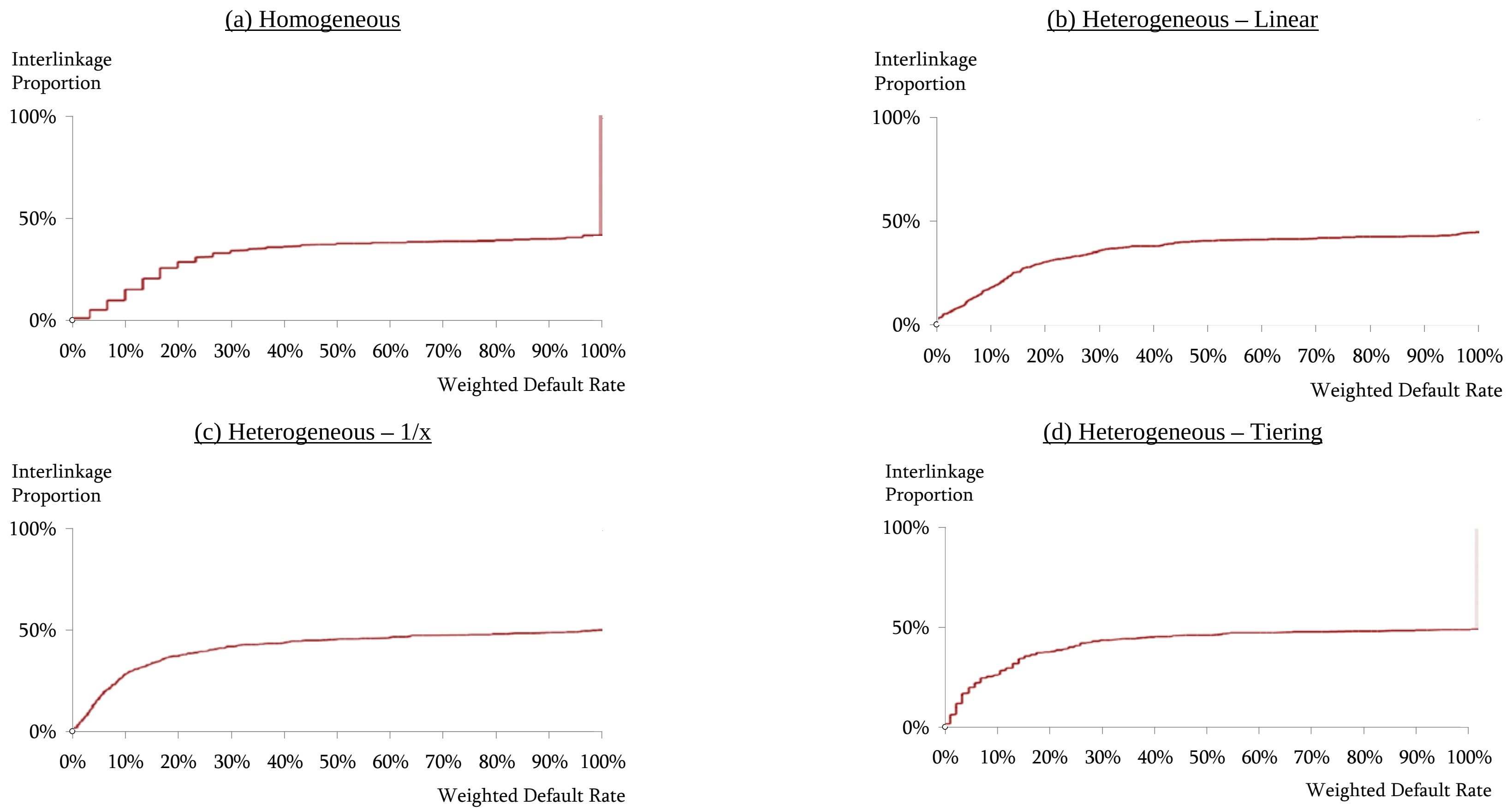


Figure 4: Influence of financial market parameters on the weighted default rate

The different bars of financial market parameters indicate the importance of each parameter for the financial stability in terms of weighted default rate. The variation interval of the model parameters for the sensitivity analysis are: **Interlinkage proportion** $I_i = 0\% \ldots 100\%\ \forall i$ (continuous); **amount of banks** $N = 5, \ldots, 30$ (discrete); **market volatility** is fitted to the BIX index; **amount of macroeconomic shocks** $k = 1, 2, 3$ (discrete); **initial capital ratio** $CR_i = 9\% \ldots 15\%\ \forall i$ (continuous); **severity of shocks** $h = 10\% \ldots 30\%$ (continuous); **borrowing yield** $r_D = 0\% \ldots 5\%$ (continuous); **financial network structure**: *fixed to heterogeneous-tiering*. Note that no bank bail-out is allowed in this sensitivity analysis, i.e. $V_{TBTF} = 100\%$.

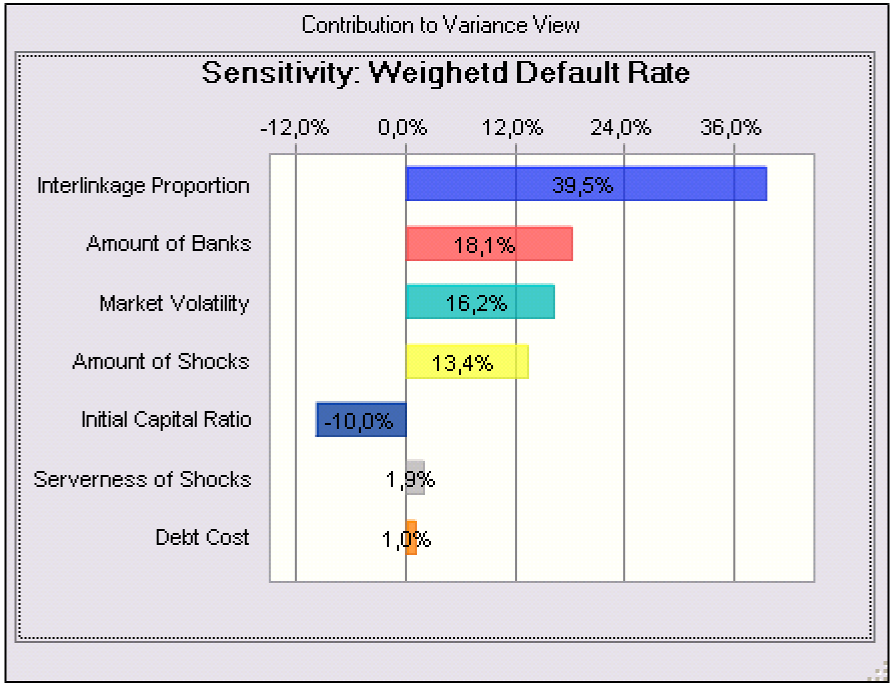


Figure 5: Economic costs of the TBTF-bail-out and the soft-bail-out approach (*without* connection between bank tax and the interlinkage proportion)

The (nearly) parallel shift of the two regression lines shows that the new soft-bail-out concept is at even a lower level of weighted default rate less costly. This means less costs for the soft-bail-out approach, compared to the TBTF-bail-out approach, at a lower rate of insolvencies. The model parameters used in the simulation are: the **interlinkage proportion** $I_i = 0\%, ..., 100\% \ \forall i$ (continuous) and the stochastic elements of the firm value process as stated above. The fixed model parameters are: **amount of banks** $N = 20$; **amount of macroeconomic shocks** $k = 1$; **severity of shocks** $h = 20\%$ (i.e. a decrease of 20% in equity); **borrowing yield** $r_D = 2.5\%$; **initial capital ratio** $CR_i = 12\% \ \forall i$; **financial network structure**: *heterogeneous-tiering*; the TBTF-borderline $V_{TBTF} = 5\%$; and only 50% of the biggest banks are bailed-out. However, all other (realistic) parameter values and other network structures would lead to comparable result.

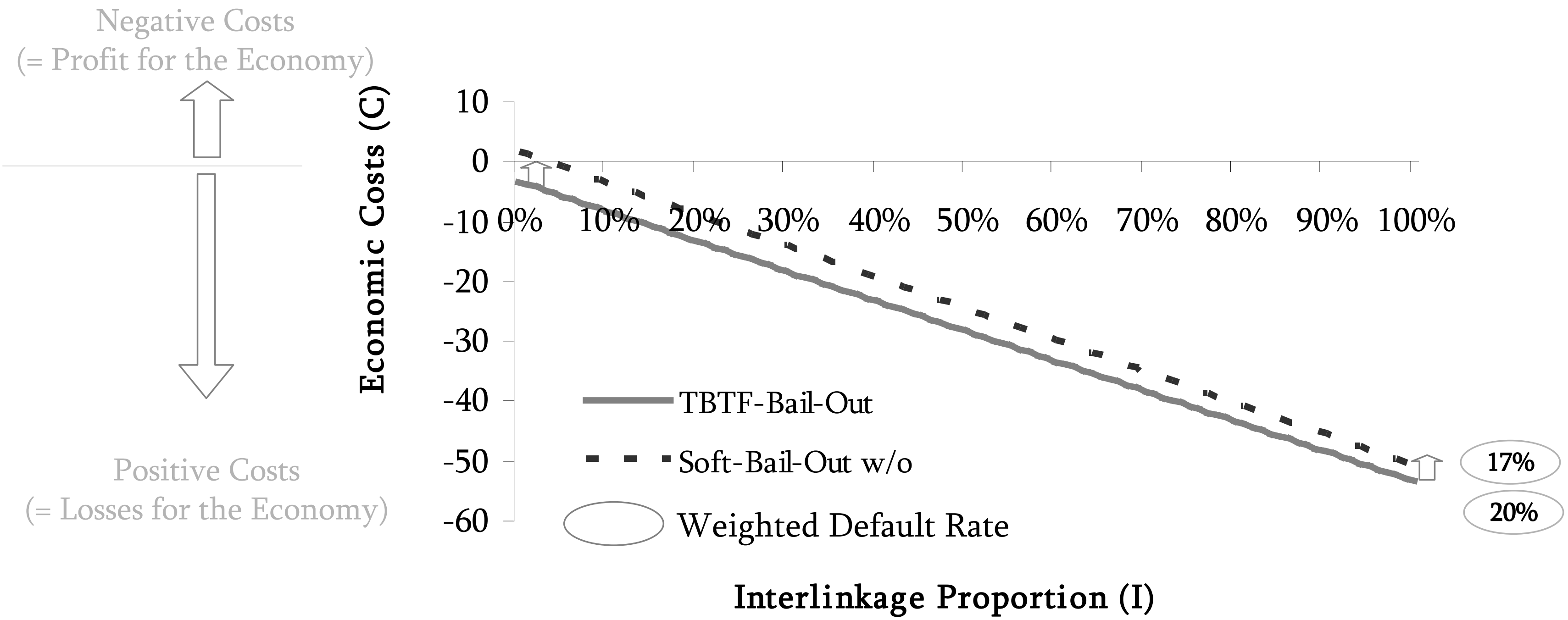


Figure 6: Economic costs of the TBTF-bail-out and the soft-bail-out approaches *with* and *without* connection between bank tax and the interlinkage proportion

The variable model parameters used in the simulation are: the **interlinkage proportion** I_i = *0%, ..., 100%* $\forall i$ (continuous) and the stochastic elements of the firm value process. The fixed model parameters are: **amount of banks** *N = 20*; **amount of macroeconomic shocks** *k = 1*; **severity of shocks** *h = 20%*; **borrowing yield** r_D = *2.5%*; **initial capital ratio** CR_i = *12%* $\forall i$; **financial network structure**: *heterogeneous-tiering*; the TBTF-borderline V_{TBTF} = *5%*; and only 50% of the biggest banks are bailed-out. However, all other (realistic) parameter values would generate comparable results (see sensitivity analysis results in Figures 7 and 8).

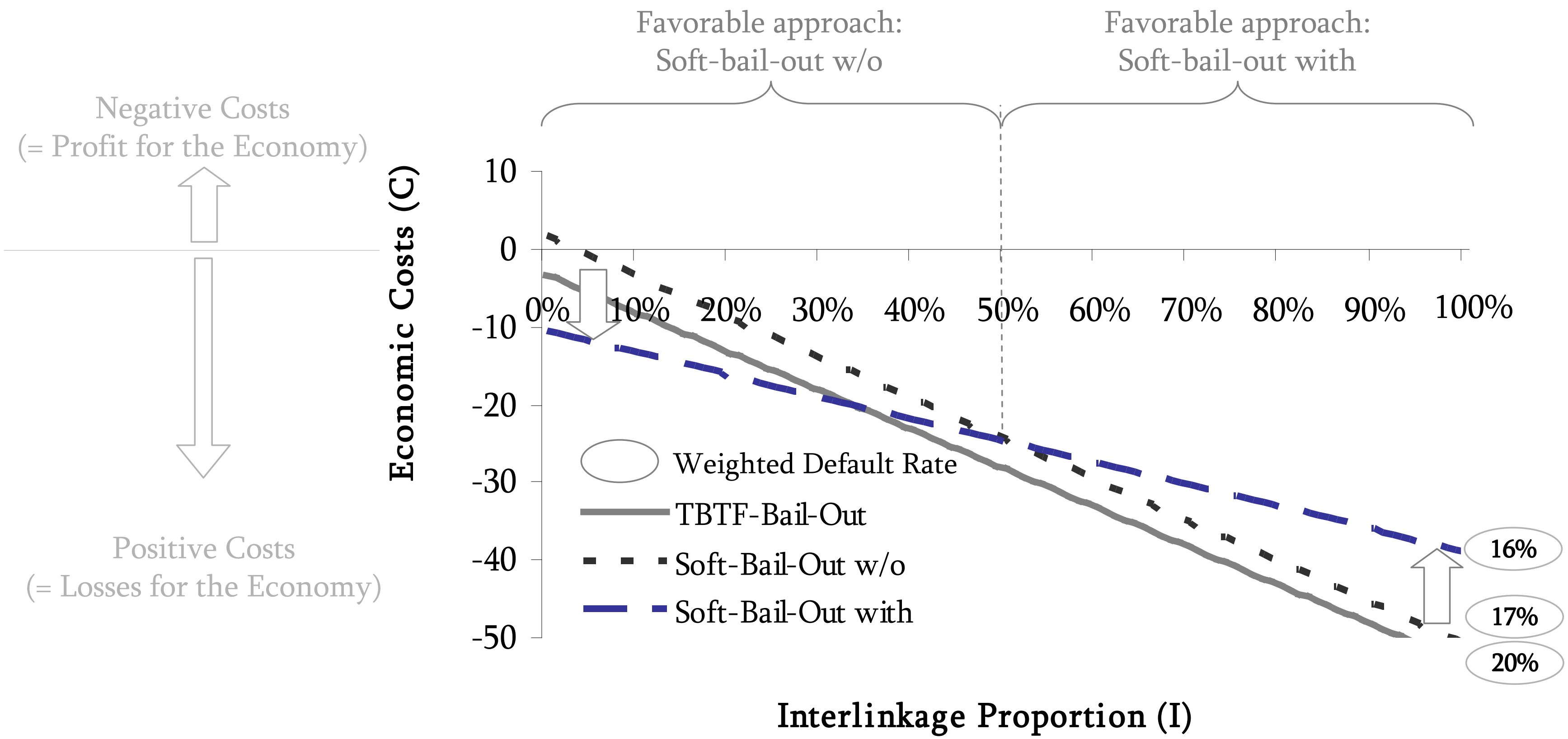
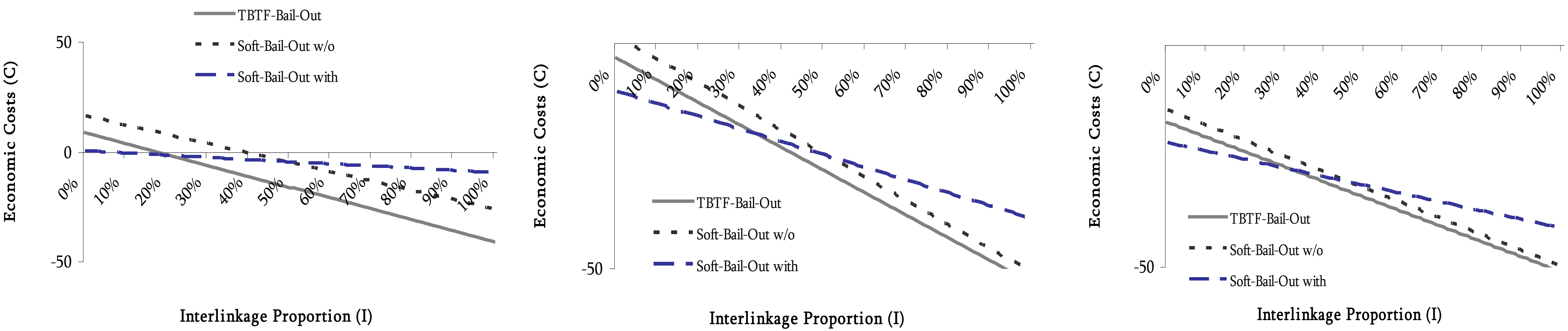


Figure 7: Model parameter sensitivity analysis: Simulation result of a best-, base-, and worst-case scenario

The model parameters of the **best case** are: the interlinkage proportion $I_i = 0\%, ..., 100\%\ \forall i$ (continuous), amount of shocks $k = 0$, initial capital ratio $CR = 15\%$, amount of banks $N = 10$, severity of shocks $h = 10\%$, debt costs r_D = 0%. The model parameters of the **base case** are: the interlinkage proportion $I_i = 0\%, ..., 100\%\ \forall i$ (continuous), amount of shocks $k = 1$, initial capital ratio $CR = 12\%$, amount of banks $N = 20$, severity of shocks $h = 20\%$, debt costs r_D = 2.5%. The model parameters of the **worst case** are: the interlinkage proportion $I_i = 0\%, ..., 100\%\ \forall i$ (continuous), amount of shocks $k = 3$, initial capital ratio $CR = 9\%$, amount of banks $N = 30$, severity of shocks $h = 30\%$, debt costs r_D = 5%. The parameter financial network structure is fixed for all cases to a *heterogeneous-tiering* structure and the market volatility is fitted by using the S&P Banking Index BIX.

(a) Best case | (b) Base case | (c) Worst case



Parameters Best Case

Amount of Shocks (k)	0
Initial Capital Requirement (CR)	15%
Amount of Banks (N)	10
Serverness of Shocks (h)	10%
Debt Costs (r_D)	0%

Parameters Base Case

Amount of Shocks (k)	1
Initial Capital Requirement (CR)	12%
Amount of Banks (N)	20
Serverness of Shocks (h)	20%
Debt Costs (r_D)	2.5%

Parameters Worst Case

Amount of Shocks (k)	3
Initial Capital Requirement (CR)	9%
Amount of Banks (N)	30
Serverness of Shocks (h)	30%
Debt Costs (r_D)	5%

Figure 8: Model sensitivity checks: Parameter-wise variation of the base case

Consideration of parameter-wise variation of the base case, as illustrated in Table 2. The eight graphs exhibit the results for the base case plus variation of the specified parameter (e.g. I.(a) Base case plus k = 0). The model parameters of the **base case** are: the **interlinkage proportion** I_i = *0%, ..., 100%* $\forall i$ (continuous), **amount of shocks** k = *1*, **initial capital ratio** CR = *12%*, **amount of banks** N = *20*, **severity of shocks** h = *20%*, **debt costs** r_D = 2.5%. The parameter **financial network structure** is fixed for all cases to a *heterogeneous-tiering* structure and the **market volatility** is fitted by using the S&P Banking Index BIX.